(N° 9081460)

THE UNIVERSITY OF NEW ENGLAND

MEMORANDUM

To: Mrs Robyn Warwick, Collection Management Unit
Dixson Library

From: Paul McFarland, Secretary, *Research Doctoral Committee*

Date: 27 July 2004

Re: **PhD Thesis – Mr R A Villano**

Enclosed herewith is the unbound library copy of the PhD thesis submitted by Mr R A Villano and entitled "An Investigation of Production Risk, Risk Preferences and Technical Efficiency: Evidence from a Rainfed Lowland Rice Environment in the Philippines".

Also enclosed is the Right of Access to Thesis/Permission to Microfilm form (no restriction). Would you please acknowledge receipt.

Received the above [redacted]

LIBRARIAN

Date: 28/7/04

THE UNIVERSITY OF NEW ENGLAND

RIGHT OF ACCESS TO THESIS

FULL RENATO ANDRIN VILLANO NAME:

TITLE OF THESIS: AN INVESTIGATION OF PRODUCTION RISK, RISK PREFERENCES AND TECHNICAL EFFICIENCY: EVIDENCE FROM A RAINFED LOWLAND RICE ENVIRONMENT IN THE PHILIPPINES

A candidate submitting a thesis under the provisions of General Rule 11 shall complete the following **DECLARATION:**

1. I have read General Rule 11 and I understand I am bound by it.

2. I give permission for my thesis to be copied by the Library for purposes of preservation and:

(Strike out the options not elected leaving only one of (a), (b), (c) or (d))
(Note that a 24 month maximum applies to 2(b) and that a 3 year maximum applies to 2(c))

(a) I agree that the thesis may be freely available both for inspection and for copying.

~~(b)~~ I note that under section 51(2) of the Copyright Act 1968 (see overleaf) the Librarian may make a copy of the thesis for the purposes of research or private study. I ask, however, that the Librarian obtain the approval of the appropriate Head of Department before either copying the thesis or making the thesis available. This restriction is to apply for .... months unless I otherwise agree and thereafter the thesis may be freely available as in (a) above.

~~(c)~~ I request that the thesis be withheld from any use whatsoever for .... years from this date but I agree that a Committee consisting of the Librarian and the Chairman of the Academic Board or their nominees, and the appropriate Head of Department, may upon request, and after consultation with me if in the Committee's opinion I am reasonably available, make the thesis available for research or private study (not including copying) under such conditions as the Committee thinks fit.

~~(d)~~ I request that the thesis be withheld from any use whatsoever for a period in excess of three years and no less than .... years from this date but I agree that a Committee consisting of the Librarian and the Chairman of the Academic Board or their nominees, and the appropriate Head of Department may, after consultation with me if in the Committee's opinion I am reasonably available, reject this request and may determine the right of access to my thesis to be in accordance with Option 2(c) above.

3. **Must be completed by an author who selects option 2(b) or 2(c) above**
To assist those who will consider and determine my request to restrict access to my thesis as I have indicated above, I give the following reasons and details*:

REASONS: ....
....

....
....

4. An author who selected option 2(d) above must attach a submission (maximum of one A4 page) outlining the reasons for his/her request.

5. I agree to my thesis being microfilmed by University Microfilms International and an abstract (maximum 350 words) being published in Dissertation Abstracts International subject to adherence to my declaration in 2. above[redacted]

6. Signature of candidate......[redacted].Date.....10 march 2004

* a non detailed statement may b[redacted]pace here

AN INVESTIGATION OF PRODUCTION RISK, RISK PREFERENCES AND TECHNICAL EFFICIENCY: EVIDENCE FROM A RAINFED LOWLAND RICE ENVIRONMENT IN THE PHILIPPINES

A Thesis Submitted for the Degree of
Doctor of Philosophy

RENATO ANDRIN VILLANO
BAgEc (Hons) (New England)

School of Economics
Faculty of Economics, Business and Law
University of New England
Armidale, NSW 2351
Australia

March 2004

Declaration

I certify that the substance of this thesis has not already been submitted for any other degree and is not currently being submitted for any degree.

