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FROM WHOM DO FARMERS LEARN?
AN ANALYSIS OF TECHNICAL EFFICIENCY DETERMINANTS FOR THE INDIAN GREEN REVOLUTION

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ABSTRACT

Technological innovation has been recognized as a major source of economic growth with the potential to be an effective force for alleviating economic inequality around the world. Hence, articulating the mechanism of technological adoption and diffusion has been of special interest to development economists. The Green Revolution as a case in point has been the subject of many studies since it necessitated a drastic change in production practices by farmers. The change led by the Green Revolution generated a great deal of "learning" opportunities in the production of High Yielding Varieties (HYV).

Learning is a dynamic process spanning the adoption of technologies to the realization of their yield potentials. Capturing such a dynamic process is a crucial issue. Learning is generally regarded as an increase in the stock of knowledge and skills in production processes that are associated with new technologies. In the economics literature, productivity improvement is assumed to reflect learning, and it is often indicated by output or profit increase, or cost reduction.

This study employs efficiency measurement in connection with production frontier analysis as a gauge of individual learning in the case of HYV castor production in Aurepalle village, India over the period 1975 to 1984. Specifically, we investigate a) whether learning, as well as other determinants, impact the technical efficiency in production and b) the existence of systematic patterns in learning-from-others.

First, estimation of the stochastic frontier production function yields technical inefficiencies of individual farms. Then, inefficiency is regressed on its potential determinants, which include variables representing learning, i.e. experiences, where the coefficients of the learning terms indicate learning impacts on inefficiency reduction. Among the potential determinants, human

capital-related variables, such as schooling, experiences, and age, are of special interest to ascertain how much they contribute to the efficiency gain. Three models are specified to reflect the impact of learning-from-others, especially learning within a reference group, which is defined based on similar farm-size, similar household size, and caste rank.

One of the major motivations characterizing learning in a framework of the stochastic frontier analysis is to achieve a careful measurement of learning. There exists a body of individual learning literature capturing learning through the effects of experiences with new technologies on outputs (or profits). However, this approach is not capable of distinguishing changes in outputs (or profits) driven by technological changes as opposed to those driven by learning. On the other hand, the stochastic frontier approach enables the separation of productivity gains led by the technological progress from efficiency gains through learning of the technology. This separation is crucial when impacts of technological changes on production processes are substantial.

The learning-by-doing effect is robust, but modest. The learning-from-others' effect varies across the reference group models, indicating the importance of farmers' learning opportunities. The learning-from-others is statistically significant only when learning from others within the same household size. The result suggests that learning randomly from neighbors may not guarantee efficiency gains since farms cannot simply imitate neighbors' experiences to enhance efficiency. The results further imply that technological dissemination is better targeted to the reference group level rather than at the village level. This study finds that the potential reference group can be based on household size.

Farm size and household size dominate the effects of efficiency enhancement with respect to magnitude and significance, which, in addition to the result of scale elasticities, implies that scale economies play an important role in castor production, especially in HYV production. Age is another efficiency-enhancing factor although its significance is not robust across the models. The dependency ratio, on the contrary, has a consistent and negative impact on efficiency levels. Education is also confirmed to enhance efficiency. This result highlights the importance of investing in children's schooling and providing quality education.

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Chapter 1

INTRODUCTION

The introduction of high-yielding varieties (HYV), beginning in 1960s, has transformed the nature of agricultural practice from simple and static to complex and dynamic in the poorer regions of the world. Extensive and rapid adoption of HYV is one of the most significant technological changes in agriculture known as the "Green Revolution." However, the adoption of HYV alone does not guarantee productivity gains. Successful adoption often involves chemical (fertilizer and pesticide) use and timely water application. Such a technologically complementary package is often significantly different from the traditional input use.

Green Revolution technology has been the major instrument behind the impressive gains in food grain output in India. Food grain yields in India doubled during the mid-1960s to the mid-1990s. Wheat, especially, has been the stellar performer, nearly tripling the yields during the same period. Yields of rice and coarse grains approximately doubled while yields of oilseeds increased by 150 percent. On the contrary, pulse yields recorded only a minimal improvement in yields.

As the degree of success varied across crops, the degree of adjustment required from farmers depended on the type of crop. HYV production for certain crops (such as rice) necessitates an intensive use of seeds, chemical, and fertilizers, and timely application of water. On the other hand, such intensive input use is not crucial for other crops (such as coarse grains, pulses, and oilseeds).

1.1. Statement of the Problem

In agriculture, unlike technological changes common in non-agricultural industries, realization of potential profits from the agricultural technologies depends largely on farmers' adjustment efforts in production. For instance, the Green Revolution created substantial opportunities for farmers to learn new practices associated with the HYV production since HYV require sensitive use of inputs to realize yield potentials. Did learning really take place during the course of the HYV diffusion? What is the nature of the learning? This study investigates evidence of learning in the HYV production using the notion of technical efficiency in the stochastic frontier approach.

1.2. Motivation

Technological adoption has been studied extensively since the 1970s. In particular, the Green Revolution has been one of the major topics of interest due to the significance of its impact. Studies of agricultural technological adoption fall into three categories. The first makes use of cross-sectional data to identify determinants of technological adoption. The second employs time-series data to elucidate the overall diffusion process. The third class of studies makes use of panel data to illustrate individual learning, which had not been initiated until the 1990s due to a lack of data.

Panel data enabled and motivated scholars to investigate individual learning process of new technologies. All the studies of this kind made use of data from the Indian Green Revolution mainly due to their availability. They modeled individual learning process and demonstrated that learning was significant in profit (or output) growth associated with the HYV production (*e.g.*, Foster and Rosenzweig 1995, Besley and Case 1997). Another characteristic of those studies is that learning has been explicitly or implicitly discussed in connection with the concept of human capital (*e.g.*, Foster and Rosenzweig 1995).

This study introduces the frontier analysis to the learning literature. The frontier function approach is capable of estimating inefficiency level of each producer. In contrast, the conventional estimation approach assumes all producers act efficiently, implying there exists no inefficiency in production. Furthermore, the frontier function approach enables separation of the efficiency component of productivity from the technological component. Since learning is measured through the efficiency component, accurate estimation of the efficiency component is crucial for this study.

The Green Revolution provides an excellent opportunity to identify learning within the framework of the frontier analysis for the following reasons: 1) at the outset of the technological adoption, farmers are technically inefficient; 2) efficiency gain, which varies across farmers, can be achieved through learning.

1.3. Objectives

The specific objectives of this study are as follows:

1. to specify and estimate a stochastic frontier production function using the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) household panel data to determine each farm's technical efficiency level;
2. to specify the efficiency level as a function of farm-specific variables (efficiency model), and estimate the model to identify determinants of the efficiency;
3. to characterize a methodology which empirically investigates the presence of learning-by-doing and learning-from-others in a framework of stochastic frontier analysis;

4. to characterize the structure of castor production using output and scale elasticities as well as Morishima elasticity of substitution;
5. to examine whether learning, as well as other determinants, impact the technical efficiency in castor production; and
6. to investigate whether any systematic pattern exists in learning-from-others.

Chapter 2

LITERATURE REVIEW

Technological innovation has been recognized as a major source of economic growth with the potential to be an effective force for alleviating economic inequality around the world. Hence, articulating the mechanism of technological adoption and diffusion has been of special interest to development economists. The Green Revolution as a case in point has been the subject of many studies since it necessitated a drastic change in production practices by farmers. The change led by the Green Revolution generated a great deal of "learning" opportunities in the production of HYV.

Learning is a dynamic process spanning the adoption of technologies to the realization of their yield potentials. Capturing such a dynamic process is a crucial issue. Learning is generally regarded as an increase in the stock of knowledge and skills in production processes that are associated with new technologies. In the economics literature, productivity improvement is assumed to reflect learning, and it is often indicated by output or profit increase, or cost reduction.

This study employs efficiency measurement in connection with the frontier analysis as a gauge of individual learning. First, estimation of the stochastic frontier production function yields technical inefficiencies of individual farms. Then, inefficiency is regressed on its potential determinants, which include variables representing learning where the coefficients of the learning terms indicate learning impacts on inefficiency reduction.

This chapter is organized into three sections. Section 2.1 reviews the literature of technological adoption and learning. Section 2.2 provides an overview of the frontier analysis and measurement of efficiency as well as relevant empirical studies. Section 2.3 surveys empirical studies of identification of efficiency determinants with an emphasis on human capital factors.

2.1. ADOPTION AND LEARNING OF AGRICULTURAL TECHNOLOGY

Development of empirical studies of the subject has been undertaken according to the type of data available. Technological adoption has primarily been studied with the use of either cross-sectional or time-series data. Many cross-sectional and time-series studies are found in two comprehensive surveys conducted by Feder *et al*. (1985) and an updated summary by Feder and Umali (1993) focusing on studies of agricultural innovations reaching maturity.

Studies with cross-sectional data analyze technological adoption conditional on a specific time period since such data only contain information at one point in time. Those studies employing time-series data investigate diffusion of the technology following the adoption at an aggregate level. Such investigations can capture a multi-period aspect of adoption, but it cannot grasp an underlying process of the aggregate adoption. Recent development of micro-level (or household) panel data permits us to study individual learning of technologies. Besley and Case (1993) provides a theoretical review of possible empirical models of technology adoption based on this type of data.

In the following, Sections 2.1.1 and 2.1.2 review cross-sectional and time-series studies, respectively. Discussion on panel data studies follows in Sections 2.1.3 and 2.1.4.

2.1.1. Cross-sectional Studies

Both cross-sectional and time-series data have been extensively used to analyze technological adoption and diffusion. Cross-sectional data provide only a snapshot of farms' technology use at a point in time. As such, cross-sectional studies are conditional on time-specific farming environments as well as farms' characteristics such as knowledge about the new technology.

A large number of cross-sectional studies on technological adoption can be categorized according to the factors affecting the adoption process. However, the significance of those factors on technological adoption varies depending on the phases of the diffusion process.

Studies of the early phase of diffusion processes show that farm size, credit constraints, and tenure status can significantly affect technological adoption. The majority of evidence indicates a positive correlation between technological adoption and farm size (*e.g.*, Binswanger 1978, Jamison and Lou 1982, Wozniak 1987). Also, a number of studies find that lack of credit does significantly limit technological adoption (*e.g.*, Willis 1972, Khan 1975, Bhalla 1979). In contrast, empirical studies on the impact of tenure status is mixed. Some studies show that tenants have a lower tendency to adopt new technologies than owners (*e.g.*, Parthasarathy and Prasad 1978), while others reach the opposite conclusion (*e.g.*, Vyas 1975). Schutjer and Van der Veen (1977) claim that the conflicting empirical results may be due to the implied relationships between tenure and access to credit, input markets, product markets, and technical information.

However, current studies demonstrate that farm size and tenure status are no longer essential in technological adoption at the final phase of the diffusion process. For example, Ramasamy *et al.* (1992) find that tenure and farm size are not significant in the adoption of modern variety of rice in Tamil Nadu, India. David and Otsuka (1990) and Otsuka and Gascon (1990) also find the same result using data on Philippines rice farmers.

The other significant determinants of technological adoption are human capital, which are represented by several different variables such as household head's education and experience, and access to extension services. Wozniak (1987) demonstrates that schooling and frequency of extension access are positively correlated with the probability of adoption and that experience is negatively correlated with the adoption for the case of Iowa farmers. Lin (1991) finds that schooling as well as farm size has a positive and significant impact on the probability of adoption of hybrid rice in Chinese. On the contrary, Pitt and Sumodiningrat (1991) find that schooling does not play an important role in the adoption of HYV of rice in Indonesia.

Smale *et al*. (1994) present a unique approach to explaining adoption of HYV of maize in Malawi. The study finds that four competing factors (input fixity, portfolio selection, safely-first behavior, and learning) seem to jointly explain decisions on land allocation in the HYV adoption, suggesting that employing approaches based on single explanations may lead to inappropriately narrow conclusions.

2.1.2. Time-Series Studies

What is known about the adoption of new technologies also comes from time-series evidence. With this kind of data, one observes only an aggregate measure of adoption or diffusion, such as the percentage of farms employing the new technology at a given point in time and how the percentage changes over time (Besley and Case 1993). Studies with time-series data usually aim at capturing the shape of the diffusion process in a certain period. They also identify either the major determinants of diffusion speed or the characteristics of farms determining how long they delay adoption. Much of this kind of research has been inspired by frequent empirical findings of S-shaped patterns of aggregate diffusion over time (Feder *et al.* 1985). The shape signifies that the proportion adopted is an increasing function of time which is initially convex but eventually concave.

Griliches (1957) empirically illustrates that the difference in diffusion patterns of hybrid corn among selected states in the US stems from the profitability of the adoption of the hybrid corn. Mansfield (1961), using data on various American industries, explains an S-shaped diffusion path assuming that the driving force of the diffusion process is imitation. This empirical study finds that the rate of imitation tends to be faster for innovations that are more profitable and that require relatively small investments.

There is a stream of literature emphasizing the effect of learning on innovation diffusion in an agricultural context. An underlying assumption is farmers' imperfect information about the profitability of adopting new technologies. In those studies, information acquisition plays a vital role in the diffusion processes.

As one of the early efforts focusing on learning and innovation diffusion, Hiebert (1974), using data from Philippines rice farmers, examines the effect of "learning" under uncertainty on the decision to adopt fertilizer use, specific to seed varieties. The author demonstrates that additional information and enhanced ability to decode information increases the likelihood of adoption.

Many of aggregate learning studies after Hiebert (1974) formulate learning in Bayesian specifications, rather than ad hoc specifications, where prior beliefs about the innovation are updated based on information from observed performance. Linder *et al.* (1979) introduce a theoretical model of adoption using the specification of Bayesian learning. Feder and O'Mara (1982) theoretically provide justification for the use of cumulative adoption as an index of learning and experience in formulating a perceived production function. Feder and Slade (1984) find that larger Indian rice farmers are likely to allocate more resources to acquire information, resulting in higher levels of knowledge about the production process. The study also implies that farmers with easier access to information or better endowments of human capital acquire higher levels of information. Shampine (1998) derives a Bayesian model of technology diffusion and discusses it from the social planner's point of view, regarding non-adopters' learning from adopters as information externalities.

Although a number of time-series studies have investigated the role of learning in diffusion processes with rigorous specifications of learning, these kinds of studies are limited in what it can be said about the underlying dynamic process at an individual producer level (Besley and Case 1993).

2.1.3. Panel Data Studies

Compared to a large number of time-series and cross-sectional studies, panel data had not been used in the area of technological adoption until Besley and Case (1993) affirmed that household panel data enables economists to explore the learning processes of individual farms over time, as well as to control for unobservable household heterogeneity.

Learning is defined "as a relatively permanent change in behavioral potentiality that occurs as a result of reinforced practice" (Kimble 1961, pg.6). Learning has played a minor role in economics historically since the concept of rationality has dominated economics for many decades. Since rational economic agents are assumed to process all of the available information to realize the economically optimal action, there is neither a place nor a need for an understanding of learning processes. The emergence of dynamics in economics, especially on the micro-level, has provoked a more detailed consideration of learning processes over time (Brenner 1991).

Brenner (1991) defines learning in the context of economics as any cognitive or non-cognitive processing of experience leading to a direct or latent change in economic behavior, or to a change of cognitive pattern influencing future learning processes. Brenner also argues that learning needs to be inferred from a change in behavior or consequences led by the behavioral change since learning cannot be observed directly. In economics, the consequences (changes in economic indicators, such as output and profit) are employed as measures of learning. For example, firms learn new technologies with a view toward profit maximization while farms in developing counties may act under a different objective since they are not only producers, but also consumers of their own products and managing consumption, production, and other household allocation decisions.

Learning of production technologies is considered to occur through formal and informal channels.[1] The formal learning channel includes extension visits and vocational training, while the informal learning channel involves various forms of experience. Informal learning can be further categorized into own experience (learning-by-doing) and observing (or gaining information of) others' experiences (learning-from-others). Learning-by-doing not only benefits the one who experiments, but also generates information externalities benefiting other farmers (Bardhan and Udry 1999). Whether benefits from other farmers' experiences can be realized or not depends on transferability of the experiences and a farmer's ability to learn.

Although there is always some room for farmers to learn how to improve productivity, technological changes as well as changes in market and political regimes bring about significant learning opportunities. Thus, opportunities for learning depend on how significantly different a new technology is from its traditional counterpart. If the new technology requires a whole set of new inputs or practices, there will be significant potential for learning. If the new technology can be utilized based largely on traditional inputs and skills, there may be little potential for

[1] Schooling has a potential impact on the fluidity of the learning channels (*i.e.*, an ability to learn).

learning. Thus, the nature of technological change determines whether or not learning is crucial in technological adoption.

2.1.4. Empirical Panel Data Studies

Following Besley and Case's affirmation, several studies have employed household panel data, all of which focus on establishing the importance of learning in a dynamic aspect of adoption at the farm level. They include Foster and Rosenzweig (1995), Besley and Case (1997), Cameron (1999), and Munshi (2000), which all use data from the Indian Green Revolution. In addition to the use of household panel data to capture the dynamic aspect of adoption, the adoption of a Bayesian learning model is another common feature of those studies.

Besley and Case (1997) model farmers as being uncertain about the profitability of a new seed variety relative to an old one. The authors simulate the subgame-perfect number of plots to be sown to the new seed and compare this with the pattern found in their data.

In contrast, Foster and Rosenzweig (1995) employ a target-input model, in which the optimal input use was unknown and stochastic, for two reasons. One is that optimal input use appears to be empirically central to farmers' concerns in environments subject to technological change. The other model is in contrast to models with uncertainty about exogenous profits where the profitability of any new technology grows over time as knowledge accumulates. Therefore, it is possible to test directly for learning externalities in terms of productivity rather than by inference from the adoption behavior of the farms. Foster and Rosenzweig argue that farmers learn about the optimal combination of input use through their experiences and those of their neighbors. The article empirically demonstrates that learning both from own experiences and learning from neighbors' experiences significantly increase the profitability of the HYV cultivation and the effects diminish over time.

Cameron (1999) assumes that farmers are uncertain about the profitability of the HYV production relative to that of traditional seeds and learn about the profitability over time from their own experiences with the HYV cultivation. The study demonstrates that learning from own experience plays an important role in the adoption process thus providing further evidence of the importance of learning. It also illustrates that unobservable household heterogeneity also plays a significant role in the process.

Munshi (2000) presumes that yields from the HYV production are uncertain and that the uncertainty decrease as own and village-level acreage allocation to the HYV cultivation increases. The study contrasts the adoption of HYV rice with that of HYV wheat. The HYV rice is known to be sensitive to imperfectly observed farm and soil characteristics, while the HYV wheat is remarkably robust to growing conditions. The study then demonstrates that learning-from-others is significant in the production associated with the HYV wheat, but not in the production of the HYV rice at both the farm- and district-levels. Finding that unobservable heterogeneity influences learning-from-others, the study concludes that learning from own experiences compensates for a lack of learning-from-others in the adoption of the HYV rice.

Although a study done by Conley and Udry (2001) did not use panel data, it is noteworthy since it illustrates how learning occurs based on a survey of Ghanaian farmers. The study presents that 1) farmers learn about the use of new technologies through social networks rather than randomly through neighbors' experimentation and 2) the constituent links are not based solely on geographic proximity. This study also finds that farmers are more likely to know broad facts (*e.g.*, the other farmers had a good harvest) rather than specific details on actual harvest or input use.

2.2. FRONTIER ANALYSIS AND MEASUREMENT OF EFFICIENCY

The frontier function approach is a method to measure productive inefficiency of individual producers. Inefficiency is measured by the deviation from the frontier, which represents a best-practice technology among all observed farms. Farrell (1957) presents computational measures for productive inefficiency based on Debreu (1951) and Koopmans (1951), who provides a definition of technical efficiency. Farrell also characterizes efficiency as having two components: "technical efficiency" and "allocative efficiency" (or "price efficiency"). The former reflects the ability of a farm to obtain maximum output from a given set of inputs, while the latter reflects the ability of a farm to use the inputs in optimal proportions, given their respective prices.

Coelli (1995) presents two reasons to estimate frontier functions, rather than average functions, which are conventionally estimated by the OLS method. First, the frontier function is consistent with theoretical representation of production activities, which is derived from an optimization process. For example, the production function consists of a series of outputs attainable, given different combinations of inputs, while cost and profit functions are represented by frontiers derived from optimization. Second, the estimation of frontier function provides a tool for measuring the efficiency level of each farm within a given sample.

2.2.1. Nonparametric vs. Parametric Approach to Frontier Analysis

The frontier analysis is classified into two techniques depending on how the frontier is specified and estimated. One is the nonparametric technique and the other is the parametric technique. The nonparametric technique constructs frontiers and measures efficiency relative to the constructed frontiers using linear programming techniques. The approach frequently goes by the descriptive title of *data envelopment analysis* (DEA) [see Ali and Seiford (1993), Charnes *et* *al*. (1995), Lovell (1993, 1994), Seiford (1996), and Seiford and Thrall (1990) details of DEA]. The nonparametric approach can be categorized according to the type of data available (cross-sectional or panel), and according to the type of variables available (quantities only, or quantities and prices). With quantities only, technical efficiency can be calculated, while allocative efficiency requires both quantities and prices.

The parametric technique estimates frontiers and provides efficiency using econometric techniques. The parametric approach can also be categorized according to the type of data as well as the type of variables available. In particular, the use of panel data enables one to overcome two important problems associated with estimation using cross-sectional data, which are also common to the parametric approach in the non-frontier analysis. First, panel data provide observations of each producer more than once, which makes it possible to earn more accurate estimates of efficiency for each producer than can be obtained from cross-sectional data. Second, panel data make it possible to control individual heterogeneity, which can cause inconsistent estimation due to the problem of endogeneity.