I certify that, to the best of my knowledge, any help received in preparing this thesis, and all sources used, have been acknowledged.

[redacted]

Renato Andrin Villano

Abstract

This study is motivated by the fact that rice is the staple food and principal crop of almost half of the world's population, especially in the humid and sub-humid regions of Asia. The main challenge facing the rice sector is to keep up with the increasing demand for rice. Rainfed rice environments offer substantial potential for increasing total rice production. However, these environments are associated with a high incidence of poverty, mainly because of low and unstable yields. Farmers in these environments face adverse biophysical, socioeconomic and cultural constraints to increasing rice productivity.

The study of risk and technical efficiency is an important topic in agricultural development. The themes of risk and technical efficiency have not been adequately studied in rainfed rice environments. Risk plays a vital role in farmers' decisions on input allocations and, therefore, output supply. Low technical efficiency is believed to be one of the constraints to production in these environments. A more comprehensive and up-to-date study on the nature of risk and technical efficiency in rainfed rice production is needed to target technology developments and policy interventions. This study seeks to provide empirical evidence on the nature of production risk, risk preferences and technical efficiency. An eight-year panel data set of 46 rice farmers from a representative rainfed lowland environment in Central Luzon, Philippines is used.

Production risk is first analysed using a heteroscedastic production function model. This permits the examination of marginal effects of inputs on production risk independently of the effects of inputs on mean output. In this study, tests for the absence of heteroscedasticity provide evidence that the variance of the error term in the output function varies with changes in input levels, and, accordingly, indicate that output risk is significant in the production of rainfed rice. The results suggest that area, fertiliser and labour have significant positive effects on the mean output of rice. The fertiliser and labour inputs have significant and positive effects on the variance of output, indicating that they are risk-increasing inputs. Herbicide is a risk-reducing input, although its coefficient is not statistically significant.

A stochastic frontier production function is then used to investigate the technical efficiency of rainfed rice farmers. The results show a mean technical efficiency of 79 per cent was achieved by the rainfed rice farmers in the study area. Thus, there is scope for increasing rice production by 21 per cent with the present technology. A significant variation was observed in the mean level of technical efficiency across farmers over the eight-year period. Several characteristics of farm operators, such as age and educational attainment, ratio of adults in the farm households and income from non-farm activities, were found to have significant effects on the technical inefficiency of rice production in the rainfed lowland environment.

Simultaneous estimation of production risk, risk preferences and technical efficiency is then conducted using a stochastic frontier production function model with an additive heteroscedastic error structure. The risk preference function in the model developed by Kumbhakar (2002) is used to investigate risk preferences of farmers. The results revealed that the estimated output elasticities of inputs are consistent with estimates obtained using both the heteroscedastic production function model and the traditional stochastic frontier production function model. Higher estimates of mean technical efficiency were obtained. The results also revealed that all of the rainfed rice farmers were risk-averse, such that the degree of risk aversion varied across farms and over time.

The empirical results emphasise the importance of risk and efficiency in the rainfed rice environments of the Philippines and, therefore, need to be given careful attention by research managers and policy makers. The results obtained in this study should help agricultural policy makers formulate better strategies and programs for the improvement of the rainfed rice industry.

Table of Contents

List of Tables

List of Figures

List of Appendices

Acknowledgements

I would like to acknowledge those who have, in one way or another, contributed to the completion of this thesis. First, I am most grateful to my supervisors, Associate Professor Euan Fleming, Dr. George Battese and Dr. Christopher O'Donnell, for their strong support and guidance in the conduct of this study. Their patience, suggestions, constructive comments and leadership enabled me to complete this study. I feel privileged and fortunate to have them as my supervisory team throughout my PhD program.

I would like to acknowledge the scholarships granted by the University of New England – the UNE Research Scholarship and International Postgraduate Research Scholarship – which enabled me to pursue my PhD degree in Economics.