The two approaches differ in many ways, but the essential differences reduce to two characteristics. One is that the nonparametric approach typically does not take statistical noise into account, which consequently provides inaccurate efficiency measures, while the parametric approach with stochastic frontier specification can accommodate statistical noise. The other is that the nonparametric approach does not require specific functional forms to be imposed on the data while the parametric approach is subject to potential specification error since estimated frontiers and efficiency measures are conditional on the functional form chosen. Hence, the selection of an appropriate functional form is a vital factor in the parametric approach.

2.2.2. Deterministic vs. Stochastic Specification

The parametric technique forms the frontier employing econometric estimation. Frontier functions have been estimated with either a deterministic or stochastic specification, which are presented, respectively, as:

(2-1) $y_i = f(x_i;\beta) - u_i \qquad i = 1, \dots, N$

(2-2) $y_i = f(x_i;\beta) - u_i + v_i \qquad i = 1, \dots, N$

where i indexes producers; $y_i \geq 0$ is an output scalar; $x_i = (1, x_{i1}, \dots, x_{iN}) \geq 0$ is a vector consisting of inputs and an intercept; $\beta = (\beta_0, \beta_1, \dots, \beta_N)$ is a vector of coefficient estimates; $u_i \sim$ *i.i.d.* $N^+(\mu, \sigma_u^2)$ is a random variable representing technical inefficiency associated with production of farm i; and $v_i \sim$ *i.i.d.* $N(0, \sigma_v^2)$ is a stochastic error term.

As seen in equation (2-2), the stochastic frontier specification involves a stochastic error term, v_i, which is added to the deterministic specification in equation (2-1). The stochastic frontier specification was simultaneously introduced by Meeusen and van den Broeck (1977) and Aigner *et al*. (1977). The stochastic frontier specification has been more widely used than the deterministic specification since the former can handle statistical noise, resulting in more accurate specification. A more complete specification is essential for accurate efficiency measures since the estimated frontier is conditional on the functional form.

One common criticism of the stochastic frontier method is that there is no *a priori* justification for the selection of any particular distributional form for the technical inefficiency term, u_i. The specification of general distributional forms, such as the truncated-normal (Stevenson 1980) and the two-parameter gamma (Green 1990) is preferred to the half-normal and the exponential distributions for two reasons. First, the half-normal and the exponential distributions are prone to having relatively high technical efficiency since those distributions have a mode at zero indicating the highest probability that the inefficiency terms are in the neighborhood of zero. Second, the truncated-normal and the two-parameter gamma distributions allow for a wider range of distributional shapes (including the ones with non-zero modes), but this comes at the cost of computational complexity.

There are two objectives in stochastic frontier analysis (Kumbhakar and Lovell 2000). The first is the estimation of a stochastic frontier function serving as a benchmark against which to estimate technical (or allocative) efficiency of producers (*e.g.*, Battese and Coelli 1988, Kumbhakar *et al*. 1989, Green 1990, and Atkinson *et al*. 2001). Its goal is to estimate an efficiency level of each producer. The second objective is the incorporation of exogenous variables, which are neither inputs to the production process nor outputs of it, but which nonetheless affect producer performance with the intent to identify the determinants of efficiency (*e.g.*, Pitt and Lee 1981, Kalirajan 1981, Battese and Coelli 1995, and Ali and Flinn 1989). This second objective is much less explored despite its importance while the first has been studied to a great extent.

2.2.3. Primal vs. Dual Approach

The stochastic frontier analysis has been employed for both primal and dual representations of production technologies. Production and distance functions are used for primal representation, whereas cost and profit functions are employed as the dual counterpart. The two approaches differ largely in three aspects. First, the primal approach only permits the estimation of technical efficiency while the dual approach allows the measurement of both technical and allocative efficiencies.[2] Second, production and distance functions are based on a

[2] Allocative efficiencies have been investigated in a number of papers, including Schmidt and Lovell (1979, 1980), Kopp and Diewert (1982), Zieschang (1983), Kumbhakar (1988), Kumbhakar *et al*. (1989), Bailey *et al*. (1989), Ali Flinn (1989), Kumbhakar *et al*. (1991), and Atkinson and Cornwell (1993, 1994).

technical assumption: output-maximization given a set of inputs. On the other hand, cost and profit functions are based on behavioral assumptions. Cost functions assume cost-minimization given a set of input prices while profit functions assume profit-maximization given a set of input and output prices. The other aspect pertains to data requirements. Production and distance functions require input and output quantities. On the other hand, cost, input prices and output quantities are needed for cost functions, whereas profit as well as input and output prices are needed for profit functions.

Although the dual approach is appealing because it yields both technical and allocative efficiencies, there are two reasons that the primal approach, especially production functions, has been extensively employed. First, the dual approach requires input prices (and output prices) to be observable and to vary across farms. In reality, farms in a given village face the same prices. Even when they face different prices, such data are difficult to acquire. Second, the approach adopted by Schmidt and Lovell (1979) to estimate systems of equations, which consists of a production function and the first order conditions of cost minimization, and efficiency measurement is potentially a useful method. However, it is limited to the use of self-dual functional forms, such as the Cobb-Douglas function (Coelli 1995). Once more flexible functional forms are specified, such as the translog form, it is difficult to represent the link between allocative inefficiency errors in the input demand equations and the allocative inefficiency error appearing in the cost (or profit) function. This problem, sometimes referred to as “the Green Problem”, was first noted by Green (1980) and was discussed by Nadiri and Schankerman (1981). Recently, Kumbhakar (1997) established a theoretical link between those allocative inefficiency errors using a translog cost function for the first time.

2.3. IDENTIFICATION OF EFFICIENCY DETERMINANTS

While identification of efficiency determinants is one of the main components of the frontier analysis, it is also a subject of interest in the non-frontier analysis. Section 2.3 refers not only to the frontier analysis, but also to the non-frontier analysis for a comprehensive review of efficiency determinants.

Section 2.3.1 briefly explains the methodology of identification of efficiency determinants and empirical results of the non-frontier analysis. Section 2.3.2 discusses the methodological development of the incorporation of efficiency determinants in the frontier analysis. Section 2.3.3 reviews efficiency determinants examined in the frontier analysis, with emphasis on education.

Reviews of empirical studies, which are discussed in Sections 2.3.1 and 2.3.3, focus mainly on human capital factors, especially education, since human capital factors have been extensively examined in both analyses and they are also of importance to this study.

2.3.1. Non-frontier Analysis and Empirical Results

In the non-frontier analysis, there are two different ways of examining potential efficiency determinants, depending on the kinds of efficiency to be analyzed. The effects of determinants on technical efficiency can be examined by incorporating the determinants in a production function as inputs and then estimating their coefficients as arguments of the production technology (*e.g.*, Azhar 1991, Jamison and Moock 1984). The investigation of these effects on allocative efficiency can be implemented by first creating an indicator representing an efficient allocation of inputs and regressing it on efficiency determinants (*e.g.*, Huffman 1977, Khaldi 1975, Stefanou and Saxena 1988).

Although there are a number of empirical studies analyzing the determinants of technical efficiency in a framework of non-frontier function, the main conclusions in a developing country context reduce to three points [see Lockheed *et al*. (1980)].[3] First, the effect of education on technical efficiency is positive and usually significant. Second, the effect of more education (more than 4-6 years of schooling) on this type of efficiency is more significant than those of primary education (less than 3-5 years of schooling).[4] Third, the dynamic environments of production enhance the impact of education on technical efficiency, which indicates that changes in production environments increase not only allocative efficiency, which has been claimed by Schultz (1975) and others, but also technical efficiency.

Other than the studies reviewed in the survey, Moock (1981) and Jamison and Moock (1984) also concur with the first two conclusions using Kenyan and Nepali data, respectively. The two studies find substitutability between education and extension contact in terms of their effects on technical efficiency. Azhar (1991) reaches all three conclusions using Pakistani data.

The effects of education on allocative efficiency are studied by Fane (1975), Khaldi (1975), Huffman (1977), and Stefanou and Saxana (1988). Fane (1975) and Khaldi (1975) present a positive effect of education on allocative efficiency using US farm data. Huffman (1977) reaches two conclusions on US agricultural production: 1) positive effects of education and extension on allocative efficiency, and 2) substitutability of education and extension in terms of their effects on efficiency. Stefanou and Saxena (1988) demonstrate significant roles of education and experience on allocative efficiency and substitutability of education and experience, using farm-level Pennsylvania dairy data.

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[3] Lockheed *et al*. (1980) conducted an extensive survey of 18 farm efficiency studies, which used 37 data sets from 13 countries of Africa, Asia, European, and Latin America.

2.3.2. Frontier Analysis – Methodological Point of View

There are also different ways to incorporate efficiency determinants in frontier functions depending on how the determinants are assumed to affect output productivity. The determinants can be assumed to affect output directly by influencing the frontier (*e.g.*, Kalirajan 1981, Pitt and Lee 1981). Such determinants play the role of inputs in the production process. However, this specification does not accommodate the variation in productivity caused by factors that do not directly affect the production process, but influence producer performance. Examples of such factors include socio-economic characteristics of the producers.

One of the merits of the frontier analysis is to enable the explanation of such variations. In the context of the frontier analysis, the determinants can also be assumed to influence output indirectly by influencing the efficiency with which inputs are converted to output (*e.g.*, Battese and Coelli 1995, Kumbhakar *et al*. 1991). Once inefficiency is derived from the estimated frontier, it is regressed on the efficiency determinants, where the regression is called an *inefficiency function*. This specification is unique in the frontier analysis while the previous specification is common in the non-frontier analysis.

Although the frontier function approach is able to account for the variation in productivity using the inefficiency function, how to specify and estimate the inefficiency function together with the frontier function has generated extensive discussions. The development in methodology is explained thoroughly by Simar *et al*. (1994). A brief illustration of the major methodological developments follows.

The methodology is categorized by depending on 1) whether the frontier function and the inefficiency function are estimated sequentially or simultaneously, or 2) whether the inefficiency

[4] Some of the previous studies found a negative effect of primary education on technical efficiency (*e.g.*,

function includes a stochastic error term or not. According to these categorizations, three specifications are introduced.

The following specification, denoted specification I, involves sequential estimation:

(2-4) $\ln y_i = \ln f(x_i; \beta) + v_i - u_i, \qquad i = 1, \dots, I,$

(2-5) $E(u_i|v_i - u_i) = g(z_i; \gamma) + e_i$

where i indexes producers; $y_i \geq 0$ is an output scalar; $x_i = (1, x_{i1}, \dots, x_{iN}) \geq 0$ is a vector consisting of inputs and an intercept; $\beta = (\beta_0, \beta_1, \dots, \beta_N)$ is a vector of the coefficient estimates; $u_i \sim i.i.d.\ N^+(\mu, \sigma_u^2)$ is a random variable representing technical inefficiency associated with production of farm i; $v_i \sim i.i.d.\ N(0, \sigma_v^2)$ is a stochastic error term; $z_i = (z_{i0}, \dots, z_{iQ})$ is a vector of exogenous variables; $\gamma = (\gamma_0, \dots, \gamma_Q)$ is a vector of the coefficient estimates; $e_i \sim N(0, \sigma_e^2)$ is a stochastic error term.

Equations (2-4) and (2-5) are estimated in a two-stage procedure. First, the stochastic production frontier function, (2-4), is estimated and then the inefficiency function, (2-5), is estimated. The underlying assumption of specification I is that the elements of x_i are uncorrelated with each disturbance component of v_i and u_i. Examples of this kind of specification include Ali and Flinn (1989) and Kalirajan (1991).

Unfortunately, there are serious econometric problems with specification I (Kumbhakar and Lovell 2000). First, it must be assumed that the elements of z_i are uncorrelated with the elements of x_i. If they are correlated, the coefficient estimates as well as the estimated inefficiencies will be biased. Second, it is assumed in the first stage that the inefficiencies are identically distributed, *i.e.*, $E(u_i)$ is constant, but this assumption is contradicted in the second-

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Moock 1981, Azhar 1991).

stage regression in which predicted efficiencies are assumed to have a functional relationship with z_i.

To overcome the drawbacks of the specification above, Deprins and Simar (1989) present specification II:

(2-6) $\ln y_i = \ln f(x_i; \beta) - u_i$

(2-7) $E(u_i|z_i) = \exp(\gamma' z_i)$

where the exponential operation ensures that $E(u_i|z_i) > 0$. Combining equations (2-6) and (2-7) and adding a stochastic error term yields the single-stage production frontier model

(2-8) $\ln y_i = \ln f(x_i; \beta) - \exp(\gamma' z_i) + e_i$

where the requirement that $u_i \geq 0$, in turn, requires that $e_i \leq \exp(\gamma' z_i)$, which implies that e_i is not identically distributed. Specification II presents an improvement on the previous formulation. However, it was based on a deterministic frontier model containing no systematic error term to capture the effects of random noise on the production process.

To accommodate stochastic noise, Kumbhakar *et al*. (1991) develop specification III:

(2-9) $\ln y_i = \ln f(x_i; \beta) + v_i - u_i$

(2-10) $u_i = \gamma' z_i + e_i$

where, in contrast to specification II, a stochastic error term, v_i, is introduced in the production process. Inserting equation (2-10) into equation (2-9) yields the single-stage model

(2-11) $\ln y_i = \ln f(x_i; \beta) + v_i - (\gamma' z_i + e_i)$.

To satisfy the condition that $u_i \geq 0$ requires $e_i \geq -\gamma' z_i$. Although this formulation does not require $\gamma' z_i$ to be non-negative, it is still necessary to impose distributional assumptions on v_i and e_i to obtain the likelihood function. Kumbhakar et al. (1991) impose distributional assumptions on v_i and u_i, and omitted e_i. The authors assume that $v_i \sim i.i.d.\ N(0, \sigma_v^2)$ and $u_i \sim N^+(\gamma' z_i, \sigma_u^2)$, and that v_i and u_i are distributed independently.

2.3.3. Frontier Analysis – Empirical Results

Human capital factors have been extensively examined also in the frontier analysis context. They are represented by schooling, extension contact, experience, and age. In particular, their effects on technical efficiency have been studied more intensively than those on allocative efficiency.

Table 2-1: Efficiency Determinants of the Frontier Analysis

Author	Country	Crop	Number of Exogenous Variables	Exogenous Variables[1]					
				Schooling	Extension	Experience	Age	Farm Size	Others[2, 3]
Primal Approach									
Cross-Sectional									
Kalirajan (1981)	India	Rice	6	+	++	++			Understanding of the technology (++) Tenancy (i.s.), Keenness to remove doubts about the technology (-)
Kalirajan (1990)	Philippines	Rice		++					Non-farm income (++), Tenancy (s.) Timing of crop establishment (++) Knowledge about the technology (++)
Ajibefun, Battese, & Daramola (1996)	Nigeria	Multi[4]	4			++	-	-	Hired labor ratio to the total labor (- -)
Panel									
Kalirajan (1991)	India	Rice	4	+	++			+	Confidence in technology (++)
Battese & Coelli (1995)	India	Multi	3	+			-		Year (+)
Coelli & Battese (1996)	India	Multi	4	+			+	++	Year (++)
			4	-			+	+	Year (+)
			4	++			-	++	Year (++)

(Continued on next page)

Table 2-1 Continued

Author	Country	Crop	Number of Exogenous Variables	Exogenous Variables[1]					
				Schooling	Extension	Experience	Age	Farm Size	Others[2, 3]
Audibert (1997)	Mali	Rice	13		++		+		Year (+), Dependency ratio (++) Household size (++), Village cohesion Production scheme, Ethnicity Output of other crop, Condition of irrigation and soil
Battese & Broca (1997)	Pakistan	Wheat	5	++			++		Credit (s.), Tenancy (i.s.), Year (++)
Dual Approach									
Cross-sectional									
Ali & Flinn (1989)	India	Rice	11	++				-	Off-farm employment ratio (--) Credit (s.), Tenancy (i.s.), Access to resources, Institutional factors
Ali, Parich, & Shah (1994)	Pakistan	Multi	12	++	++			--	Off-farm employment ratio (-) Household size (++), Credit (i.s.)

[1] + and - indicate efficiency-enhancing and -reducing, respectively. ++ and—indicate efficiency-enhancing and -reducing, respectively, at the 5 percent level of significance.
[2] s. indicates significance at the 5 percent level; i.s. indicates not significant at the 5 percent level.
[3] Some of variables in this column do not have signs or statistical significance indicated since those variables are specific to individual studies.
[4] Multi indicates multi-crops.

Effects of human capital variables on technical efficiency are described in Table 2-1.[5] There are several conclusions that can be reached from the table. First, schooling has a positive impact on technical efficiency in all studies except one of the estimations done by Coelli and Battese (1996), where the effect of schooling is not significant. Second, effects of schooling on technical efficiency are significant in some of the studies. Third, effects of age are mixed and not significant. Fourth, extension contact and experience are technical efficiency-enhancing and always significant.[6]

Other than human capital variables, farm size is usually positive and sometimes has significant effects on technical efficiency. The time trend, indicated by year, is often used to capture a general trend of the efficiency change. It has a positive and often significant effect on technical efficiency. Tenancy is occasionally examined and its effect on efficiency is mixed.

There are also studies investigating allocative efficiency determinants. Examples include Ali and Flinn (1989) and Ali *et al*. (1994) (see Table 2-1). According to those studies, schooling has a positive and significant impact on allocative efficiency. Extension contact and household size are examined in the study of Ali *et al*. (1994) and have positive and significant effects on efficiency. Farm size and the proportion of adults who work off-farm to all adults in the household have negative impacts on allocative efficiency and are significant in one of the studies.

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[5] Table 2-1 does not contain studies of non-agricultural sector since they usually do not concern human capital variables. Examples include studies of Indonesian weaving industry (Pitt and Lee 1981), of Kenyan manufacturing firms (Lundvall and Battese 1998), and of railway companies of the developed countries (Deprins and Simar 1989)).

[6] One of the reasons why extension contact and experience were rarely included is a lack of the data.

2.4. Concluding Comments

Processes of individual learning of new technologies have been studied recently by taking advantage of panel data as seen in this chapter. They all analyze the Indian Green Revolution for its importance and availability of the data.

However, this study is unlike the others with respect to learning measurement. Previous studies try to capture learning through effects of experiences with production of HYV on output, cost, or profit using the non-frontier approach. This thesis employs efficiency measurement within the stochastic frontier analysis to represent learning. The major advantage of this approach is the ability to isolate the efficiency component from productivity and to identify efficiency determinants.[7]

There are two reasons for the use of the efficiency measure in this study rather than the other productivity measures. First, given the cross-sectional aspect of the data, efficiency variation among farmers is likely to explain productivity variation among the farmers. Given that all the farmers are sampled from one village, productivity, technological, or environmental differences among these farmers are unlikely to be substantial. Second, the isolation of efficiency from the total productivity is essential in capturing learning. Given the progressive and substantial technological change during the period, productivity variation is explained by both technological and efficiency changes. It is assumed that the 10 year-period spanning this data series is not long enough to change the production environment substantially. The technical change is represented by adoption of HYV while efficiency increase is indicated by learning of the HYV production. Therefore, use of the efficiency notion is appropriate to describe learning.

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[7] Lovell (1993) says that productivity varies due to differences in production technologies, differences in the efficiency of the production process, and differences in the environment in which production occurs.

Chapter 3

METHODOLOGY

Adoption of new technologies may be seen as an event at a point in time, which ignores the dynamics of the adoption process. On the other hand, it can be viewed as a process from adoption to acquisition. The process is an entire course of learning until the full yield potentials of the new technologies are realized. The Green Revolution is one of the most drastic agricultural technological changes that have taken place in developing countries. The remarkable difference in farming practices before and after the change required substantial adjustment by farmers, which also implies substantial opportunities for learning. In this respect, it is vital to consider the dynamic aspect of adoption by explicitly incorporating "learning" into a model of the adoption process.

This study estimates a stochastic frontier production function and a technical inefficiency function simultaneously to identify the determinants of technical efficiency. Among all the potential determinants, human capital-related variables, such as schooling, experiences, and age, are of special interest to ascertain how much they contribute to the efficiency gain.[8] Furthermore, the contribution of formal education on learning will be empirically examined.

The primal approach involving direct estimation of the production function, is selected over the dual approach since the data set used for this study does not record price data which vary across farms. The rest of the chapter presents the theoretical framework and empirical application.

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[8] Other human capital variables such as extension visits and vocational training are not available in the data set.

3.1. THEORETICAL FRAMEWORK

3.1.1. Stochastic Frontier and Technical Inefficiency Functions

A stochastic frontier production function is specified as:

(3-1) $\ln y_{it} = f(\ln x_{it}; \beta) - u_{it} + v_{it}$

where i and t index producers and time periods, respectively; $y_{it} \geq 0$ is an output scalar; $x_{it} = (1, x_{it1}, \ldots, x_{itK}) \geq 0$ is a vector consisting of inputs and an intercept; $\beta = (\beta_0, \beta_1, \ldots, \beta_K)$ is a vector of coefficient estimates; $u_{it} \sim N^{+}(\mu, \sigma^2)$ is independently distributed at truncations of the $N(z_{it}\delta, \sigma^2)$ distribution and represents technical inefficiency associated with the production of farm i; $v_i \sim i.i.d.\ N(0, \sigma_v^2)$ is a stochastic error term; and, v_{it} and u_{it} are independently distributed. The inefficiency component, u_{it}, is formulated as a function of its exogenous determinants as:

(3-2) $u_{it} = z_{it}\delta + e_{it}$

where $z_{it} = (z_{it0}, \ldots, z_{itQ})$ is a vector of exogenous variables; $\delta = (\delta_0, \ldots, \delta_Q)$ are vectors of coefficient estimates; $e_{it} \sim N(0, \sigma^2)$ is a stochastic error term. The restriction $u_{it} \geq 0$ requires that $e_{it} \geq - z_{it}\delta$, with equation (3-2) known as the technical inefficiency function. Fundamental assumptions of this formulation are $\mathrm{corr}(z_{it}, u_{it}) \neq 0$ and $\mathrm{corr}(z_{it}, y_{it}) = 0$. For the technical efficiency measure, the inefficiency of farm i at time t, u_{it}, is transformed as $TE_{it} = \exp(-u_{it})$, which now represents technical efficiency index.