Grateful acknowledgement is expressed to the Social Sciences Division (SSD) of the International Rice Research Institute (IRRI) for allowing me to use the data set in this study. I am particularly grateful to Dr. Sushil Pandey for his guidance, support and encouragement and for inspiring me to work on risk analysis in rice farming systems. Likewise, my appreciation goes to my former colleagues, Ludy Velasco, Doris Malabanan, Lina Diaz, Joyce Luis, Fred Lagasca, Josie Narciso, Pie Moya, Nels Garcia, Mirla Domingo, Pio Cenas, Joel Reaño, Lyds Damian and Abedullah for sending me supplementary data, maps and reference materials.

I wish to thank the staff of the School of Economics for the invaluable assistance they have extended to me and for providing an environment conducive to work and study. I also wish to thank Dr. Christie Chang, Associate Professor Oscar Cacho, Associate Professor Phil Simmons, Emeritus Professor Brian Hardaker, Professor Malcolm Treadgold and Professor Chris Lloyd, Professor Roley Piggott and my postgraduate colleagues for providing helpful suggestions during my seminar presentations.

Special thanks go to Professor Prasada Rao and Ms. Pauline Fleming for their encouragement and moral support. It has been a great pleasure to work with them. I thank them for their patience, trust and confidence in me. They have been great mentors to me.

I wish to thank my friends in Armidale for the support they extended to me and my family while I was completing my study. To the Del Socorro Family, Frank, Menchie, Annie, Angie, Jim, Steve, Marichu, Minda, Maryann, Doreen, Noor, Lisa and Stella – thanks for making me feel like at home all the time.

My deep gratitude goes to my family. I thank my wife, Precy, and daughter, Kyanna, for their support, patience and understanding over the past three years when I have spent more time at the university than with them. I thank my mother and brothers and sisters for their love, support, encouragement and constant prayers during my studies at the University of New England.

This thesis is dedicated to all my family especially to *Inay* and to the memory of our dear *Ama*.

Above all, I am thankful to God Almighty for the wisdom, knowledge and strength He has given to me to make possible the completion of this thesis.

Chapter 1
Introduction

1.1 Background

Rice is life. It is considered the staple food and principal crop of almost half of the world's population, especially in humid and sub-humid regions of Asia. It is the major source of calorie intake of the people in these regions. Rice is likewise the single most important source of employment and income of rural people.

Rice is grown in four different environments. The irrigated system is the dominant ecosystem in terms of the share of output and area. Despite the overwhelming importance of irrigated ecosystems in generating the bulk of the rice supply, there are indications that this environment alone will not be able to generate the additional supplies needed in the coming decades. Rainfed lowland rice offers substantial potential for increasing total rice production (Pandey 1997). However, rainfed rice areas are still associated with a high incidence of poverty because of low and unstable yields. Farmers in the rainfed lowland rice environments face adverse biophysical, socioeconomic and cultural constraints to increasing rice productivity (IRRI 2003). The seasonally variable and erratic rainfall, heterogeneous land types and soil types, and diverse socioeconomic groups are some of the major characteristics of the rainfed lowland rice environments.

This study investigates production risk, risk preferences and technical efficiency in the rainfed rice environment. Risk plays an important role in input allocations and output supply. Production risk and technical efficiency are estimated using a heteroscedastic production model and the stochastic frontier model, respectively. In addition, the risk preferences of farmers are estimated using a joint estimation approach. Appropriate indicators of the nature and extent of production risk and technical inefficiency are essential information for targeting policy and research interventions that will promote agricultural development and poverty alleviation in these environments.

The objective of this chapter is to outline the structure of the study. In section 1.2, the trends and challenges facing the rice industry are discussed. This is followed by the discussion of the research problem in section 1.3. In section 1.4, the research objectives are outlined, followed by a brief statement of the method of analysis that is presented in section 1.5. The organisation of the thesis is presented in section 1.6.