3.1.2. Estimation of Stochastic Frontier and Technical Inefficiency Functions

The parameters of the stochastic frontier and the technical inefficiency functions are estimated simultaneously by the method of maximum likelihood, using the computer program, FRONTIER Version 4.1 (see Coelli (1994)).

The estimation is carried out in three steps. First, ordinary least squares (OLS) estimation of the stochastic frontier production function yields estimates of β coefficients. All the estimates except the one for the intercept, β_0, are unbiased. Second, a grid search finds γ, using the OLS estimates of β coefficients and the estimates of β_0 and σ^2 which are adjusted according to the corrected ordinary least squares formula presented in Coelli (1995). The coefficients δ are set to zero and γ is limited between zero and one and defined as:

(3-3) $\gamma = \sigma^2/\sigma_s^2$.

Lastly, inserting equation (3-2) into equation (3-1) yields the regression for the estimation:

(3-4) $\ln y_{it} = f(\ln x_{it}; \beta) - (z_{it}\delta + e_{it}) + v_{it}$.

The regression is estimated using the values selected in the grid search as starting values in an iterative procedure to obtain the final maximum likelihood estimates of the coefficients β and δ, together with the variance parameters which are expressed as:

(3-5) $\sigma_s^2 = \sigma_v^2 + \sigma^2$.

3.2. EMPIRICAL APPLICATION

3.2.1. Specification of the Stochastic Frontier Production Function

For this empirical analysis, translog functional form is chosen since the estimated model is consistent with a well-behaved production function (positive marginal product and diminishing marginal product of each input, positive output elasticity of each input, and reasonable magnitude of scale elasticity) besides its flexibility.[9] The translog frontier production function with six inputs, two soil dummy variables, and the HYV ratio variable is specified as:

[9] Although some of the output elasticities are negative, which is later shown in Table 4-6, they are small in magnitude and statistically significant except the one of animal. The justification regarding the elasticity of animal is provided in Section 4-4.

(3-6) $\ln y_{it} = \beta_0 + \Sigma^9_{k=1} \beta_k \ln x_{kit} + 0.5\, \Sigma^9_{k=1} \Sigma^9_{l=1} \beta_{kl} \ln x_{kit} \ln x_{lit} - u_{it} + v_{it}$

$i = 1, 2, \ldots, N.$

Table 3-1: Variables for Production Function

Variable	Definition of Variable
Dependent	
y	Castor Output (kg/acre)
Independent	
x_1	Seed (kg/acre)
x_2	Family Labor (hours/acre)
x_3	Hired Labor (hours/acre)
x_4	Farm Animal (bullocks) (hours/acre)
x_5	Fertilizer (kg/acre)
x_6	Pesticide (kg/acre)
x_7	HYV Ratio: acreage of plots used for the HYV production to the acreage for the total production.
x_8	Dummy for Good Soil[1]
x_9	Dummy for Bad Soil[2]

[1] Soil type in the original data ranges from 1 to 9 depending on the characteristics of soil. Good soil indicates soil type 1 to 3 representing deep, medium, or shallow black soil.
[2] Bad soil indicates soil type 6 to 9 representing shallow red, gravelly, problem, and sandy soil.

The HYV ratio is included in the production function as a variable representing the technological change to account for the technological difference across the farms. The ratio ranges from zero to one with zero indicating no adoption, unity indicating full adoption. The underlying idea is that production functions should vary across farms when their adoption rates differ. The choice of the HYV ratio was made since conventional ways of representing technological changes (*i.e.*, an inclusion of a time trend) do not seem to be appropriate in this study. First, the technological change cannot be characterized accurately by a time trend since it is likely to fluctuate over the period. Second, the technological change cannot be characterized by a village-level index for all the farms since extension of the HYV adoption varies across the farms. Third, a dichotomous variable representing adoption or non-adoption of HYV is not sufficient to describe to what extent they use the HYV technology since the separation of productivity gains due to the technological change from those due to efficiency changes is crucial for accurate measurement of learning in this thesis.

3.2.2. Specification of the Technical Inefficiency Function

The technical inefficiency function is specified as:

(3-7) $u_{it} = \Sigma^{11}_{q=1} \delta_q z_{qit} + e_{it}$.

Table 3-2: Variables for Technical Efficiency Function

Variable	Definition of Variable
Dependent	
u	Technical Inefficiency
Independent	
z_1	Age of the Household Head[1]
z_2	Level of Schooling of the Household Head (categorical from 1 to 9)[2]
z_3	Own Experience: cumulative acres of plots in which farms have experienced HYV castor production[3]
z_4	Reference Group Experience: cumulative acres of plots in which other farms with similar attributes have experienced HYV castor production[4]
z_5	Non-reference Group Experience: cumulative acres of plots in which farms other than reference group members have experienced HYV castor production[5]
z_6	Farm size (categorical from 1 to 4)[6]
z_7	Household Size (number of household members)
z_8	Dependency Ratio[7]
z_9	Dummy for the highest caste[8]
z_{10}	Dummy for the 2nd highest caste
z_{11}	Dummy for the 3rd highest caste

[1] If the head of the household does not engage in cropping, information of *de facto* head of the household in cropping activity is identified and used.

[2] Education ranges from 1 to 9 in the original data. Level 5 is the highest in the data used for this study. Type 1 indicates illiterate. Type 2 indicates ability to read and write. Type 3, 4, and 5 indicate studying in primary school, middle school, and high school, respectively.

[3] All the experience terms are lagged since knowledge gained from experience affects production in the next period.

[4] Three kinds of reference group experience A, B, and C, are constructed depending on the kinds of attributes employed for the construction of the variables. Experience A, B, and C are formed based on farm size, household size, and caste rank, respectively

[5] Three kinds of non-reference group experience A, B, and C, are constructed according to respective reference group created for the reference group experience.

[6] Farm size ranges from 0 to 3 depending on the size of operational land holdings, which is owned land minus land leased out/sharecropped out plus leased in/sharecropped in. Farm size 0 indicates no land holdings. Farm size 1, 2, and 3 indicates 0.2 to 2.5, 2.51 to 5.26, and over 5.26 hectares, respectively.

[7] Dependency Ratio indicates percentage of members younger than 14 or older than 64 to the total household members.

[8] Caste rank is represented by four kinds in the original data. Caste dummy 1 to 3 indicate the highest to the second lowest caste in contrast to no dummy variable representing the lowest caste.

Technical efficiency is assumed to be determined by two kinds of factors: 1) familiarity with production associated with HYV and 2) farm-specific socioeconomic characteristics. Unfamiliarity with the HYV production is considered substantial at the outset of its adoption. Owing to the unfamiliarity, farmers cannot find the optimal allocation of inputs since input use for the HYV production is different from that required for the production of traditional varieties (TV), which results in inefficiency in the HYV production. The inefficiency diminishes through two kinds of learning: learning from own experiences (learning-by-doing) and learning from neighbors' experiences (learning-from-others) (see Appendix A for explanation of the learning variables).

Compared to learning-by-doing, the process of learning-from-others can be complex since the decision-maker must interpret to their own production environments what they learn from farms possessing different production attributes and facing different production environments. In this sense, it may be more beneficial for farmers to learn from someone who has similar production attributes with the similar production environment. Learning-from-others is further categorized into learning from reference group and learning from non-reference group. Different groupings for the reference will be examined according to farm size, household size, and caste. This examination can reveal whether farmers learn from a specific group and, if so, what kinds of attributes are important in learning-from-others.

Socioeconomic characteristics of farms are the determinants of technical efficiency that most previous studies emphasized. They are represented by educational level and age of the household head, farm size, household size, and caste. The dependency ratio is added under the assumption that a high dependency ratio may require substantial production of subsistence crops, which can affect technical efficiency of castor production.

3.2.3. Elasticities

Various elasticities are presented to illustrate the nature of castor production and the determinants of technical inefficiency. Output elasticities with respect to each input, scale elasticity, and Morishima elasticities of substitution are derived from coefficient estimates of the production function. The output elasticity with respect to input k is defined as:

(3-8) $$\varepsilon_k = \frac{\partial \ln y}{\partial \ln x_k} = \beta_k + \sum_{l=1}^{9} \beta_{kl} \ln x_l \qquad k = 1, 2, \dots, 9.$$

The scale elasticity is defined as:

(3-9) $$\varepsilon = \frac{\sum_{k=1}^{9} f_k x_k}{y} = \sum_{k=1}^{9} \varepsilon_k \quad \text{where } f_k = \frac{\partial y}{\partial x_k}.$$

The Morishima elasticity of substitution between input k and i is defined as:

(3-10) $$\varepsilon_{ki} = \frac{f_k}{x_i}\frac{F_{ki}}{F} - \frac{f_i}{x_i}\frac{F_{ki}}{F} \qquad \text{for } i \neq k.$$

$$= 0 \qquad \text{for } i = k.$$

where F is the determinant of the bordered Hessian of the production function and F_{ki} is the associated cofactor of $f_{ki} = \frac{\partial^2 y}{\partial x_k \partial x_i}$.

The inefficiency elasticity of determinant q is defined as:

(3-10) $$IE_q = \frac{\partial u}{\partial z_q}\frac{z_q}{u} = \delta_q \frac{z_q}{u} \qquad q = 1, \dots, 11.$$

3.3. DATA[10]

During the 1975/76-1984/85 period, the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) collected farm-level data on the agricultural operations of a sample of farmers in three different regions in India. These village level studies were designed to obtain reliable data on the broad agro-climatic sub-regions in the semi-arid tropics of India, for a better understanding of traditional agriculture in the region. This study focuses, in particular, on Aurepalle village in Andhra Pradesh, one of the villages of the ICRISAT studies.

3.3.1. Region of Study: India's Semi-arid Tropics

Semi-arid tropics are often characterized by scanty and uncertain rainfall, on which agricultural production largely depends in the presence of infertile soil, poor infrastructure, extreme poverty, rapid population growth, and high risks. The semi-arid tropics of India, is no exception. Agroclimatically, the semi-arid tropics includes those tropical regions where rainfall exceeds potential evaporation four to six months of the year. Mean annual rainfall in the semi-arid tropics ranges from about 400 to 1200 mm. India's semi-arid tropics are vast and encompass about 15 to 20 large regions, each embracing several districts.

Aurepalle is a village in Mahbubnagar district, Telengana region in the state of Andhra Pradesh. Annual growth rate in cereal production from 1950s to 1980s in Mahbubnagar region was 1.5 percent. Major crops are castor, paddy, pearl millet, sorghum, pigeonpea, and groundnut. The soil characteristic of the district is represented by red soil with low water-retention capacity. Mean annual rainfall is 630mm with 31 percent coefficient of variation.

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[10] Information in this chapter is mostly provided by *Village and Household Economies in India's Semi-arid Tropics* (Walker and Ryan 1990).

3.3.2. Data Characteristics

The ICRISAT study of villages in the semi-arid tropics of India was initiated in May 1975. Households relying heavily on agriculture, either as cultivators or as landless laborers were selected as samples. Within Aurepalle village, a total of 40 households were surveyed (10 landless labor households and 30 cultivator households representing small, medium, and large farmers). Table 3-3 presents an overview of information on the households available in the data set.

Table 3-3: General Characteristics of the ICRISAT India Data

Household members
Number of members; age, sex, marital status, education level, and main and secondary occupations of each member; places of work of members living outside village and their remittance to their home
Labor
Hours and wages for the following activities in which each family member engages: cropping, animal husbandry, building, repairing, trading, domestic work, and other work (school, fuel and food) total wage days, non-farm days, days unemployed, reason for not working
Plot characteristics
Total area, cultivated area, irrigated area, irrigation source, soil type, plot ownership status, plot value per acre, revenue rate per acre, cropping patterns
On-farm operation
Date of operation; hours and value of own and hired bullock labor; hours and value of family and hired labor; quantity and value of output; quantity, value, and source of inputs (seed, organic manure, fertilizer, and pesticide)
Farm assets
Quantity and value of animals, farm equipment, farm buildings, and physical stocks (such as food grains, fodder, farm inputs, fuel, building materials, etc)
Household transactions
Cash inflow: account receiving money value, quantity of goods/services out, and money value in; cash outflow: account paying money value, quantity of goods/services in, and money value out
Financial assets
Value, use, source, interest rates, and payment conditions
Stock inventory
Value, use, and source
Monthly prices
Of a broad range of commodities for the village
Yearly rainfall by village

Sources: Overview of ICRISAT village level studies data for India

3.3.3. Sample Selection

The original sampling procedure to construct the ICRISAT village level data followed four stages. First, districts representing broad agroclimatic regions within the India's semi-arid tropics were identified. Three districts, Mahbubnagar, Sholapur, and Akola, were selected based on rainfall, soil, and cropping criteria. Second, within those districts, typical *talukas* (*i.e.*, smaller administrative units) were chosen mostly based on secondary data. Third, within those *talukas*, representative villages were chosen. Aurepalle is selected for Mahbubnagar district. Finally, within the village, a random sample of agricultural households was selected. Considering the amount of data to be collected, the memory bias inherent in longer periods between interviews, and the need for formal statistical analysis to explain variation in interhousehold behavior, a sample size of forty households is chosen in each selected village. Every village was surveyed in the village early in 1975, and that village census provided the basis for drawing the sample. The sample was selected mainly on the size of operational holding and the occupation of the household. Since households relying heavily on agriculture were the focus of this survey, full-time village artisans, shopkeepers, and traders, about 5 percent of the village households, were excluded from the sample.

3.3.4. Demographic Background

The population of the ICRISAT study villages increased by 35 to 50 percent between 1951 and 1981 partly due to low rate of out-migration despite declining fertility. Recent immigration into Mahbubnagar, with unassured rainfall, has been negligible.

Seasonal migration, frequently within the same states, by one or more family members (usually male) is widespread and appears to be increasing. For example, in Aurepalle, about 40 percent of the households contained an individual who left the village for at least a month to pursue employment opportunities in 1985/86.

Regarding family structure, four-tenths are stem, in which one or both parents live with their son's family; one-half of the sample households are nuclear; and one-tenth are joint-stem, where the parents reside with more than one married son. However, the incidence of extended households, stem and joint-stem, has increased gradually over the time as the sample aged.

Most residents in the village are Hindus.[11] Relatively few of the Hindus are Brahmins. The majority belong to communities whose traditional occupation is farming. Measured by population, political power and wealth, Reddis[12] are dominant in Aurepalle. Undeniably, caste influences many aspects of human endeavors. Whom one marries, where one lives in the village, with whom one eats, and where one fetches water are all conditioned by caste (Walker and Ryan 1990).

3.3.5. Education

The education level has risen by generation although there are still a number of illiterate adult villagers. In the late 1970s, about 50 percent of men and 85 percent of women were literate. About 62, 28, and 8 percent of individuals aged 6 to 11, 12 to 17, 18 to 23, respectively, attended school. There are two reasons for the increasing level of education. Growing awareness that a higher level of education is required for non-farm employment motivated the villagers to seek higher levels of education. In addition, greater access to a higher-level of schooling within the village also explains the phenomena. In Aurepalle, only about a half of the boys enroll in primary school in the late 1970s.

There are some empirical findings about education to be mentioned. First, the education of parents clearly matters in the schooling of the child. However, parents' education only helps to augment the schooling prospects of children of the same gender (Laufer 1983). Second, the education of the head of the household has a sizable impact on income determination and asset accumulation (Binswanger and Singh 1988). On the other hand, the education of the household

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[11] Indians can be grouped into Hindus and non-Hindus (*e.g.*, Muslims, Christians, etc.). Hindus are further categorized into four castes: Brahmins, Kshatriyas, Vaishyas, and Shudras.
[12] Reddis belong to an upper caste.

head does not explain disparities in wages paid to agricultural labor, which is probably because the average years of schooling for 240 heads of household was only a little over two years.

3.3.6. Product and Input Markets

The majority of villagers market their products by the auction system in nearby regulated markets, which seem to be quite efficient and receive infrastructural support from the government (Raju and von Oppen 1982). On the contrary, inputs markets, especially for seed and fertilizer, need to be improved. Farmers do not get their desired improved inputs, especially the seeds of modern varieties since it is supply constrained more than any other items.

Chapter 4

RESULTS

Among various crops produced in Aurepalle, castor, an oilseed, is chosen for the analysis. It is appropriate for learning studies for two reasons. First, castor is one of the major crops in Aurepalle. Land allotted to castor in relation to the total land ranged from 32.0 to 54.9 percent during the period (see Appendix B). Household production accounts for over 72.4 percent throughout the period (see Appendix C). Second, among all the crops involving HYV, castor is the only crop whose data is available from the outset of the HYV adoption. Thus, learning of the HYV castor can be measured from the first year of adoption.

The rest of this chapter is organized in four sections. Section 4.1 summarizes statistics of the variables used for estimation. Section 4.2 briefly evaluates estimation results, which are used for analyses in the following sections. Section 4.3 presents hypotheses testing on model specification and significance of groups of the variables. Section 4.4 describes the nature of castor production and identifies inefficiency determinants, using various elasticities.

4.1. Castor Production and Summary Statistics

Focusing on castor production in Aurepalle village from 1975 to 1984, HYV castor was produced in 1981 for the first time in this village. Compared to HYV of some other crops, HYV castor was widely adopted from its introduction (see Table 4-1). HYV castor remained high in use in the years shown in Table 4-1.

Table 4-1: Village-Level Castor Production by Kinds of Varieties: 1975-1984

	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	Mean
Production (kg)											
HYV & TV[1]	7075	6937	19050	10449	6267	5892	10193	10086	10293	11463	9771
HYV	-	-	-	-	-	-	8954	9409	10058	10855	9819
	-	-	-	-	-	-	(87.8)	(93.3)	(97.7)	(94.7)	
TV	7075	6937	19050	10449	6267	5892	1239	677	235	608	5843
	(100)	(100)	(100)	(100)	(100)	(100)	(12.2)	(6.7)	(2.3)	(5.3)	
Land Area (acre)[2]											
HYV & TV	96.7	158.8	80.6	104.5	95.6	94.9	124.8	107.3	115.2	107.5	108.6
HYV	-	-	-	-	-	-	90.2	96.8	106.6	91.2	96.2
	-	-	-	-	-	-	(72.3)	(90.2)	(92.5)	(84.8)	
TV	96.7	158.8	80.6	104.5	95.6	94.9	56.5	15.6	14.1	18.3	73.6
	(100)	(100)	(100)	(100)	(100)	(100)	(45.3)	(14.5)	(12.2)	(17.1)	
Number of Farms											
HYV & TV	21	24	19	24	24	23	25	26	24	23	23.3
HYV	-	-	-	-	-	-	18	20	22	18	19.5
	-	-	-	-	-	-	(72.0)	(76.9)	(91.7)	(78.3)	
TV	21	24	19	24	24	23	14	7	6	8	17
	(100)	(100)	(100)	(100)	(100)	(100)	(56.0)	(26.9)	(25.0)	(34.8)	

Values in parentheses indicate percentages of HYV or TV to the total.
[1] HYV and TV indicate high-yielding and traditional varieties, respectively.
[2] Sum of HYV and TV percentages exceeds 100 percent in both land area and number of farms since HYV and TV are sometimes grown in the same plot or by the same farms in the same year.

Table 4-1 describes the diffusion of HYV castor with respect to three indicators: production, land area, and number of farms. HYV castor production started out with 87.8 percent of the total castor production and accounted for over 90 percent of production in the following years. Approximately 90 percent of castor production derives from HYV through the period 1981 to 1984.

Changes in land area suggest a slightly different diffusion pattern. Acreage of HYV production was 72.3 percent in 1981, increased to over 90 percent in 1982 and 1983, then dropped to 84.8 percent in 1994. In terms of TV, acreage in 1981 was 45.3 percent and dropped to less than 20 percent in 1982. Acreage stayed below 20 percent in 1983 and 1984. This indicates that farms kept producing the TV to a substantial extent when they first adopted HYV, which may be accounted for by risk-averse attitude of the farms.

The fact that diffusion did not occur in a complete manner can also be revealed from the number of farms. In 1981, more than a half of the castor producers continued producing TV while 72.0 percent of the farms adopted HYV. In the following two years, diffusion progressed steadily, then dropped slightly in 1984.

While four years is too short to grasp the nature of diffusion, these data suggest that HYV had spread in a significant manner from the year of its introduction and remained high in use in the following years.

The steady diffusion pattern needs to be explained by considering the farms' standpoint. Table 4-2 provides an aggregate description of whether HYV production had been more productive than TV production and to what extent.

Table 4-2: Village-Level Castor Yields by Kinds of Varieties: 1975-1984 (kg/acre)

	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984
HYV[1]										
Mean	-	-	-	-	-	-	111.3	86.3	115.0	120
Standard Deviation	-	-	-	-	-	-	112.8	39.9	80.8	88.9
Maximum	-	-	-	-	-	-	460.8	192.5	309.7	317.3
Minimum	-	-	-	-	-	-	0	22.6	0	11.3
TV[2]										
Mean	77.3	56.0	224.1	103.0	65.9	54.7	30.8	57.9	13.8	42.2
Standard Deviation	46.6	52.5	82.7	30.8	46.9	39.4	32.4	66.2	19.2	22.6
Maximum	182	241.6	329.5	186.3	201.4	146.2	93	203.3	39.6	80
Minimum	11.19	2.17	0	40	0	0	0	15	0	17

[1] HYV indicates high-yielding varieties of castor.
[2] TV indicates traditional varieties of castor.

In terms of mean values, HYV yields are consistently over 80kg per acre while TV yields are below 80kg per acre for eight years out of ten years. Standard deviations are also high in HYV yields, implying that farms face greater yield variation with HYV production than with TV production. It may further imply HYV production is riskier than TV production. High maximum values in HYV yields imply high potential yields of HYV, while the minimum values are similar for both HYV and TV. Whether the potential yields of HYV can be attained or not depends on the farms.

Evidence of the HYV castor diffusion has been presented at the village level. Appendix D provides a sketch of adoption behavior of the farms by visually illustrating evidence of learning by contrasting acreage of plots allotted to HYV castor and its yields at the farm level. There are several significant patterns to be gleaned from these figures. First, farms that once adopted HYV do not necessarily continue producing HYV, which may imply that they exhibit trial-and-error type of behavior to learn about HYV. Second, experiences with HYV production do not seem to guarantee high yields to every farm. Summary statistics of the variables used for estimation is available in Table 4-1, covering the period 1975 to 1984 by year.

Table 4-3: Summary Statistics of the Variables

Variable	Statistics	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984
PRODUCTION FUNCTION											
Castor (kg)	Mean	336.90	309.82	1002.63	435.38	272.48	256.15	466.02	402.48	445.53	497.20
	Standard Deviation	374.82	313.44	783.95	357.85	265.62	285.55	605.64	478.57	386.88	505.61
	Minimum	35	36	0	20	44	0	28.5	6	0	34
	Maximum	1660	1405	3115	1230	1158	1177	2703	1665	1326	2125
Seed (kg)	Mean	20	19.84	17.12	24.13	16.46	15.04	16.19	15.16	17.61	17.85
	Standard Deviation	16.65	16.77	12.14	19.66	11.70	12.02	11.95	12.43	11.72	11.75
	Minimum	4	4	3	3	7	1	4	2	4	2.5
	Maximum	77	76	48	77	52	51	45	47	42	50
Family Labor (hours)	Mean	345	301.59	268.05	190.42	234	194.13	275.10	200.84	240.36	226.14
	Standard Deviation	331.83	201.50	178.41	110.28	141.34	176.10	171.48	200.81	204.37	180.76
	Minimum	59	56	9	20	0	27	44	15	15	0
	Maximum	1561	868	596	456	622	626	573	579	627	681
Hired Labor (hours)	Mean	180.48	348.18	522.42	234.79	165.13	221.39	278.43	166.24	221.32	293.73
	Standard Deviation	287.27	504.05	748.87	354.63	276.40	361.41	467.25	339.97	323.60	527.53
	Minimum	0	0	0	0	0	0	0	0	0	0
	Maximum	1147	1836	3038	1269	1212	1660	1979	1282	1135	2186
Animal Labor (hours)	Mean	225.86	318.73	146.89	105.17	152.13	223.04	261.43	175.24	174.05	255.27
	Standard Deviation	298.77	248.90	129.97	112.61	130.78	192.96	171.74	160.33	112.31	237.55
	Minimum	41	43	22	0	48	35	44	13	17	28
	Maximum	1373	856	536	464	648	812	805	631	381	1067
Fertilizer (kg)	Mean	0.02	0.41	5.26	0.00	2.91	5.87	18.24	5.96	15.05	32.80
	Standard Deviation	0.11	1.92	15.77	0.00	8.18	21.25	36.56	17.93	21.19	50.35
	Minimum	0	0	0	0	0	0	0	0	0	0
	Maximum	0.5	9	50	0	30	100	150	74	65	230
Pesticide (kg)	Mean	0.05	0.09	0	0	0.09	0.53	1.50	0.34	0.73	0.24
	Standard Deviation	0.15	0.21	0	0	0.18	1.09	2.21	0.59	0.66	0.65
	Minimum	0	0	0	0	0	0	0	0	0	0
	Maximum	0.5	0.7	0	0	0.5	5	7.01	2	2	2.25

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Table 4-3 Continued

Variable	Statistics	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984
HYV Ratio	Mean	0	0	0	0	0	0	0.58	0.78	0.87	0.70
	Standard Deviation	0	0	0	0	0	0	0.40	0.41	0.28	0.43
	Minimum	0	0	0	0	0	0	0	0	0	0
	Maximum	0	0	0	0	0	0	1	1	1	1
Good Soil Dummy	Mean	0.10	0	0	0.17	0.04	0.04	0.05	0.08	0.09	0.09
	Standard Deviation	0.30	0	0	0.38	0.21	0.21	0.22	0.28	0.29	0.29
	Minimum	0	0	0	0	0	0	0	0	0	0
	Maximum	1	0	0	1	1	1	1	1	1	1
Bad Soil Dummy	Mean	0	0.14	0.05	0.13	0.09	0.09	0.05	0.04	0.05	0.05
	Standard Deviation	0	0.35	0.23	0.34	0.29	0.29	0.22	0.20	0.21	0.21
	Minimum	0	0	0	0	0	0	0	0	0	0
	Maximum	0	1	1	1	1	1	1	1	1	1
Cultivated Area[1] (acres)	Mean	4.45	6.92	4.24	4.35	4.13	4.13	4.82	4.18	4.74	4.63
	Standard Deviation	4.05	5.89	3.15	3.67	2.74	3.37	3.46	3.40	2.96	3.22
	Minimum	1	0.8	0.8	0.5	1.25	0.5	1	0.4	1	0.5
	Maximum	19.3	20	14	14	12	13.95	12	11.75	11	12.95
INEFFICIENCY FUNCTION											
Age (years)	Mean	47.76	49.00	49.32	48.08	50.00	51.04	51.24	53.32	51.95	53.09
	Standard Deviation	9.99	10.55	12.06	11.76	11.50	10.71	10.02	10.25	12.52	12.41
	Minimum	22	23	24	25	26	30	31	32	30	31
	Maximum	60	66	67	68	69	70	66	72	73	74
Education (categorical)	Mean	1.05	0.86	0.95	0.83	1.04	0.87	0.81	0.76	0.86	0.86
	Standard Deviation	1.24	0.83	0.85	0.82	1.19	0.81	0.87	0.83	0.89	0.89
	Minimum	0	0	0	0	0	0	0	0	0	0
	Maximum	5	4	4	4	5	4	4	4	4	4
Own Experience (acres)	Mean	0	0	0	0	0	0	0	1.74	4.45	6.72
	Standard Deviation	0	0	0	0	0	0	0	2.02	3.57	5.46
	Minimum	0	0	0	0	0	0	0	0	0	0
	Maximum	0	0	0	0	0	0	0	7	11	18.5

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Table 4-3 Continued

Variable	Statistics	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984
Reference Group Experience Based on Farm Size (acres)	Mean	0	0	0	0	0	0	0	1.50	3.80	6.06
	Standard Deviation	0	0	0	0	0	0	0	1.16	1.51	2.84
	Minimum	0	0	0	0	0	0	0	0	1.70	0
	Maximum	0	0	0	0	0	0	0	3.34	5.89	9.99
Reference Group Experience Based on Household Size (acres)	Mean	0	0	0	0	0	0	0	1.62	3.79	5.97
	Standard Deviation	0	0	0	0	0	0	0	0.85	1.54	2.53
	Minimum	0	0	0	0	0	0	0	0	0.986	0
	Maximum	0	0	0	0	0	0	0	3.67	7.83	11
Reference Group Experience Based on Caste Rank (acres)	Mean	0	0	0	0	0	0	0	1.52	3.73	5.90
	Standard Deviation	0	0	0	0	0	0	0	0.92	1.23	2.32
	Minimum	0	0	0	0	0	0	0	0	1.55	0
	Maximum	0	0	0	0	0	0	0	3.09	5.53	9.48
Non-reference Group Experience Based on Farm Size (acres)	Mean	0	0	0	0	0	0	0	1.58	3.62	5.89
	Standard Deviation	0	0	0	0	0	0	0	0.77	0.83	1.96
	Minimum	0	0	0	0	0	0	0	0	2.70	0
	Maximum	0	0	0	0	0	0	0	2.31	4.58	7.91
Non-reference Group Experience Based on Household Size (acres)	Mean	0	0	0	0	0	0	0	1.59	3.83	6.30
	Standard Deviation	0	0	0	0	0	0	0	0.49	0.30	1.52
	Minimum	0	0	0	0	0	0	0	0	3.32	0
	Maximum	0	0	0	0	0	0	0	1.93	4.14	7.13
Non-reference Group Experience Based on Caste Rank (acres)	Mean	0	0	0	0	0	0	0	1.60	3.67	5.96
	Standard Deviation	0	0	0	0	0	0	0	0.62	0.53	1.60
	Minimum	0	0	0	0	0	0	0	0	3.04	0
	Maximum	0	0	0	0	0	0	0	2.04	4.34	7.13
Farm Size (categorical)	Mean	2.24	2.18	2.26	2.04	2	2.17	2.24	1.88	2.23	1.82
	Standard Deviation	0.83	0.85	0.81	0.86	0.85	0.83	0.83	1.01	0.81	1.10
	Minimum	1	1	1	1	1	1	1	0	1	0
	Maximum	3	3	3	3	3	3	3	3	3	3

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Table 4-3 Continued

Variable	Statistics	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984
Household Size (heads)	Mean	7.81	7.5	7.05	6.96	7.09	7.26	7.14	6.76	6.73	5.64
	Standard Deviation	2.64	2.92	3.15	3.24	3.63	3.63	3.23	3.05	2.90	2.75
	Minimum	3	2	3	2	2	2	2	2	2	1
	Maximum	14	15	15	16	17	16	12	14	15	14
Dependency Ratio	Mean	0.26	0.27	0.27	0.33	0.28	0.24	0.26	0.23	0.27	0.18
	Standard Deviation	0.16	0.20	0.18	0.20	0.20	0.19	0.18	0.19	0.18	0.20
	Minimum	0	0	0	0	0	0	0	0	0	0
	Maximum	0.5	0.75	0.6	0.71	0.63	0.57	0.57	0.57	0.6	0.57
Caste Dummy 1	Mean	0.43	0.41	0.47	0.33	0.39	0.35	0.38	0.28	0.36	0.32
	Standard Deviation	0.51	0.50	0.51	0.48	0.50	0.49	0.50	0.46	0.49	0.48
	Minimum	0	0	0	0	0	0	0	0	0	0
	Maximum	1	1	1	1	1	1	1	1	1	1
Caste Dummy 2	Mean	0.14	0.05	0.11	0.08	0.13	0.04	0	0	0	0
	Standard Deviation	0.36	0.21	0.32	0.28	0.34	0.21	0	0	0	0
	Minimum	0	0	0	0	0	0	0	0	0	0
	Maximum	1	1	1	1	1	1	0	0	0	0
Caste Dummy 3	Mean	0.24	0.27	0.21	0.25	0.26	0.30	0.33	0.44	0.36	0.41
	Standard Deviation	0.44	0.46	0.42	0.44	0.45	0.47	0.48	0.51	0.49	0.50
	Minimum	0	0	0	0	0	0	0	0	0	0
	Maximum	1	1	1	1	1	1	1	1	1	1

[1] Although cultivated area does not appear as an explanatory variable in the production function, the output and six inputs in the function are normalized by cultivated area prior to log transformation.

4.2. MODEL ESTIMATION

The model to be estimated proposes the translog production specification and an inefficiency function. Three different models are created depending on the way learning-from-others' terms are specified by separating out the reference group experience and the non-reference group experience (see Appendix A for construction of the learning terms). Three models include all the same variables except two variables for reference group experience and non-reference group experience.

These two forms of learning-from-others' components are created based on the farm characteristics to reveal how a farmer may choose the other farmers' experiences to learn from and how. The underlying idea is that learning within the reference group may be more efficiency-enhancing when the others' experiences can be imported and utilized without considering differences in their production environments arising from the farms' attributes. Conversely, learning may occur within the same caste since cultural norms can dictate with whom they communicate frequently in their daily lives.

For convenience, models with learning-from-others' terms based on farm size, household size, and caste rank are denoted Model FS, Model HS, and Model CS, respectively, in the following part of the thesis. Each model is estimated with FRONTIER 4.1. (Coelli 1994) using an unbalanced panel data set with a total of 222 observations that include 36 farms and 10 years. Estimation results are available in Appendix E, F, and G.[13] This section discusses overall estimation results as well as the coefficient estimates.

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[13] Interaction terms between the learning variables and education were primarily included in the inefficiency function to capture the effects of education on learning. However, they are dropped since inclusion of the interaction terms lead to an estimation problem due to high correlations among them as well as with the individual learning terms.

The coefficient estimates of the translog production function are similar across models in terms of signs, magnitude, and statistical significance, while those of the inefficiency function vary across the models. In terms of the production function, Models FS, HS, and CS, respectively, have 14, 13, and 11 coefficient estimates, which are statistically significant at 10 percent out of 52 estimates. The individual terms, family and hired labor variables as well as the "bad soil" dummy variable are statistically significant at 1 percent in each model. The "good soil" dummy variable is statistically significant at 10 percent in Model FS and at 5 percent in Model HS. Besides, approximately a half of the interaction terms of family and hired labor are statistically significant, at least, at 10 percent in all models.

In terms of the inefficiency function, 10 coefficient estimates out of 11 (excluding the intercept term) are statistically significant at the 10 percent level in Models FS and HS while six estimates are statistically significant at the 10 percent level in Model CS (see Table 4-4). Several results are consistent across the models. First, signs of the estimates of the non-learning variables (age, education, farm size, household size, the caste dummy) are all negative, indicating efficiency-enhancing, while the dependency ratio is positive, indicating efficiency-reducing impact. The sequence of the caste dummies with respect to magnitude indicates that the higher the caste rank, the more efficient farms are. Second, in all of the models, farm size, household size, the caste dummy 1 (highest caste) as well as the intercept are all statistically significant, at least, at 5 percent while education, the dependency ratio, and the caste dummy 2 are all statistically significant, at least, at 10 percent.

Table 4-4: Marginal Efficiency Impacts

Determinants	Model FS[1]	Model HS[2]	Model CS[3]
Age	–*	–**	–
Education	–*	–*	–*
Own Experience	–**	–	–
Reference Experience	+	–***	–
Non-reference Experience	–*	+*	+
Farm Size	–***	–***	–**
Household Size	–***	–***	–***
Dependency Ratio	+**	+*	+**
Caste 1	–***	–***	–***
Caste 2	–**	–*	–*
Caste 3	–*	–*	–

– indicates a marginal impact is efficiency-enhancing.

+ indicates a marginal impact is efficiency-reducing.

***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

[1] Model FS includes learning-from-others terms generated, based on farm size.

[2] Model HS includes learning-from-others terms generated, based on household size.

[3] Model CS includes learning-from-others terms generated, based on caste rank.

Own experience is efficiency-enhancing in all the models although it is only statistically significant in Model FS. Results of the learning-from-others terms differ across the models in terms of signs and significance. In Model FS, non-reference group experience is efficiency-enhancing and statistically significant while reference group experience is efficiency-reducing. In Models HS and CS, in contrast, reference group experience is efficiency-enhancing whereas non-reference group experience is efficiency-reducing. Reference and non-reference group experiences are statistically significant in Model HS while neither of them is statistically significant in Model CS.

Finally, farm-specific efficiency scores are produced from the predicted inefficiencies gained in the estimation and presented in Appendix H and I.[14] Appendix H provides efficiency scores by household and year, illustrating substantial variations in efficiency across the households. The appendix also indicates some fluctuations of efficiency over time at the village level. The village-level mean efficiency score over time is 0.626.[15] Appendix I plots efficiency levels by household, highlighting sizable variations in efficiency over time at the household level.

4.3. HYPOTHESES TESTING

Four hypotheses are tested on each model using the Likelihood Ratio Test. Test results are presented in Table 4-5.

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[14] The derivation of the efficiency scores is explained in Section 3.1.1. Efficiency scores are presented just for Model HS since they do not substantially vary across the models.

[15] Previous studies earned different efficiency scores. For example, Coelli and Battese (1996) predicted efficiency mean ranging from 0.711 to 0.747. Kalirajan (1991) yielded the mean of 0.693.

Table 4-5: Results of Hypotheses Testing

Null Hypothesis	Model	Log Likelihood	Test Statistic	Critical Value[4]	Decision
HYPOTHESIS 1:					
H_0: $\beta_7 = \beta_{i7} = \beta_{7j} = 0$	Model FS	-178.00	19.79	15.99 (10)	Reject
$i = 1, \ldots, 7;\ j = 7, 8, 9$	Model HS	-178.58	22.17		Reject
	Model CS	-172.66	10.29		Not Reject
HYPOTHESIS 2:					
H_0: $\beta_{ij} = 0$	Model FS	-268.71	201.20	61.66 (42)[5]	Reject
$i = 1, \ldots, 7;\ j = 1, \ldots, 9;\ i \leq j$	Model HS	-262.52	190.05		Reject
	Model CS	-262.62	190.22		Reject
HYPOTHESIS 3:					
H_0: $\delta_i = 0$	Model FS	-243.08	149.94	17.28 (11)	Reject
$i = 1, \ldots, 11$	Model HS	-243.08	151.17		Reject
	Model CS	-243.08	151.14		Reject
HYPOTHESIS 4:					
H_0: $\gamma = \delta_i = 0$	Model FS	-266.41	196.61	19.81 (13)	Reject
$i = 0, \ldots, 11$	Model HS	-266.41	197.84		Reject
	Model CS	-266.41	197.81		Reject

Notes:
HYPOTHESIS 1 indicates insignificance of HYV ratio and its interaction terms.
HYPOTHESIS 2 indicates Cobb-Douglas functional form.
HYPOTHESIS 3 indicates linearity of the inefficiency effects with respect to the regressors of the inefficiency function.
HYPOTHESIS 4 indicates OLS estimation.
Footnotes:
[1] Model FS includes learning-from-others terms generated, based on farm size.
[2] Model HS includes learning-from-others terms generated, based on household size.
[3] Model CS includes learning-from-others terms generated, based on caste rank.
[4] Critical values are based on the chi-square distribution at 5 percent. Values in parentheses indicate numbers of restrictions.
[5] The critical value is indicated for 45 degrees of freedom for its availability.

Hypothesis 1 examines whether the HYV ratio and its interaction terms are collectively significant in all the models. Test results show their significance for Models FS and HS despite the observation that the coefficient estimates of those variables are individually statistically insignificant. The HYV ratio is included in the production function since technologies are likely to be different between TV and HYV production and the difference must be embedded in the model for a theoretically reasonable model specification.

Results of Hypothesis 2 indicate that the translog form fits the data better than the Cobb-Douglas form in every model. Hypothesis 3 tests whether the regressors of the inefficiency function are jointly insignificant, which rejects the test. Hypothesis Test 4 reveals that stochastic frontier function fits the data better than the non-frontier function estimated by the OLS. These results assure that the model of the translog production and inefficiency functions are better specified to explain the data than the other alternatives.

4.4. Elasticities

Scale and output elasticities with respect to all six inputs are computed for the three models (see Table 4-6). Elasticities of each variety are similar to one another in terms of signs, magnitude, and significance across the models. However, there are some noticeable differences across varieties. Consideration on those elasticities can provide insight into the nature of castor production despite the concern on high standard errors.

Table 4-6: Output and Scale Elasticities of Castor Production

Elasticities	HYV & TV[1]			HYV			TV		
	Model FS[2]	Model HS[3]	Model CS[4]	Model FS	Model HS	Model CS	Model FS	Model HS	Model CS
Output Elasticity									
Seed	0.267	0.295	0.301	0.697	0.717	0.757	0.052	0.084	0.072
	(2.950)	(2.942)	(2.943)	(3.592)	(3.590)	(3.635)	(2.628)	(2.618)	(2.597)
Family Labor	1.164	1.159	1.157	1.080	1.087	1.082	1.205	1.195	1.194
	(1.105)	(1.102)	(1.124)	(1.261)	(1.255)	(1.277)	(1.027)	(1.026)	(1.047)
Hired Labor	0.436	0.440	0.442	0.480	0.486	0.483	0.414	0.417	0.422
	(0.479)	(0.490)	(0.488)	(0.525)	(0.535)	(0.536)	(0.456)	(0.467)	(0.464)
Animal	-0.623	-0.611	-0.617	-0.511	-0.479	-0.479	-0.680	-0.678	-0.687
	(1.107)	(1.102)	(1.102)	(1.467)	(1.456)	(1.459)	(0.928)	(0.925)	(0.924)
Fertilizer	-0.054	-0.038	-0.037	-0.029	-0.029	-0.025	-0.067	-0.042	-0.043
	(0.406)	(0.390)	(0.401)	(0.525)	(0.514)	(0.521)	(0.343)	(0.324)	(0.339)
Pesticide	-0.009	0.003	0.009	0.012	0.025	0.032	-0.019	-0.008	-0.003
	(1.058)	(1.079)	(1.061)	(1.190)	(1.209)	(1.196)	(0.992)	(1.013)	(0.993)
Scale Elasticity	1.181	1.248	1.254	1.730	1.806	1.850	0.906	0.968	0.955

Values in parentheses are standard errors.
[1] HYV and TV indicate high-yielding and traditional varieties, respectively.
[2] Model FS includes learning-from-others terms generated, based on farm size.
[3] Model HS includes learning-from-others terms generated, based on household size.
[4] Model CS includes learning-from-others terms generated, based on caste rank.