1.2 Rice Demand and Supply: Trends and Challenges

Rice is considered the staple food and the principal crop of almost half of the world's population, especially in the humid and sub-humid regions of Asia. From the Philippines in the east to eastern India in the west and from southern China in the north to Indonesia in the south, rice accounts for 30-50 per cent of agricultural incomes and provides 50-80 per cent of calories consumed by people (Hossain 1995). Nearly 150 million households in Asia depend on rice for their livelihood (IRRI 2000).

The introduction of improved varieties has increased rice output and, hence, aids efforts to achieve food self-sufficiency in many developing countries. In 1999, world rice production was about 608 million tonnes (FAO 2001), of which 90 per cent came from Asia (Hossain 1997). The expansion in rice production that has taken place in the past 30 years has been attributed to the so-called Green Revolution, comprising improvements to varieties, cropping intensification, expansion of irrigated areas, increased nutrient inputs and improved crop management practices.

The impressive success of the Green Revolution during the 1970s and 1980s has not been sustained in the 1990s (Figure 1.1). The growth rates of world rice production were recorded to be 3.1 per cent, 3.1 per cent and 1.7 per cent per annum during the periods 1965-75, 1975-85 and 1985-94, respectively (FAO 2000). Despite the success of the Green Revolution in the past several decades, the demand for rice will continue to exceed production into the future because of the ever-increasing population. The rate of growth of rice production has slowed considerably in recent years. This has resulted in food shortages in many rice-dependent countries in the developing world.

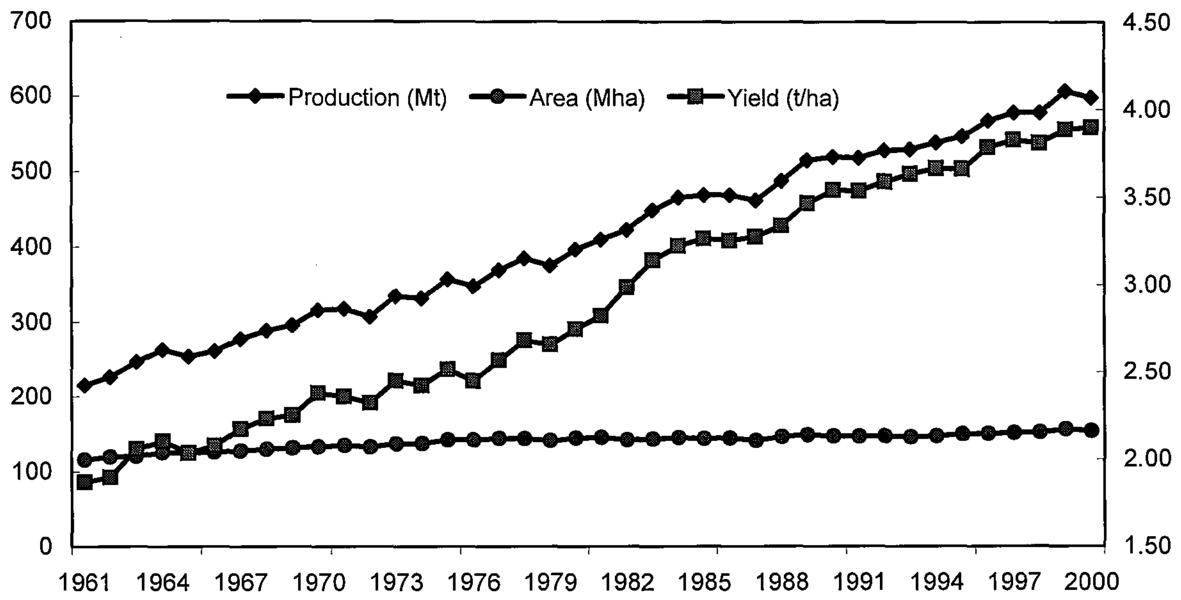


Figure 1.1: Rice production, area and yield in the world, 1961-2000.