First, the output elasticity with respect to seed for HYV is substantially larger than its counterpart for TV, indicating that an increase in seed use enhances a greater output with HYV than with TV. Second, the output elasticity of animal is consistently negative despite the difference across varieties, indicating an increase in animal use decreases output. The negative elasticity may be due to the fact that it is used more extensively in years of poorer rainfall (for week control, levy bank improvements, etc.) when yields are lower (Battese and Coelli 1995). The output elasticity of animal use is larger with TV than with HYV in absolute value, indicating that animals are used less efficiently for HYV than for TV. Third, the output elasticity of fertilizer is negative and larger in absolute value for TV than for HYV. This suggests that at least some of the farms are able to use fertilizer in a less counterproductive manner in HYV production than in TV production even thought more fertilizer is used for castor production after HYV was introduced (as indicated in Table 4-3). Fourth, the output elasticities with respect to pesticide use are positive for HYV consistently across the models while they are negative for TV. Fifth, the result of higher output elasticity of family labor than that of hired labor is robust. Lastly, the results of scale elasticity revealed that HYV castor is produced at increasing returns to scale whereas TV castor is produced at decreasing returns to scale, which is a consistent finding across the models. In summary, HYV castor seems to be more productive than TV castor due mainly to the contribution of seed and less importantly due to the contribution of fertilizer and pesticide, although their elasticities are associated with high standard errors.

Morishima elasticities of substitution, which illustrates the nature of production with respect to input-input relationships, are presented in Table 4-7. Negative signs indicate substitute relationships whereas positive signs indicate complementary relationships.

Table 4-7: Morishima Elasticities of Substitution of Castor Production

Elasticities	HYV & TV[1]			HYV			TV		
	Model FS[2]	Model HS[3]	Model CS[4]	Model FS	Model HS	Model CS	Model FS	Model HS	Model CS
Seed &									
Family Labor	-0.003	0.000	-0.001	0.000	0.002	0.001	0.000	0.000	0.000
Hired Labor	0.004	0.000	0.000	-0.001	-0.001	-0.001	0.000	0.000	0.000
Animal	-0.012	-0.001	-0.002	0.001	0.003	0.002	0.000	0.000	0.000
Fertilizer	-0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pesticide	-1.141	0.024	0.132	-0.025	-0.098	-0.091	0.220	-0.032	-0.011
Family Labor &									
Hired Labor	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Animal	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Fertilizer	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pesticide	-0.063	0.002	0.008	-0.001	-0.007	-0.006	0.012	-0.002	-0.001
Hired Labor &									
Animal	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Fertilizer	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pesticide	0.053	-0.002	-0.007	0.001	0.006	0.004	-0.011	0.002	0.001
Animal &									
Fertilizer	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pesticide	0.246	-0.007	-0.029	0.004	0.025	0.017	-0.052	0.011	0.003
Fertilizer &									
Pesticide	-0.175	0.005	0.022	-0.002	-0.008	-0.006	0.093	-0.017	-0.005

[1] HYV and TV indicate high-yielding and traditional varieties, respectively.
[2] Model FS includes learning-from-others terms generated, based on farm size.
[3] Model HS includes learning-from-others terms generated, based on household size.
[4] Model CS includes learning-from-others terms generated, based on caste rank.

The results do not differ substantially either across varieties or across the models for a particular variety. Overall, few elasticities are substantial in magnitude, which implies that input use in castor production in Aurepalle is not flexible. For example, the column of Model FS in HYV & TV shows that seed and pesticide are substitutes. However, the result is not robust across the models. There are a few elasticities noticeable in the same column: the elasticities of animal and pesticide and of fertilizer and pesticide. Those results are again not consistent with the results of the other models.

Inefficiency elasticities of each model are presented in Tables 4-8A, 4-8B, and 4-8C, respectively. All the elasticities are shown by caste. Inefficiency elasticities indicate the percent inefficiency increases when a determining factor increases by one percent. Negative signs indicate reductions of inefficiency while positive signs indicate increases of inefficiency.

One thing to note is that this analysis cannot capture the input-input relationship between factor types such as fertilizer and pesticide. Since various kinds of fertilizers and pesticides are available, there may be some input-input relationships among fertilizers or pesticides.

Table 4-8A: Inefficiency Elasticities of Determinants for Model with Learning Terms Based on Farm Size

Determinants	All[1]	Caste 1[2]	Caste 2[3]	Caste 3[4]	Caste 4[5]
Age	-3.014*	-2.814*	-3.141*	-3.232*	-3.009*
	(1.758)	(1.642)	(1.833)	(1.885)	(1.755)
Education	-1.551*	-1.619*	-2.038*	-1.697*	-1.185*
	(0.843)	(0.881)	(1.109)	(0.923)	(0.644)
Own Experience	-0.677**	-0.895**	0.000[6]	-0.680**	-0.508**
	(0.304)	(0.402)	(0.000)	(0.306)	(0.228)
Reference Group Experience	0.944	1.304	0.000[6]	0.912	0.674
	(0.856)	(1.182)	(0.000)	(0.827)	(0.611)
Non-reference Group Experience	-1.033*	-0.666*	0.000[6]	-1.435*	-1.283*
	(0.597)	(0.385)	(0.000)	(0.830)	(0.742)
Farm Size	-6.671***	-9.225***	-6.092***	-5.205***	-4.956***
	(2.137)	(2.955)	(1.952)	(1.668)	(1.588)
Household Size	-7.093***	-8.840***	-7.360***	-5.885***	-6.023***
	(2.189)	(2.728)	(2.271)	(1.816)	(1.859)
Dependency Ratio	1.769**	1.561**	2.478**	1.615**	2.094**
	(0.715)	(0.630)	(1.001)	(0.653)	(0.846)

Values in parentheses indicate standard errors.

***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

[1] All indicates all four castes.

[2] Caste 1 indicates the highest caste.

[3] Caste 2 indicates the second highest caste.

[4] Caste 3 indicates the second lowest caste.

[5] Caste 4 indicates the lowest caste.

[6] They are not available because there are no farms in caste 2 that produced HYV.

Table 4-8B: Inefficiency Elasticities of Determinants for Model with Learning Terms Based on Household Size

Determinants	All[1]	Caste 1[2]	Caste 2[3]	Caste 3[4]	Caste 4[5]
Age	-4.213**	-3.934**	-4.392**	-4.518**	-4.206**
	(1.769)	(1.652)	(1.844)	(1.898)	(1.767)
Education	-1.440*	-1.504*	-1.893*	-1.575*	-1.100*
	(0.740)	(0.773)	(0.973)	(0.810)	(0.565)
Own Experience	-0.241	-0.319	0.000[6]	-0.242	-0.181
	(0.198)	(0.261)	(0.000)	(0.198)	(0.148)
Reference Group Experience	-1.844***	-2.401***	0.000[6]	-2.058***	-1.194***
	(0.425)	(0.553)	(0.000)	(0.474)	(0.275)
Non-reference Group Experience	1.063*	0.771*	0.000[6]	1.403*	1.289*
	(0.565)	(0.410)	(0.000)	(0.746)	(0.685)
Farm Size	-5.728***	-7.921***	-5.231***	-4.469***	-4.255***
	(2.053)	(2.838)	(1.874)	(1.601)	(1.525)
Household Size	-5.720***	-7.129***	-5.935***	-4.746***	-4.857***
	(1.896)	(2.363)	(1.968)	(1.573)	(1.610)
Dependency Ratio	1.234*	1.089*	1.729*	1.127*	1.461*
	(0.645)	(0.569)	(0.903)	(0.589)	(0.763)

Values in parentheses indicate standard errors.

***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

[1] All indicates all four castes.

[2] Caste 1 indicates the highest caste.

[3] Caste 2 indicates the second highest caste.

[4] Caste 3 indicates the second lowest caste.

[5] Caste 4 indicates the lowest caste.

[6] They are not available because there are no farms in caste 2 that produced HYV.

Table 4-8C: Inefficiency Elasticities of Determinants for Model with Learning Terms Based on Caste Rank

Determinants	All[1]	Caste 1[2]	Caste 2[3]	Caste 3[4]	Caste 4[5]
Age	-2.597	-2.425	-2.707	-2.785	-2.592
	(1.846)	(1.724)	(1.924)	(1.980)	(1.843)
Education	-1.493*	-1.560*	-1.963*	-1.634*	-1.141*
	(0.895)	(0.934)	(1.176)	(0.979)	(0.684)
Own Experience	-0.247	-0.326	0.000[6]	-0.248	-0.185
	(0.253)	(0.334)	(0.000)	(0.254)	(0.190)
Reference Group Experience	-1.074	-1.398	0.000[6]	-1.198	-0.695
	(0.714)	(0.929)	(0.000)	(0.796)	(0.462)
Non-reference Group Experience	0.289	0.209	0.000[6]	0.381	0.350
	(0.581)	(0.421)	(0.000)	(0.766)	(0.704)
Farm Size	-5.378**	-7.437**	-4.911**	-4.196**	-3.995**
	(2.218)	(3.067)	(2.025)	(1.731)	(1.648)
Household Size	-6.302***	-7.855***	-6.54***	-5.229***	-5.351***
	(2.023)	(2.521)	(2.099)	(1.679)	(1.718)
Dependency Ratio	1.478**	1.304**	2.071**	1.349**	1.749**
	(0.649)	(0.572)	(0.909)	(0.592)	(0.768)

Values in parentheses indicate standard errors.
***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.
[1] All indicates all four castes.
[2] Caste 1 indicates the highest caste.
[3] Caste 2 indicates the second highest caste.
[4] Caste 3 indicates the second lowest caste.
[5] Caste 4 indicates the lowest caste.
[6] They are not available because there are no farms in caste 2 that produced HYV.

There is no difference in terms of signs and statistical significance of the elasticities across castes. Age, education, farm size, and household size are efficiency-enhancing in all of the models. The more efficient farms are associated with, on average, the older or more educated the decision maker. The more experienced with HYV castor production, the more efficient the farmers. The larger the farm or household size, the more efficient the farmers.

In particular, household size and farm size are statistically significant, at least, at the 5 percent level and education is statistically significant at the 10 percent level. On the other hand, age is statistically significant at the 10 and 5 percent levels in Models FS and HS, respectively; but not statistically significant in Model CS.

On the contrary, the dependency ratio is efficiency-reducing. The larger number of dependents with respect to household size, the less efficient farms are. This may suggest that farms with higher dependency ratios tend to focus on subsistence production to feed their dependents or tend to depend on off-farm sources of income.

Own experience is efficiency-enhancing in all of the models, but only statistically significant in Model FS. This indicates that own experience enhances efficiency, but the effect is modest. On the other hand, signs of the elasticities of the learning-from-others vary across the models. Reference experience is efficiency-enhancing in Models HS and CS, and, in particular, it is statistically significant at the 1 percent level in Model HS. Non-reference experience is efficiency-reducing also in Models HS and CS, and its significance is observed in Models FS and HS.

These observations must be carefully interpreted since efficiency-enhancing (or efficiency-reducing) do not necessarily correspond to a success in learning (or failure in learning). Efficiency-enhancing means that farmers learn from each other whether they intend to learn or not. On the other hand, efficiency-reducing indicates either that farms do not intend to learn or that farms fail to learn despite their intentions to learn.

According to this interpretation, several inferences can be made regarding learning-from-others. First, farms learn from each other within the same household size or caste rank. In particular, learning among the group of the same household size is vital. Second, farms do not learn from each other if they fall within the same farm size category, which can be interpreted in two ways: 1) they did not attempt to learn because it is too costly to collect and process information from the farms in the same farm size category, 2) they failed to learn because it is difficult to apply the information that they collected to their own production environments. Third, the positive elasticity of the non-reference experience in Models HS and CS may be interpreted as experiments of non-reference group can confuse farms' learning-from-others, since applications of non-reference group experience is not as straightforward as those of reference group experience.

There is also some difference in magnitude across castes in each model. The higher the caste, the more efficiency-enhancing the effects of farm size and household size. Farm size and household size enhances efficiency more in higher castes. Own experience also enhances efficiency more in higher castes. Reference group experience enhances efficiency more in higher castes in Models HS and CS, but presents the opposite result in Model FS. Non-reference group experience reduces efficiency more in lower castes in Models HS and CS.

Overall, there is evidence of learning in castor production. Own experience has a modest impact on efficiency enhancement whereas reference group experience has different impacts depending on which farm characteristic farmers use to identify a natural reference group. In particular, learning from farms of the same household size is the most remarkable of all. Other than the learning terms, farm size and household size have considerable impacts on efficiency improvement. The robust result of education is another important finding.

4.5. Concluding Remarks

Stochastic frontier estimation yields estimates of the production and inefficiency functions. Output, scale, and Morishima elasticities are presented to characterize the nature of castor production. There are several noticeable differences between castor seed varieties, but not across models. Output elasticity of seed and scale elasticity are consistently larger in HYV production than in TV production. Morishima elasticities show inflexible input use of the farms in castor production.

Stochastic frontier estimation also provided the ability to predict inefficiency levels of the farms. Determinants of the inefficiency levels are successfully identified using the inefficiency elasticities. In all models of learning-from-others, household size, farm size, and education have significant effects on the enhancement of technical efficiency, whereas dependency ratio has a substantial impact on the efficiency reduction. In addition, the effect of age on efficiency enhancement is statistically significant in two models.

The own-experience impact is shown to improve efficiency consistently in all the models although the effect appears to be modest. With respect to reference group experience, farmers learn from each other within the grouping of the same household size or caste rank. In particular, learning-from-others with the same household size is statistically significant at the 1 percent level. On the other hand, the non-reference group experience presents opposite effects to the reference group experience in every model. Besides, significance of household and farm size and of dependency ratio are confirmed robust in enhancing and reducing efficiency, respectively.

Chapter 5

CONCLUSIONS AND IMPLICATIONS

This study was primarily conducted to investigate the effects of learning on technical efficiency of HYV castor production in Aurepalle village, India over the period 1975 to 1984. One of the major motivations of characterizing learning in a framework of the stochastic frontier analysis is to achieve a careful measurement of learning. There exists a body of individual learning literature capturing learning through the effects of experiences with new technologies on outputs (or profits). However, this approach is not capable of distinguishing changes in outputs (or profits) driven by technological changes as opposed to those driven by learning. On the other hand, the stochastic frontier approach enables the separation of productivity gains led by the technological progress from efficiency gains through learning of the technology. This separation is crucial when impacts of technological changes on production processes are substantial.

Simultaneous estimation of the stochastic frontier production function and inefficiency function yielded the coefficient estimates and the predicted technical inefficiency levels. Output and scale elasticities and Morishima elasticities of substitution characterized the nature of the production function. As seen in the high standard errors of the output elasticities, the production function was not estimated with a great precision. However, a noticeable difference between HYV and TV productions was witnessed in the output elasticities of seed. The output elasticity of seed in HYV production is substantially larger than that in TV production, which results in the substantial difference in scale elasticity between the seed varieties. Substantial scale economies are present in HYV castor production.

The policy implication of this result is to discourage further fragmentation to fully utilize the scale economies. Most farms in the village produce castor as well as other crops for subsistence needs. The generation of off-farm jobs can present farmers with secure income so that farms do not need to focus on subsistence crop production and may consequently encourage households to specialize in castor production. In addition, it is important for policy makers to enhance the availability of HYV seeds, which enables farmers to increase their scales of HYV castor production, since area planted to HYV castor was limited by seed availability in Aurepalle during the period of the study (Walker and Ryan 1990).The difference in the elasticities between the seed varieties highlights the importance of accounting for the technological difference between HYV and TV production in modeling the castor production properly as well as to yield the technical inefficiency levels with a precision.

The learning-by-doing effect is robust, but modest across the three models. The learning-from-others' effect varies across the models, indicating the importance of farmers' learning opportunities. The learning-from-others is statistically significant only when learning from others within the same household size. The result suggests that learning randomly from neighbors may not guarantee efficiency gains since farms cannot simply imitate neighbors' experiences to enhance efficiency.

Efficiency improvement through learning-from-others requires the process of deciphering information associated with others' experiences to make it applicable to their own production environments, which is expected to vary across farms and across time. Success in the deciphering process as well as the process of collecting information depends on farmers' efforts, applicability of others' experiences, as well as their cognitive abilities. If this deciphering process can be simplified by learning from farms facing a similar production situation (such as the same household size category), farms are maybe better off learning from them. Furthermore, collecting and processing the information can be costly and demanding in terms of cognitive skills.

The result regarding learning-from-others also indicates that learning from the non-reference group may provide misinformation, which can confuse farms, resulting in potential efficiency reduction. This result also confirms that learning randomly from neighbors does not necessarily assure efficiency gains. The results of learning-from-others imply that technological dissemination is better targeted the reference group level rather than at the village level. This study finds that the potential reference group can be based on household size.

Farm size and household size dominate the effects of efficiency enhancement with respect to magnitude and significance, which, in addition to the result of scale elasticities, implies that scale economies play an important role in castor production, especially in HYV production. Age is another efficiency-enhancing factor although its significance is not robust across the models. The dependency ratio, on the contrary, has a consistent and negative impact on efficiency levels.

Education is also confirmed to enhance efficiency. Although the effect of education is not sizable when we consider the magnitude of the elasticities, its significance is robust across the models. This result highlights the importance of investing in children's schooling and providing quality education.

The methodology illustrated in this thesis provides another useful perspective to analyze learning in the economic decision-making. However, four years is a relatively short time frame to capture the dynamics of learning of HYV production. Studies employing a longer panel may provide further insights into the dynamic process of learning.

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Appendix A: CONSTRUCTION OF LEARNING VARIABLES

The own experience variable is constructed for learning-by-doing while reference group experience and non-reference group experience variables are created for learning-from-others. The own experience variable is represented by cumulative land acreage where farms have experienced HYV castor production. Reference group experience and non-reference group experience are generated using different groupings based on three different classifications, *viz.*, farm size, household size, and caste rank. First, all the farms are grouped into four categories within each of the three reference groups. Results of three groupings are tabulated in Table A1, A2, and A3.

Table A1: Reference Grouping Based on Farm Size

Farm Size	Household ID	Number of Households
$0 \leq fs < 0.2$	none	0
$0.2 \leq fs < 2.5$	1, 9, 10, 32, 33, 34, 35, 38, 44, 48	10
$2.5 \leq fs < 5.26$	5, 36, 43, 46, 51, 81, 82	7
$5.26 \leq fs$	45, 50, 52, 53, 54, 55, 56, 57, 58, 59	10

Table A2: Reference Grouping Based on Household Size

Household Size	Household ID	Number of Households
$1 \leq hs < 5$	5, 9, 36, 43, 51, 55	6
$5 \leq hs < 7.5$	10, 32, 34, 38, 44, 45, 46, 48, 53, 54, 58, 59, 82	13
$7.5 \leq hs < 10$	1, 33, 35, 56	4
$10 \leq hs$	50, 52, 57, 81	4

Table A3: Reference Grouping Based on Caste Rank

Caste Rank	Household ID	Number of Households
1st caste	45, 50, 52, 53, 54, 56, 57, 58, 59	9
2nd caste	none	0
3rd caste	10, 32, 35, 38, 43, 44, 51, 55, 81, 82	10
4th caste	1, 5, 9, 33, 34, 36, 46, 48	8

In each model, households within the same category are called a reference group. For example, in Table A1, all ten farms with farm size ranging from 0.2 to 2.5 acres are in the same reference group. Second, based on the reference grouping with respect to farm size, reference group experience and non-reference group experience are computed. For instance, reference group experience for Household #1 is represented by an average of cumulative acreage of the rest of the reference group farms (#9, #10, #32, #33, #34, #35, #38, #44, #48) that have experienced HYV castor production. Non-reference group experience for the household is indicated by an average of cumulative acreage where the farms in the different reference groups have experienced HYV castor production. That is to say, non-reference group experience is the same for all the farms in the same reference group.

According to the classifications, the reference group experience variable is represented by an average of cumulative land acreage of the HYV castor production that the farms in the same reference group experienced. The non-reference group experience variable is represented by an average of cumulative acreage of the HYV castor production that the farms in the rest of the reference groups experienced.

Table A4, A5, A6, and A7 show variations in reference groupings across the models, using Table A1, A2, and A3 in this appendix. It is important for the variations in reference groupings across the models (as shown in the tables) to be recognized since the variations result in the variations in learning-from-others' variables (reference group experience and non-reference group experience).

Table A4: Unions of Households in All Models

Subsets of households belonging to the same reference group in all three models.	(1, 33), (5, 36), (10, 32, 38, 44) (43, 51), (45, 53, 54, 58, 59), (50, 52, 57)
Households belonging to differing reference groups by model	9, 34, 35, 46, 48, 55, 56, 81, 82

Table A5: Unions of Households in Model FS and Model HS

Subsets of households belonging to the same reference group in both models.	(1, 33, 35), (5, 36, 43, 51), (10, 32, 34, 38, 44, 48), (45, 53, 54, 58, 59), (46, 82), (50, 52, 57)
Households belonging to differing reference groups by model	9, 55, 56, 81

Table A6: Unions of the Households in Model FS and Model CS

Subsets of households belonging to the same reference group in both models.	(1, 9, 33, 45, 48), (5, 36, 46), (10, 32, 35, 38, 44), (43, 51, 81, 82), (45, 50, 52, 53, 54, 56, 57, 58, 59),
Households belonging to differing reference groups by model	55

Table A7: Unions of the Households in Model HS and Model CS

Subsets of households belonging to the same reference group in both models.	(1, 33), (5, 9, 36), (10, 32, 38, 44, 82), (34, 46, 48), (43, 51, 55), (45, 53, 54, 58, 59), (50, 52, 57)
Households belonging to differing reference groups by model	35, 56, 81

Table A4 compares reference groupings across the three models. Table A5, A6, and A7 compare reference groupings between Model FS and Model HS, Model FS and Model CS, and Model HS and Model CS, respectively. Each table contains two kinds of information. The first row presents subsets of the farms belonging to the same reference group across the models. The second row presents a group of farms that do not have any other households in the same reference group across the models. These tables indicate how reference grouping can vary across the three models.

Appendix B: PERCENT OF LAND AREA USED BY PRODUCTS: 1975-1984

Products	75	76	77	78	79	80	81	82	83	84
Oilseeds										
Castor	32.0	54.9	38.5	42.1	40.0	36.6	18.8	6.0	5.3	9.3
Safflower	5.9	10.6	0.0	0.0	1.9	0.0	3.0	3.8	6.9	3.7
Groundnuts	0.2	0.1	2.3	0.8	4.0	1.1	1.1	3.3	1.0	0.0
Castor*	0.0	0.0	0.0	0.0	0.0	0.0	31.2	39.6	42.3	40.5
Mustard	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2
Sesamum	0.0	7.4	0.0	0.4	0.0	2.2	2.4	0.2	2.1	0.0
Sunflower	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.9	0.4
Cereals										
Sorghum	45.9	28.0	42.3	35.7	32.5	43.1	38.3	36.3	28.6	33.1
Pearl millet	43.6	25.2	37.9	34.9	20.5	32.7	26.0	23.9	20.7	16.6
Paddy*	8.8	9.7	14.1	9.3	15.0	11.1	11.2	8.9	14.1	13.4
Paddy	6.2	4.7	6.7	7.1	10.0	3.4	3.5	2.8	2.4	1.3
Other cereals	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Wheat	0.3	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0
Maize*	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.1
Pearl millet*	0.0	0.0	0.0	0.0	0.0	1.1	2.4	6.1	4.4	5.4
Sorghum*	0.0	1.0	0.4	1.5	0.0	0.1	1.0	0.6	0.0	3.2
Wheat*	0.0	0.7	0.0	0.0	0.2	0.1	0.0	0.3	0.1	0.2
Fiber Crops										
other than cotton	35.8	19.0	0.0	0.0	0.0	0.0	0.3	0.0	0.0	0.6
Pulses										
Redgram	43.5	26.1	34.6	36.9	28.6	46.7	48.0	52.6	45.2	24.3
Other pulses	39.0	19.8	0.4	31.0	14.5	30.8	5.7	1.5	9.5	2.4
Greengram	30.8	17.1	0.2	21.6	19.1	25.6	16.2	10.8	23.7	18.0
Bengalgram	0.0	1.1	0.0	0.0	0.0	0.0	0.4	0.1	0.2	0.0
Blackgram	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0
Cowpea	0.0	0.0	0.0	0.0	0.0	0.0	15.4	10.8	44.2	19.2
Vegetables and Spices										
Other vegetables	43.9	24.1	0.0	0.0	0.0	1.3	0.2	0.0	0.0	0.0
Chillies	6.6	3.3	2.9	1.8	2.7	1.4	1.6	0.5	0.7	1.0
Tomato	0.5	1.5	0.1	0.0	0.0	0.3	0.0	0.0	0.0	0.0
Brinjal	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Onion	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Other spices	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0
Crop Byproducts & Fodder Crops										
Rough dry fodder	53.6	39.8	58.5	51.8	53.6	57.2	55.4	53.3	48.5	51.6
Other crop byproducts	24.6	6.6	0.0	30.5	14.8	11.8	43.3	51.5	37.7	0.0
Green fodder crops	2.4	0.7	0.2	1.7	1.0	4.6	1.6	1.3	3.2	1.3
Fine dry fodder	0.0	0.3	0.9	1.5	37.7	11.0	35.2	44.3	46.6	14.5
Grass & other green fodder	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total Land Area (acre)	316.3	304.8	230.3	260.4	242.8	283.5	301.0	260.8	265.3	231.8

* indicates high-yielding varieties.
Some land area is used for multiple cropping.

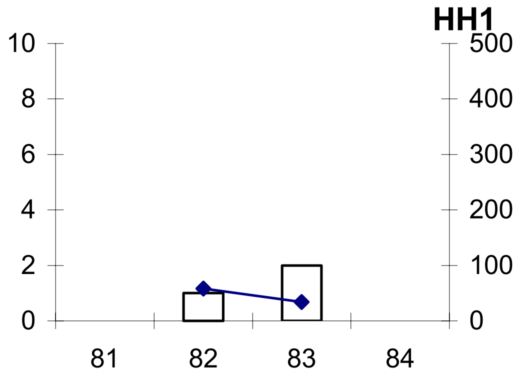
Appendix C: PERCENT OF HOUSEHOLDS PRODUCED FARM PRODUCTS BY YEAR: 1975-1984

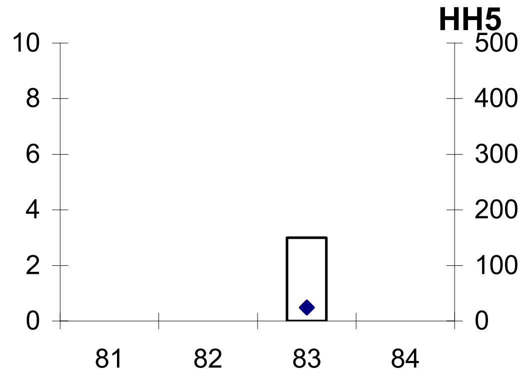
Products	75	76	77	78	79	80	81	82	83	84
Oilseeds										
Castor	79.3	92.9	72.4	92.9	86.7	83.3	43.8	23.3	20.7	37.0
Safflower	20.7	39.3	0.0	0.0	16.7	0.0	25.0	36.7	41.4	25.9
Groundnuts	3.4	3.6	6.9	3.6	30.0	10.0	12.5	13.3	10.3	0.0
Castor*	0.0	0.0	0.0	0.0	0.0	0.0	62.5	73.3	82.8	74.1
Mustard	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.7
Sesamum	0.0	28.6	0.0	3.6	0.0	10.0	6.3	3.3	6.9	0.0
Sunflower	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.4	3.7
Cereals										
Sorghum	93.1	71.4	89.7	78.6	53.3	90.0	81.3	76.7	72.4	74.1
Pearl millet	93.1	85.7	96.6	78.6	73.3	93.3	87.5	80.0	75.9	88.9
Paddy*	41.4	39.3	27.6	28.6	36.7	23.3	31.3	23.3	17.2	11.1
Paddy	31.0	42.9	37.9	35.7	43.3	36.7	31.3	33.3	37.9	33.3
Other cereals	6.9	3.6	0.0	0.0	0.0	0.0	0.0	0.0	6.9	0.0
Wheat	3.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Maize*	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.7
Pearl millet*	0.0	0.0	0.0	0.0	0.0	3.3	12.5	23.3	44.8	18.5
Sorghum*	0.0	3.6	3.4	10.7	0.0	3.3	6.3	3.3	0.0	7.4
Wheat*	0.0	7.1	0.0	0.0	3.3	3.3	3.1	10.0	3.4	7.4
Fiber Crops										
other than cotton	79.3	53.6	0.0	0.0	0.0	0.0	3.1	0.0	0.0	3.7
Pulses										
Redgram	93.1	67.9	79.3	82.1	56.7	93.3	87.5	93.3	82.8	81.5
Other pulses	86.2	71.4	3.4	60.7	46.7	76.7	28.1	13.3	31.0	14.8
Greengram	79.3	46.4	3.4	28.6	40.0	70.0	40.6	33.3	51.7	66.7
Bengalgram	0.0	3.6	0.0	0.0	0.0	0.0	6.3	3.3	3.4	0.0
Blackgram	0.0	0.0	0.0	0.0	0.0	3.3	0.0	0.0	0.0	0.0
Cowpea	0.0	0.0	0.0	0.0	0.0	0.0	40.6	23.3	75.9	74.1
Vegetables and Spices										
Other vegetables	96.6	60.7	0.0	0.0	0.0	6.7	3.1	0.0	0.0	0.0
Chillies	34.5	28.6	20.7	14.3	20.0	23.3	18.8	10.0	10.3	14.8
Tomato	10.3	3.6	3.4	0.0	0.0	3.3	0.0	0.0	0.0	0.0
Brinjal	6.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Onion	6.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.4	0.0
Other spices	0.0	0.0	0.0	0.0	0.0	3.3	0.0	0.0	0.0	0.0
Crop Byproducts & Fodder Crops										
Rough dry fodder	89.7	89.3	96.6	82.1	80.0	93.3	90.6	86.7	86.2	92.6
Other crop byproducts	62.1	10.7	0.0	67.9	40.0	16.7	81.3	93.3	75.9	0.0
Green fodder crops	24.1	3.6	3.4	10.7	10.0	30.0	18.8	16.7	13.8	18.5
Fine dry fodder	0.0	3.6	3.4	3.6	83.3	33.3	81.3	83.3	82.8	55.6
Grass & other green fodder	0.0	3.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total Number of Households	29	28	29	28	30	30	32	30	29	27

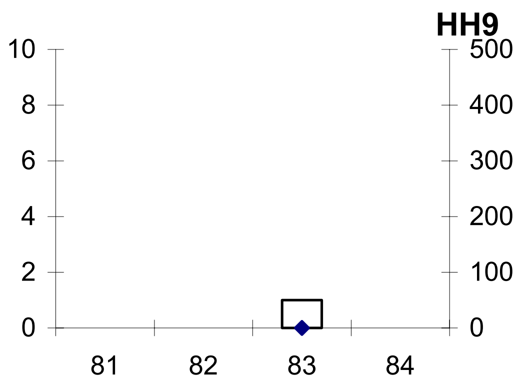
* indicates high-yielding varieties.

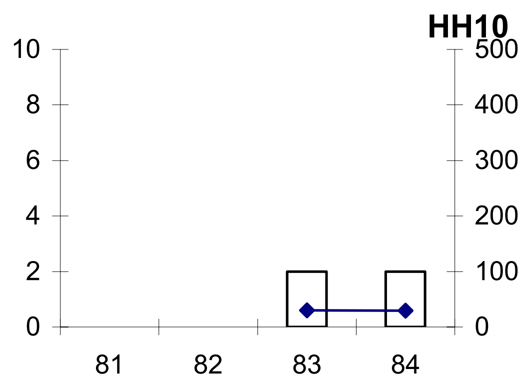
Appendix D: HYV CASTOR YIELDS AND ACREAGE BY HOUSEHOLD

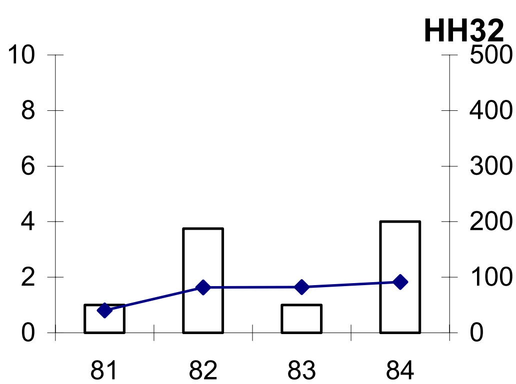
(Left Y-axis gauges acreage indicated by bar graph; right Y-axis measures yields indicated by line graph; X-axis shows years.)

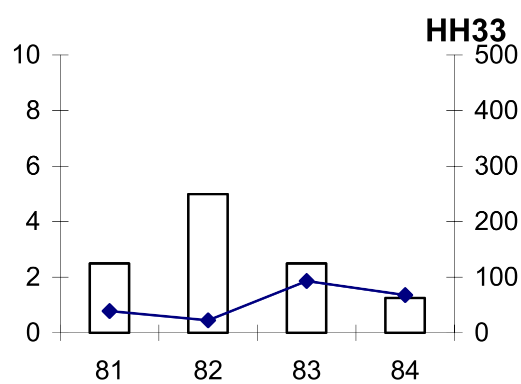












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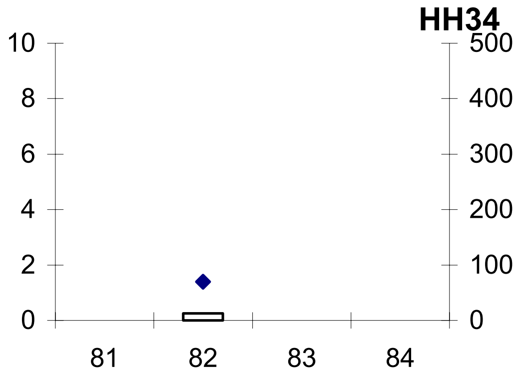

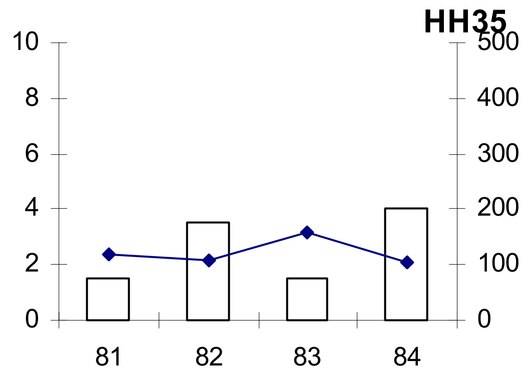

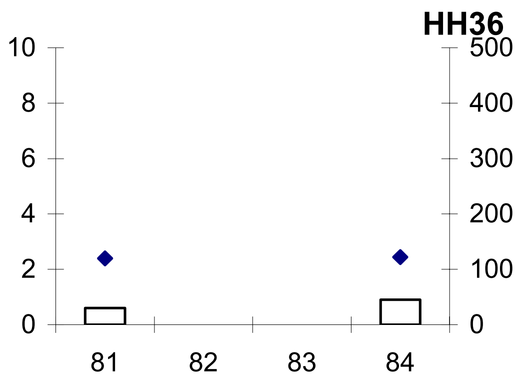

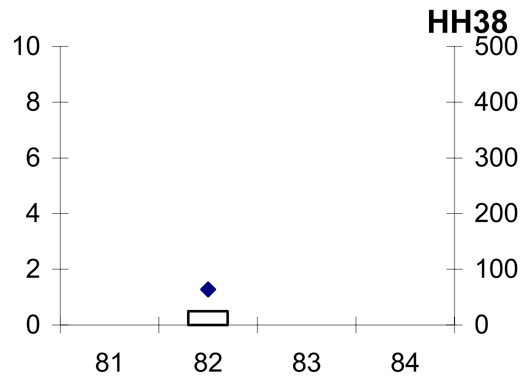

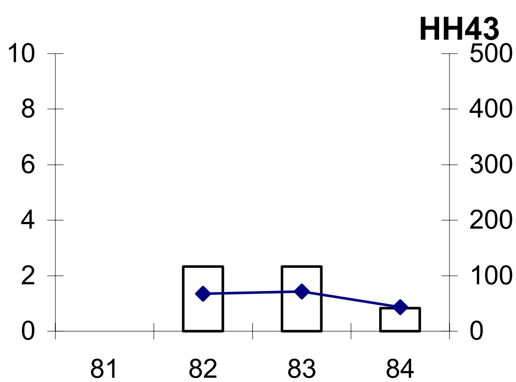

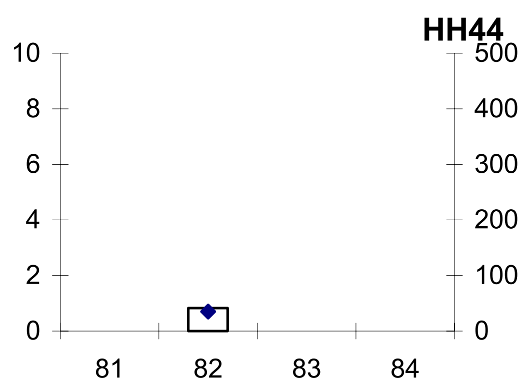

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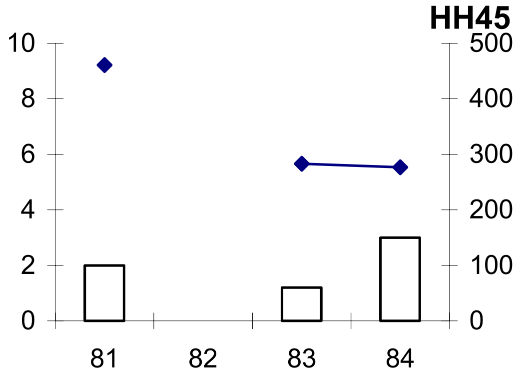

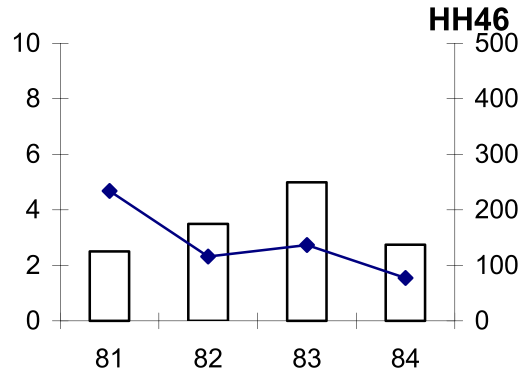

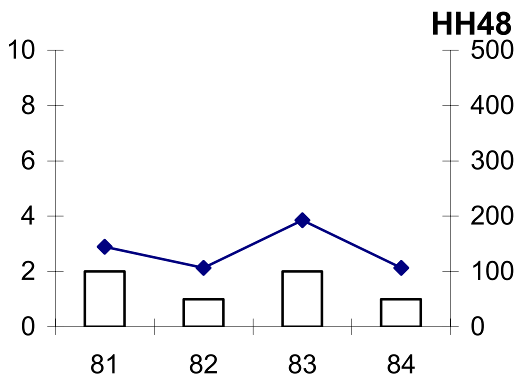

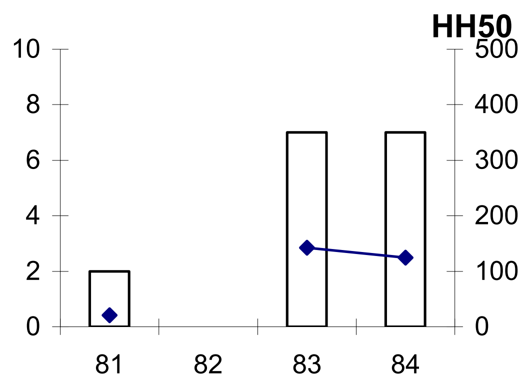

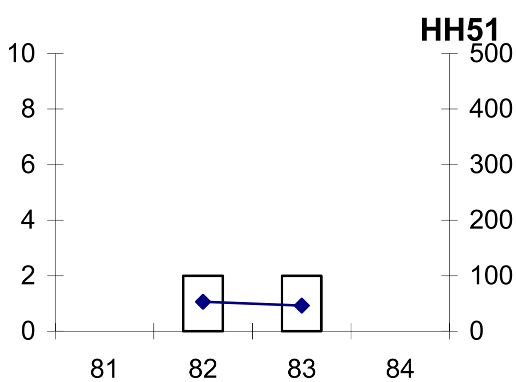

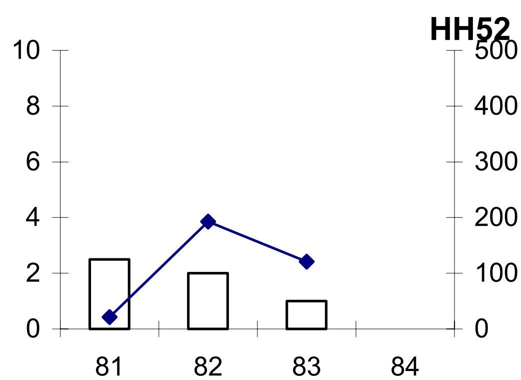

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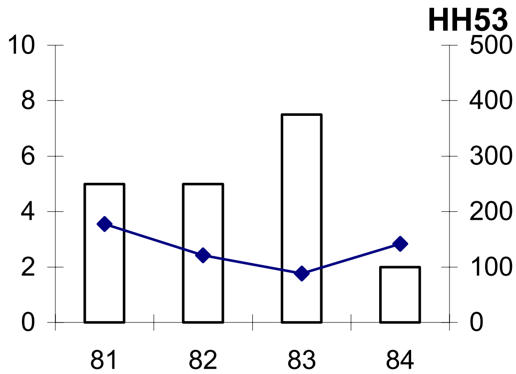

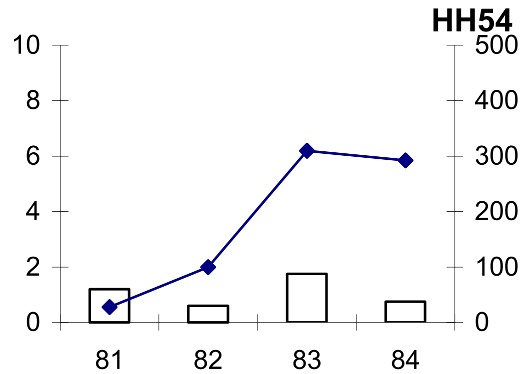

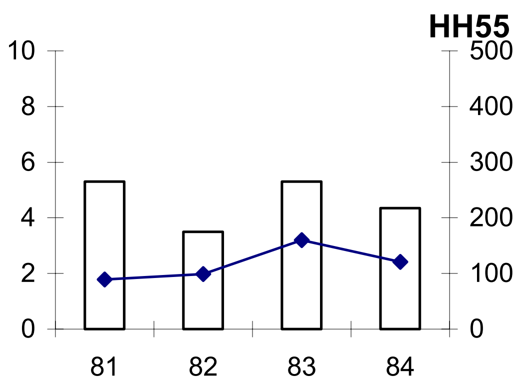

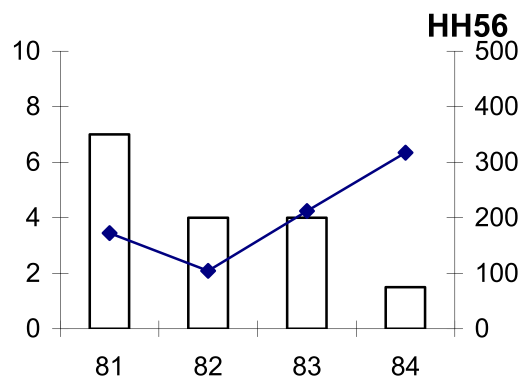

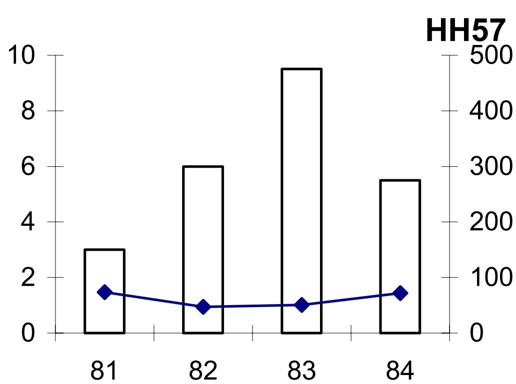

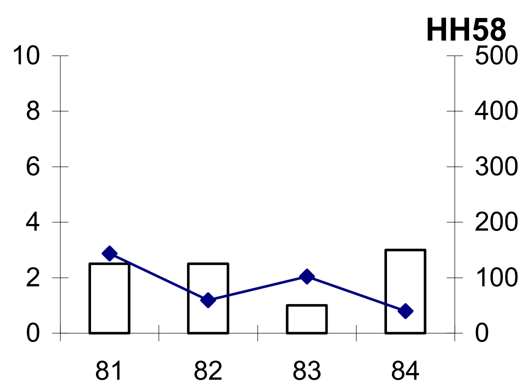

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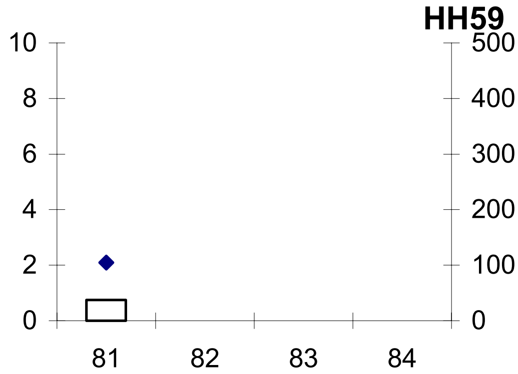

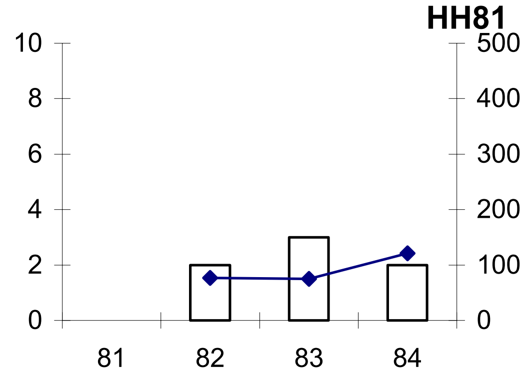

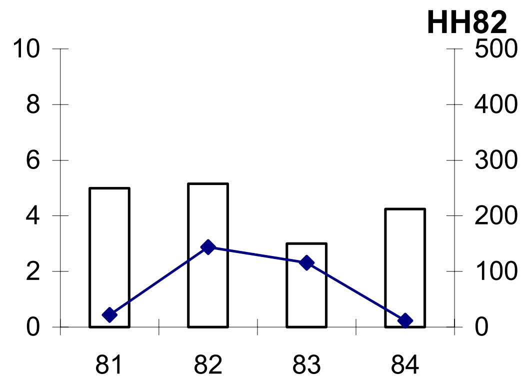

Appendix E: ESTIMATION RESULTS OF MODEL WITH LEARNING BASED ON FARM SIZE

Variables	Parameter	Coefficient	Standard Error
PRODUCTION FUNCTION			
Constant	β_0	-1.280	1.930
Seed	β_1	0.433	1.030
Family Labor	β_2	1.280***	0.435
Hired Labor	β_3	1.070***	0.174
Animal	β_4	-0.297	0.545
Fertilizer	β_5	0.210	0.190
Pesticide	β_6	-0.442	0.504
HYV Ratio	β_7	-1.740	1.300
Good Soil	β_8	-1.880*	1.010
Bad Soil	β_9	-5.400***	1.180
$(\text{Seed})^2$	β_{11}	-1.090*	0.640
Seed * Family	β_{12}	-0.062	0.216
Seed * Hired	β_{13}	0.119**	0.050
Seed * Animal	β_{14}	0.258	0.226
Seed * Fertilizer	β_{15}	-0.009	0.088
Seed * Pesticide	β_{16}	-0.048	0.181
Seed * HYV	β_{17}	0.496	0.636
Seed * Good Soil	β_{18}	0.377	0.909
Seed * Bad Soil	β_{19}	-0.055	0.450
$(\text{Family})^2$	β_{22}	0.075**	0.034
Family * Hired	β_{23}	-0.265***	0.034
Family * Animal	β_{24}	-0.009	0.089
Family * Fertilizer	β_{25}	0.004	0.022
Family * Pesticide	β_{26}	-0.045	0.042
Family * HYV	β_{27}	0.155	0.147
Family * Good Soil	β_{28}	-0.391*	0.222
Family * Bad Soil	β_{29}	0.972***	0.361
$(\text{Hired})^2$	β_{33}	0.074***	0.013
Hired * Animal	β_{34}	0.058	0.036
Hired * Fertilizer	β_{35}	0.012	0.008
Hired * Pesticide	β_{36}	0.022	0.017
Hired * HYV	β_{37}	-0.101**	0.045
Hired * Good Soil	β_{38}	-0.070	0.080
Hired * Bad Soil	β_{39}	0.275	0.362
$(\text{Animal})^2$	β_{44}	-0.175**	0.073
Animal * Fertilizer	β_{45}	-0.066	0.052
Animal * Pesticide	β_{46}	0.110	0.105
Animal * HYV	β_{47}	0.219	0.336
Animal * Good Soil	β_{48}	0.340	0.327
Animal * Bad Soil	β_{49}	-0.160	0.439

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Appendix E Continued

Variables	Parameter		
(Fertilizer)^2	β_{55}	0.012	0.043
Fertilizer * Pesticide	β_{56}	-0.003	0.013
Fertilizer * HYV	β_{57}	0.033	0.036
Fertilizer * Good Soil	β_{58}	-0.446*	0.264
Fertilizer * Bad Soil	β_{59}	-0.052	0.085
(Pesticide)^2	β_{66}	-0.054	0.073
Pesticide * HYV	β_{67}	0.052	0.079
Pesticide * Good Soil	β_{68}	0.090	0.225
Pesticide * Bad Soil	β_{69}	-0.164	0.140
(HYV)^2	β_{77}	0.915	1.040
HYV * Good Soil	β_{78}	-0.515	0.937
HYV * Bad Soil	β_{79}	0.165	0.399
INEFFICIENCY FUNCTION			
Constant	δ_0	2.830***	0.999
Age	δ_1	-0.040*	0.023
Education	δ_2	-1.160*	0.631
Own Experience	δ_3	-0.345**	0.155
Reference Group Experience	δ_4	0.547	0.496
Non-reference Group Experience	δ_5	-0.612*	0.354
Farm Size	δ_6	-2.110***	0.676
Household Size	δ_7	-0.674***	0.208
Dependency Ratio	δ_8	4.530**	1.830
Caste Dummy 1	δ_9	-3.930***	1.320
Caste Dummy 2	δ_{10}	-2.280**	1.040
Caste Dummy 3	δ_{11}	-1.770*	0.945
VARIANCE PARAMETERS			
σ^2		6.270	1.160
γ		0.992	0.003
LOG LIKELIHOOD FUNCTION		-168.110	

***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Appendix F: ESTIMATION RESULTS OF MODEL WITH LEARNING BASED ON HOUSEHOLD SIZE

Variables	Parameter	Coefficient	Standard Error
PRODUCTION FUNCTION			
Constant	β_0	-1.870	1.920
Seed	β_1	0.593	1.060
Family Labor	β_2	1.390^{***}	0.446
Hired Labor	β_3	1.070^{***}	0.178
Animal	β_4	-0.211	0.548
Fertilizer	β_5	0.132	0.187
Pesticide	β_6	-0.465	0.503
HYV Ratio	β_7	-1.850	1.300
Good Soil	β_8	-2.220^{**}	1.090
Bad Soil	β_9	-5.400^{***}	1.240
$(\text{Seed})^2$	β_{11}	-0.986	0.630
Seed * Family	β_{12}	-0.113	0.210
Seed * Hired	β_{13}	0.111^{**}	0.050
Seed * Animal	β_{14}	0.278	0.228
Seed * Fertilizer	β_{15}	0.014	0.086
Seed * Pesticide	β_{16}	-0.035	0.185
Seed * HYV	β_{17}	0.391	0.640
Seed * Good Soil	β_{18}	0.784	0.893
Seed * Bad Soil	β_{19}	-0.119	0.461
$(\text{Family})^2$	β_{22}	0.079^{**}	0.035
Family * Hired	β_{23}	-0.258^{***}	0.035
Family * Animal	β_{24}	-0.027	0.088
Family * Fertilizer	β_{25}	0.005	0.021
Family * Pesticide	β_{26}	-0.043	0.043
Family * HYV	β_{27}	0.162	0.141
Family * Good Soil	β_{28}	-0.403^{*}	0.236
Family * Bad Soil	β_{29}	0.989^{***}	0.367
$(\text{Hired})^2$	β_{33}	0.075^{***}	0.013
Hired * Animal	β_{34}	0.053	0.036
Hired * Fertilizer	β_{35}	0.011	0.008
Hired * Pesticide	β_{36}	0.022	0.017
Hired * HYV	β_{37}	-0.095^{**}	0.045
Hired * Good Soil	β_{38}	-0.050	0.082
Hired * Bad Soil	β_{39}	0.245	0.366
$(\text{Animal})^2$	β_{44}	-0.169^{**}	0.074
Animal * Fertilizer	β_{45}	-0.055	0.052
Animal * Pesticide	β_{46}	0.114	0.108
Animal * HYV	β_{47}	0.221	0.322
Animal * Good Soil	β_{48}	0.340	0.346
Animal * Bad Soil	β_{49}	-0.111	0.443

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Appendix F Continued

Variables	Parameter		
$(\text{Fertilizer})^2$	β_{55}	0.004	0.043
Fertilizer * Pesticide	β_{56}	-0.003	0.012
Fertilizer * HYV	β_{57}	0.028	0.036
Fertilizer * Good Soil	β_{58}	-0.470^{*}	0.271
Fertilizer * Bad Soil	β_{59}	-0.050	0.089
$(\text{Pesticide})^2$	β_{66}	-0.051	0.072
Pesticide * HYV	β_{67}	0.050	0.078
Pesticide * Good Soil	β_{68}	0.160	0.224
Pesticide * Bad Soil	β_{69}	-0.150	0.150
$(\text{HYV})^2$	β_{77}	1.250	1.030
HYV * Good Soil	β_{78}	-0.804	0.938
HYV * Bad Soil	β_{79}	0.067	0.411
INEFFICIENCY FUNCTION			
Constant	δ_0	3.330^{***}	0.999
Age	δ_1	-0.055^{**}	0.023
Education	δ_2	-1.070^{*}	0.550
Own Experience	δ_3	-0.122	0.100
Reference Group Experience	δ_4	-1.080^{***}	0.249
Non-reference Group Experience	δ_5	0.619^{*}	0.329
Farm Size	δ_6	-1.800^{***}	0.645
Household Size	δ_7	-0.540^{***}	0.179
Dependency Ratio	δ_8	3.140^{*}	1.640
Caste Dummy 1	δ_9	-3.310^{***}	1.140
Caste Dummy 2	δ_{10}	-2.000^{*}	1.010
Caste Dummy 3	δ_{11}	-1.780^{*}	0.958
VARIANCE PARAMETERS			
σ^2		5.830	1.060
γ		0.991	0.003
LOG LIKELIHOOD FUNCTION		-167.496	

***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Appendix G: ESTIMATION RESULTS OF MODEL WITH LEARNING MODEL BASED ON CASTE RANK

Variables	Parameter	Coefficient	Standard Error
PRODUCTION FUNCTION			
Constant	β_0	-1.080	2.000
Seed	β_1	0.484	1.130
Family Labor	β_2	1.320***	0.453
Hired Labor	β_3	1.060***	0.181
Animal	β_4	-0.361	0.553
Fertilizer	β_5	0.171	0.191
Pesticide	β_6	-0.365	0.490
HYV Ratio	β_7	-2.080	1.370
Good Soil	β_8	-1.620	1.230
Bad Soil	β_9	-5.030***	1.340
(Seed)^2	β_{11}	-1.040*	0.594
Seed * Family	β_{12}	-0.109	0.206
Seed * Hired	β_{13}	0.111***	0.050
Seed * Animal	β_{14}	0.294	0.223
Seed * Fertilizer	β_{15}	-0.004	0.088
Seed * Pesticide	β_{16}	-0.044	0.187
Seed * HYV	β_{17}	0.500	0.699
Seed * Good Soil	β_{18}	0.655	1.020
Seed * Bad Soil	β_{19}	-0.171	0.460
(Family)^2	β_{22}	0.076**	0.035
Family * Hired	β_{23}	-0.260***	0.035
Family * Animal	β_{24}	-0.011	0.091
Family * Fertilizer	β_{25}	0.005	0.021
Family * Pesticide	β_{26}	-0.048	0.041
Family * HYV	β_{27}	0.160	0.143
Family * Good Soil	β_{28}	-0.340	0.235
Family * Bad Soil	β_{29}	0.988***	0.366
(Hired)^2	β_{33}	0.074***	0.013
Hired * Animal	β_{34}	0.057	0.035
Hired * Fertilizer	β_{35}	0.011	0.008
Hired * Pesticide	β_{36}	0.022	0.018
Hired * HYV	β_{37}	-0.101**	0.048
Hired * Good Soil	β_{38}	-0.040	0.083
Hired * Bad Soil	β_{39}	0.306	0.367
(Animal)^2	β_{44}	-0.172**	0.069
Animal * Fertilizer	β_{45}	-0.061	0.051
Animal * Pesticide	β_{46}	0.102	0.107
Animal * HYV	β_{47}	0.266	0.334
Animal * Good Soil	β_{48}	0.235	0.345
Animal * Bad Soil	β_{49}	-0.220	0.434

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Appendix G Continued

Variables	Parameter		
$(\text{Fertilizer})^2$	β_{55}	0.004	0.043
Fertilizer * Pesticide	β_{56}	-0.003	0.013
Fertilizer * HYV	β_{57}	0.030	0.037
Fertilizer * Good Soil	β_{58}	-0.392	0.279
Fertilizer * Bad Soil	β_{59}	-0.041	0.087
$(\text{Pesticide})^2$	β_{66}	-0.046	0.072
Pesticide * HYV	β_{67}	0.046	0.085
Pesticide * Good Soil	β_{68}	0.151	0.231
Pesticide * Bad Soil	β_{69}	-0.131	0.145
$(\text{HYV})^2$	β_{77}	1.120	1.090
HYV * Good Soil	β_{78}	-0.692	0.982
HYV * Bad Soil	β_{79}	0.086	0.401
INEFFICIENCY FUNCTION			
Constant	δ_0	2.120^{**}	1.000
Age	δ_1	-0.034	0.024
Education	δ_2	-1.110^{*}	0.665
Own Experience	δ_3	-0.125	0.128
Reference Group Experience	δ_4	-0.629	0.418
Non-reference Group Experience	δ_5	0.168	0.338
Farm Size	δ_6	-1.690^{**}	0.697
Household Size	δ_7	-0.595^{***}	0.191
Dependency Ratio	δ_8	3.760^{**}	1.650
Caste Dummy 1	δ_9	-2.620^{**}	1.190
Caste Dummy 2	δ_{10}	-1.980^{*}	1.010
Caste Dummy 3	δ_{11}	-1.390	0.990
VARIANCE PARAMETERS			
σ^2		5.700	1.080
γ		0.991	0.003
LOG LIKELIHOOD FUNCTION		-167.511	

***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Appendix H: FARM-SPECIFIC EFFICIENCY SCORES FROM MODEL HS

Household ID	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	Household Mean
1	*	*	*	*	*	0.078	0.358	0.871	0.434	0.505	**0.449**
5	*	*	*	*	*	*	*	*	0.338	0.718	**0.528**
9	*	*	*	*	*	*	*	*	0.000	*	**0.000**
10	*	*	*	*	*	*	0.722	0.805	0.583	0.697	**0.702**
32	0.371	0.852	0.001	*	0.264	*	0.063	0.796	0.774	0.774	**0.487**
33	0.784	0.154	0.293	0.350	0.606	0.531	0.642	0.891	0.695	0.702	**0.565**
34	*	0.714	*	0.230	*	0.286	*	0.767	*	*	**0.499**
35	0.885	0.811	*	0.811	0.630	0.859	0.670	0.806	0.924	0.719	**0.791**
36	*	0.753	*	0.773	*	0.753	*	0.942	*	0.464	**0.737**
37	*	*	*	0.738	0.680	*	0.362	*	*	*	**0.593**
38	*	*	*	0.714	*	*	*	0.717	*	0.672	**0.701**
39	*	*	*	0.665	*	*	*	*	*	*	**0.665**
40	0.321	*	0.796	0.616	0.597	*	*	*	*	*	**0.583**
41	0.846	0.312	0.875	0.592	0.752	0.725	*	*	*	*	**0.684**
42	0.298	*	*	*	0.824	*	*	*	*	*	**0.561**
43	*	0.642	0.800	0.608	0.487	0.696	*	0.694	0.562	0.617	**0.638**
44	0.552	0.289	*	0.659	0.395	0.479	*	0.494	*	*	**0.478**
45	0.867	0.729	*	*	0.350	0.606	0.912	0.848	0.838	0.719	**0.734**
46	0.789	0.863	0.903	0.758	0.758	0.885	0.876	0.700	0.708	0.660	**0.790**
48	0.476	0.828	0.200	0.792	0.724	0.455	0.741	0.865	0.886	0.545	**0.651**
49	0.521	0.289	0.733	0.746	0.774	0.001	0.796	*	*	*	**0.551**
50	0.816	0.558	0.864	0.616	0.404	0.725	0.264	*	0.777	0.843	**0.652**
51	0.222	0.322	0.861	0.856	0.461	0.363	0.615	0.758	0.628	0.656	**0.574**
52	0.337	0.701	0.892	0.647	*	0.726	0.762	0.924	0.741		**0.716**
53	0.536	0.435	0.922	*	0.697	0.431	0.751	0.888	0.601	0.772	**0.670**
54	0.801	0.541	0.879	0.790	0.492	0.746	0.703	0.812	0.757	0.738	**0.726**
55	0.741	0.668	0.735	0.768	0.706	0.844	0.507	0.702	0.645	0.897	**0.721**
56	0.596	0.928	0.882	0.851	0.791	0.648	0.864	0.872	0.836	0.726	**0.799**
57	0.805	0.825	0.853	0.856	0.846	0.846	0.802	0.863	0.792	0.845	**0.833**

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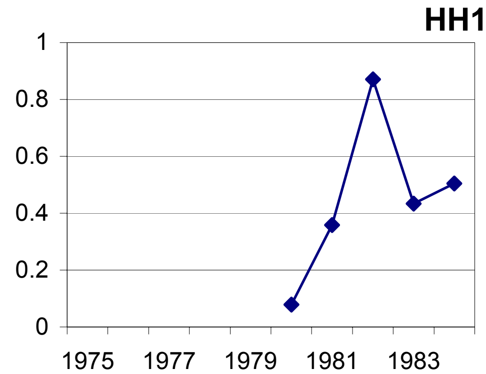
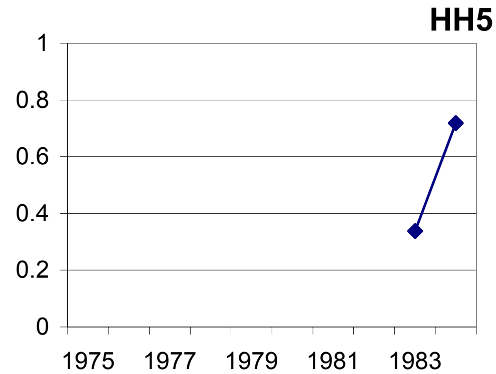
Appendix H Continued

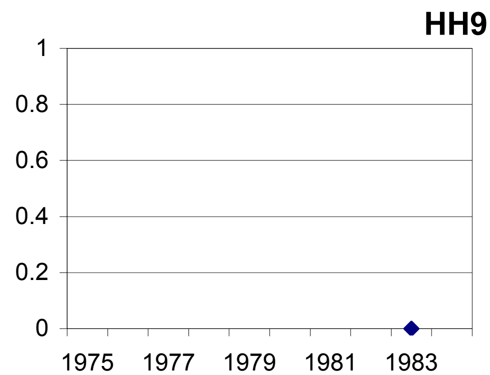
Household ID	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	Household Mean
58	0.870	0.545	0.884	0.722	0.354	0.298	0.687	0.681	0.835	0.768	**0.664**
59	0.319	0.758	0.839	0.646	0.561	*	*	*	*	*	**0.625**
61	*	*	*	*	*	*	*	0.473	*	*	**0.473**
70	*	*	*	*	*	0.037	*	0.668	*	0.879	**0.528**
80	*	*	0.821	0.784	0.443		*	*	*	*	**0.683**
81	*	*	*	*	*	0.835	0.805	0.626	0.733	0.829	**0.766**
82	*	*	*	*	*	*	0.652	0.863	0.690	*	**0.735**
Village Mean	**0.607**	**0.614**	**0.739**	**0.691**	**0.591**	**0.559**	**0.645**	**0.773**	**0.672**	**0.716**	**0.626**
Village Minimum	**0.222**	**0.154**	**0.001**	**0.230**	**0.264**	**0.001**	**0.063**	**0.473**	**0.000**	**0.464**	**0.000**
Village Maximum	**0.885**	**0.928**	**0.922**	**0.856**	**0.846**	**0.885**	**0.912**	**0.942**	**0.924**	**0.897**	**0.833**
Village Standard deviation	**0.228**	**0.225**	**0.265**	**0.149**	**0.172**	**0.274**	**0.219**	**0.123**	**0.206**	**0.114**	**0.149**

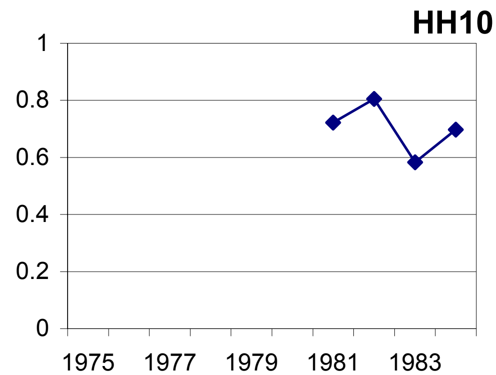
* indicates no observation.

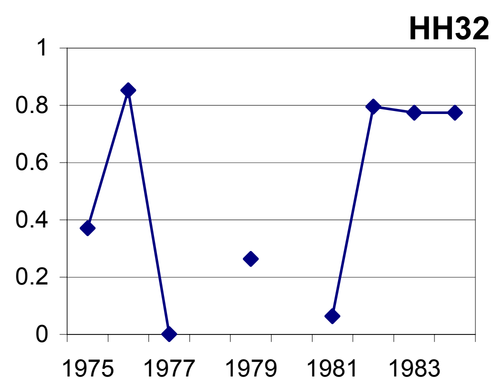
Appendix I: PLOTS OF FARM-SPECIFIC EFFICIENCY SCORES FROM MODEL HS

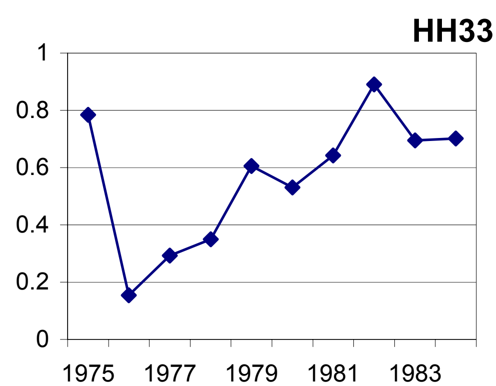












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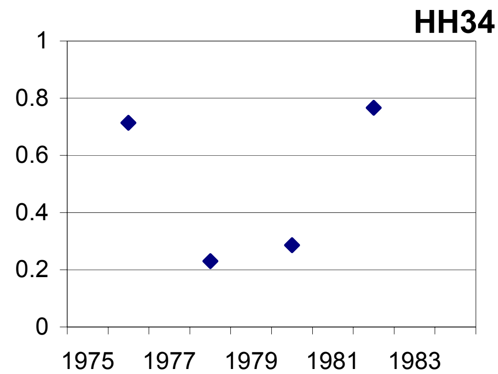

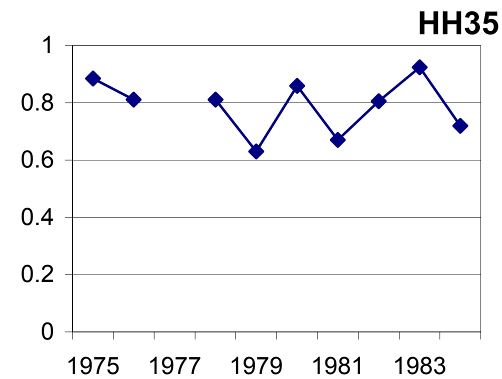

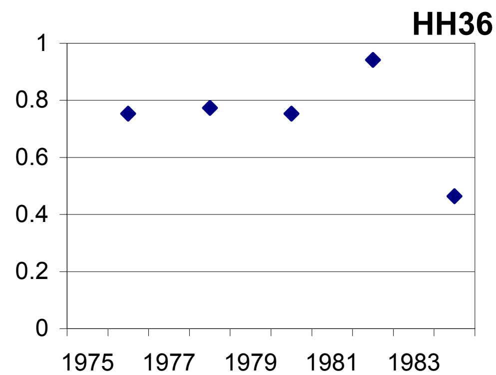

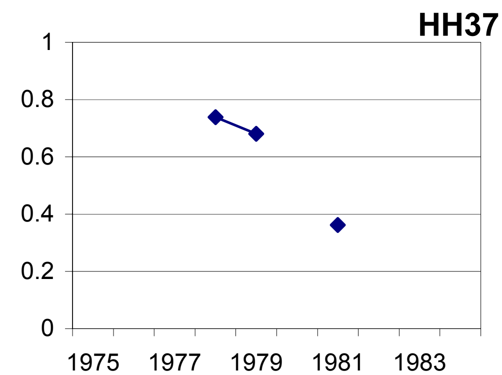

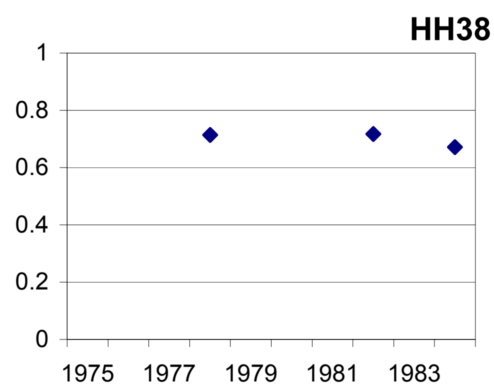

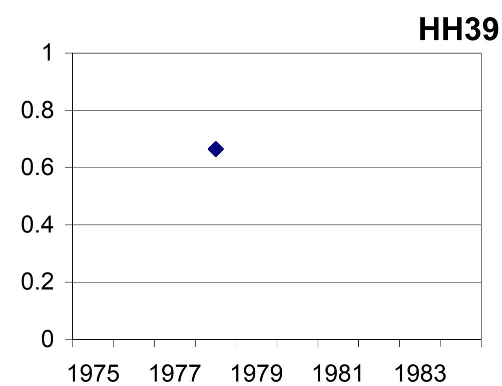

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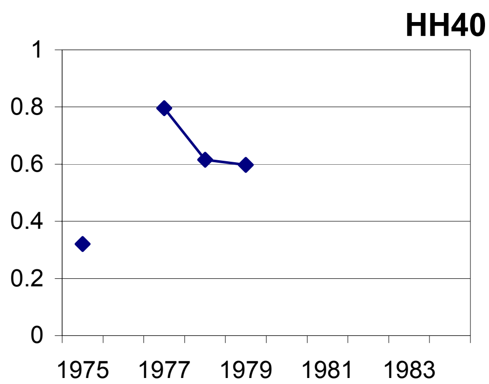

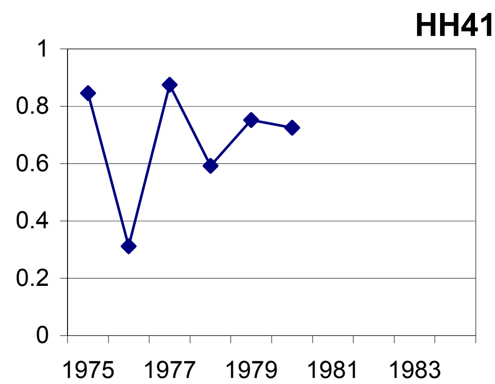

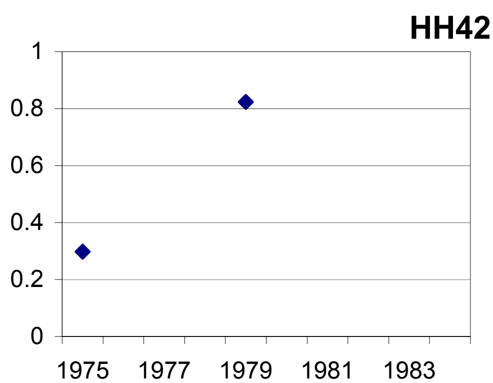

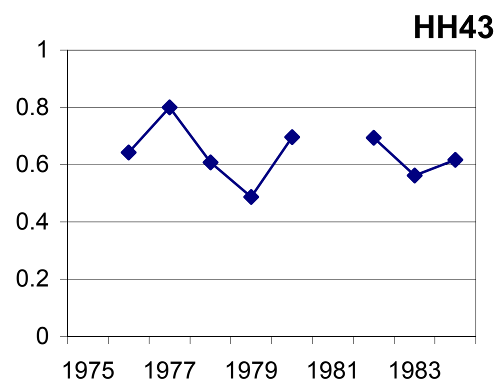

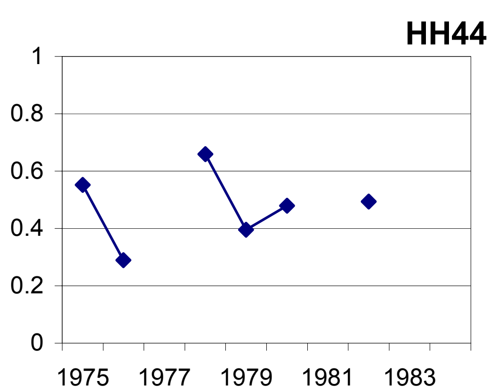

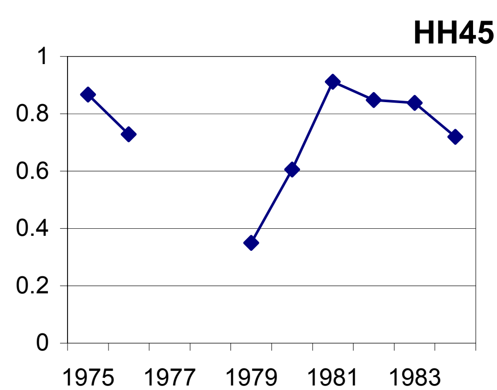

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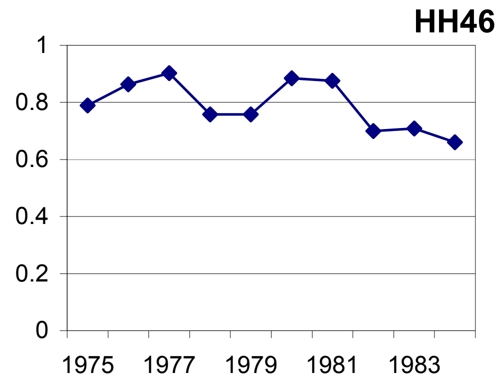

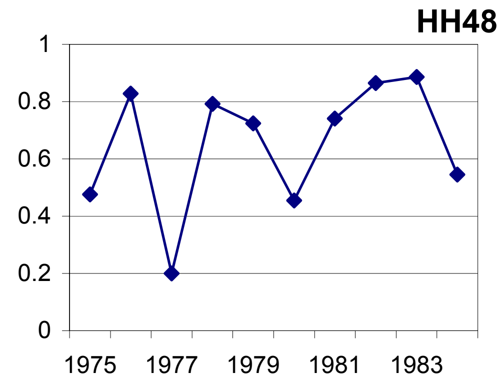

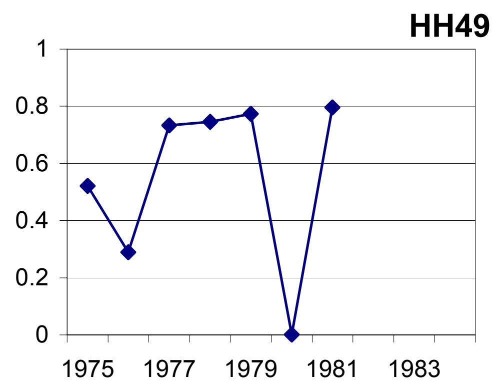

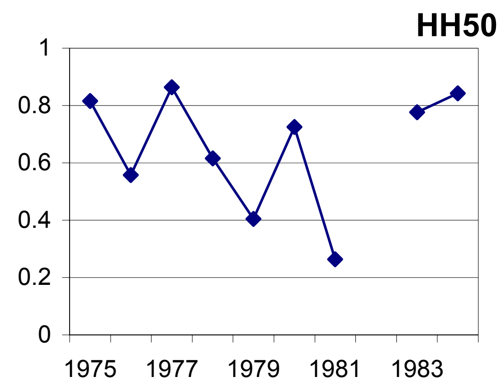

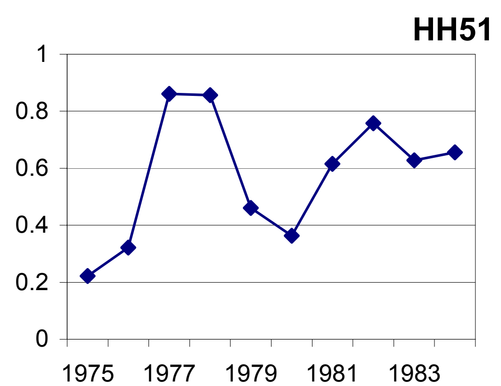

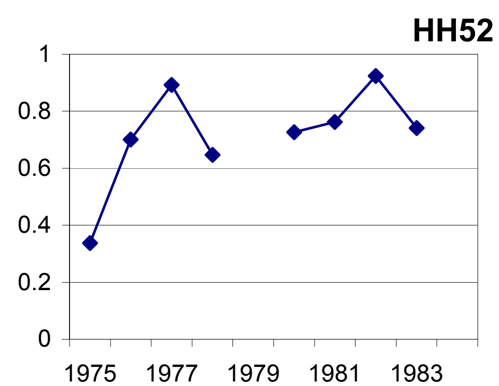

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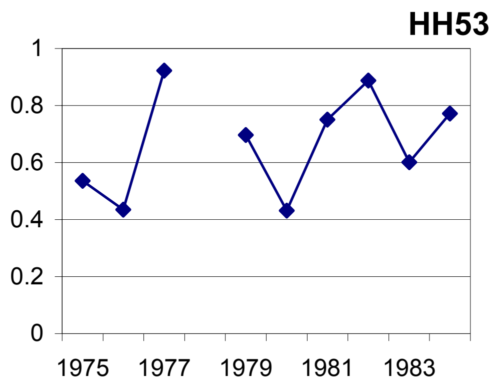

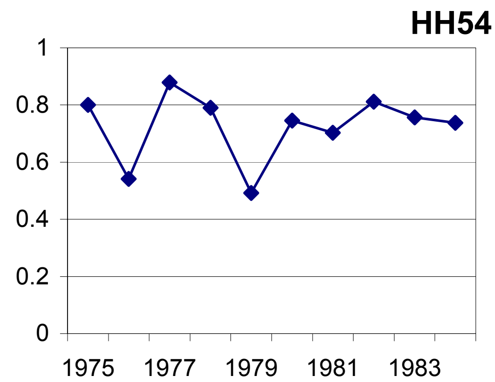

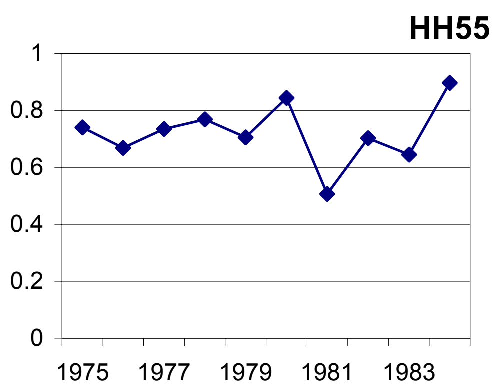

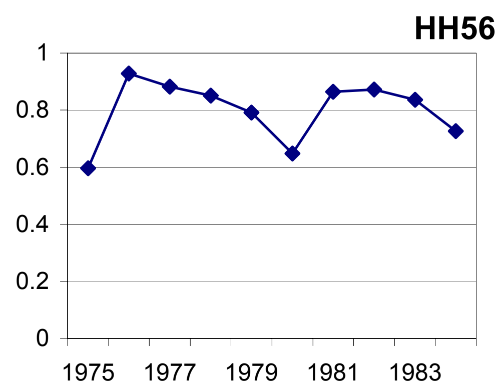

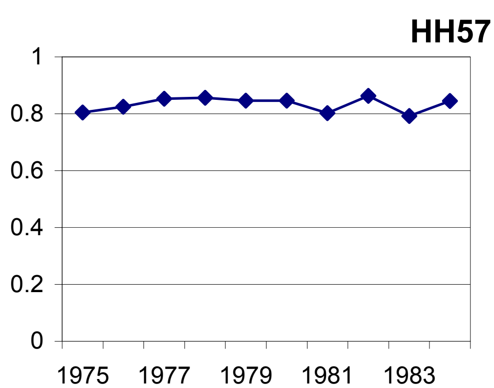

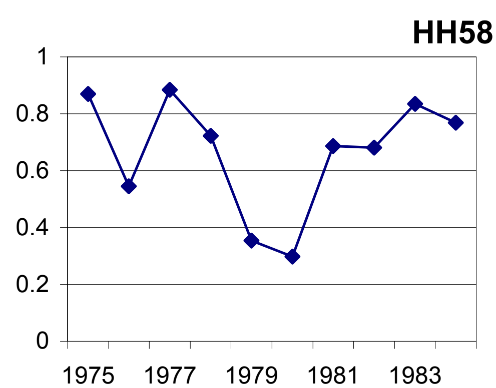

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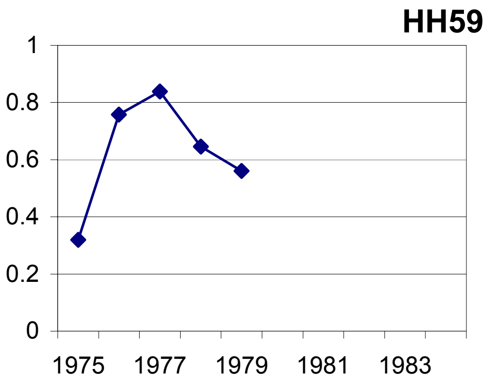

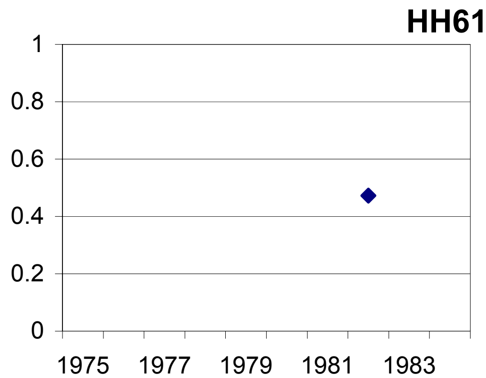

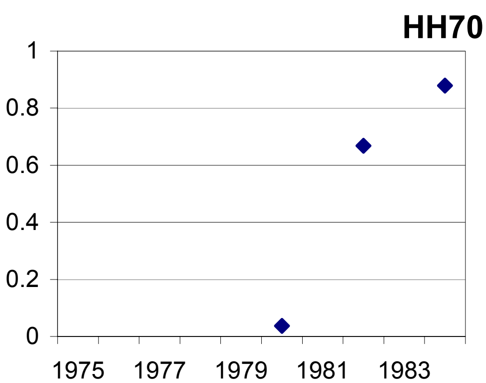

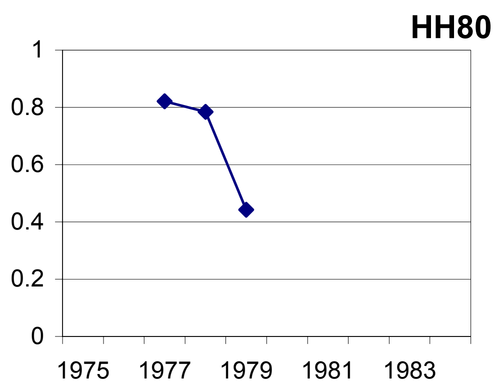

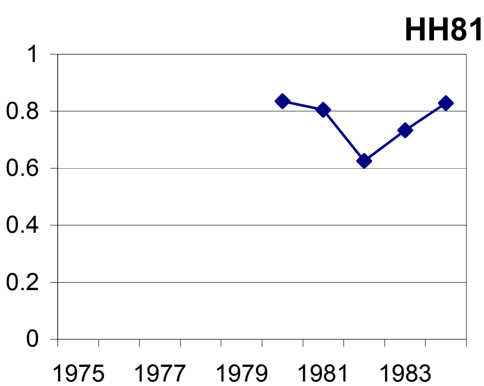

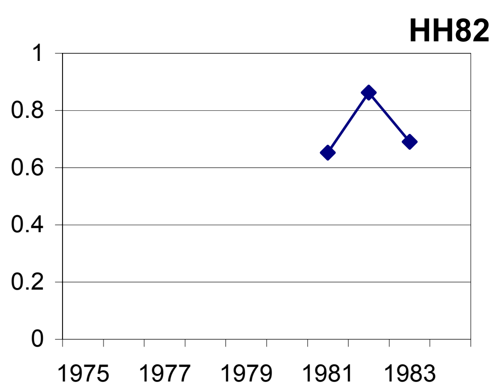

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Takeshi Ueda. "Quasi-Option Value and Irreversible Development." *Journal of Soka University Peace Research* 20 (March 2000).