Source of data: FAO (2001)

The world population is estimated to continue to increase by 85 million people a year (IRRI 1998). Although the population growth rates in most developing countries continue to decline, the absolute yearly increase in the number of people during this decade will continue to increase because the population base is expanding (IRRI 2000). Other than the population pressure, other sources that may lead to a food crisis are the increasing purchasing power that is expected to lead to the consumption of more animal products, the increasing damage to the ecological foundations of agriculture, the declining per capita availability of land and water, and the absence of technologies that can further enhance the yield potential of major food crops, such as rice.

The Philippines is one of the few developing countries in Southeast Asia that faces food security problems (Hossain, Gascon and Revilla 1996). As in many developing countries, rice is the most important staple food in the Philippines. It constitutes about 16 per cent of the total crop production, 66 per cent of the total cereal production (IRRI 2003) and about 3.5 per cent of gross domestic product (Gonsales, 1999).

In 1997, the total land area planted to rice in the Philippines was approximately 3.8 million hectares. Sixty five per cent of the total rice areas are irrigated, 31 per cent are rainfed lowland and only about four per cent are under an upland environment (IRRI 2003). Productivity of rice has substantially increased over the past two decades, from about 5.3 million tonnes in 1970 to 11.2 million tonnes in 1997 (Figure 1.2). The increase in productivity is attributed largely to the use of modern varieties, modern technologies and the development of new irrigation systems in the major rice-producing regions. Modern varieties cover 95 per cent of the total rice area and the national average yield of rice is about 2.92 tonnes per hectare (PhilRice-BAS 1998).

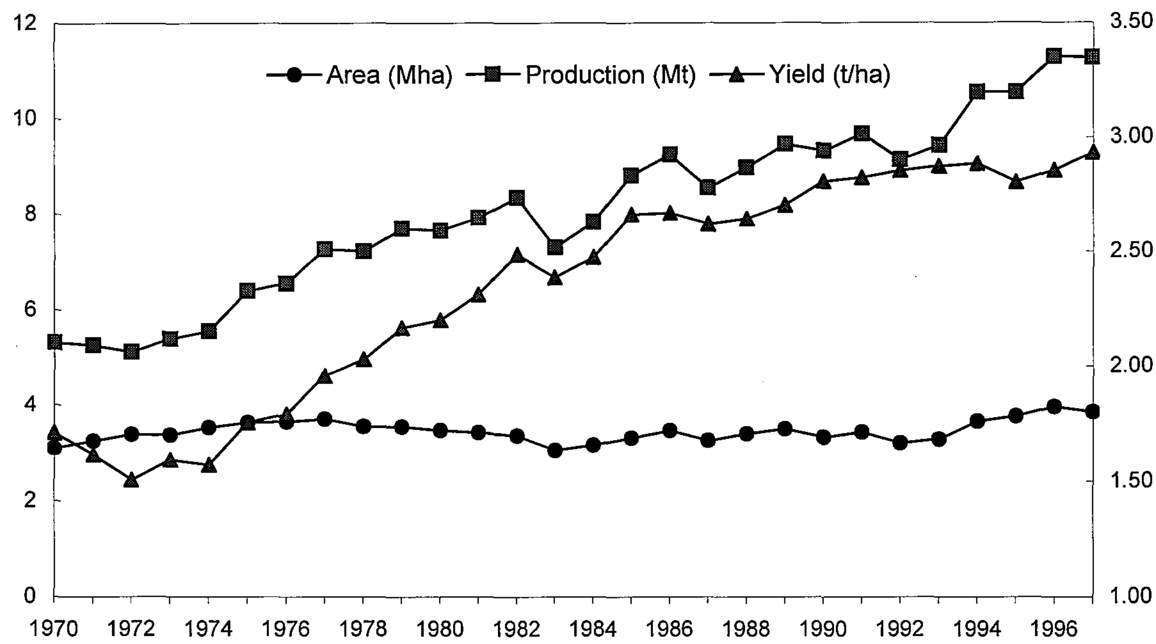


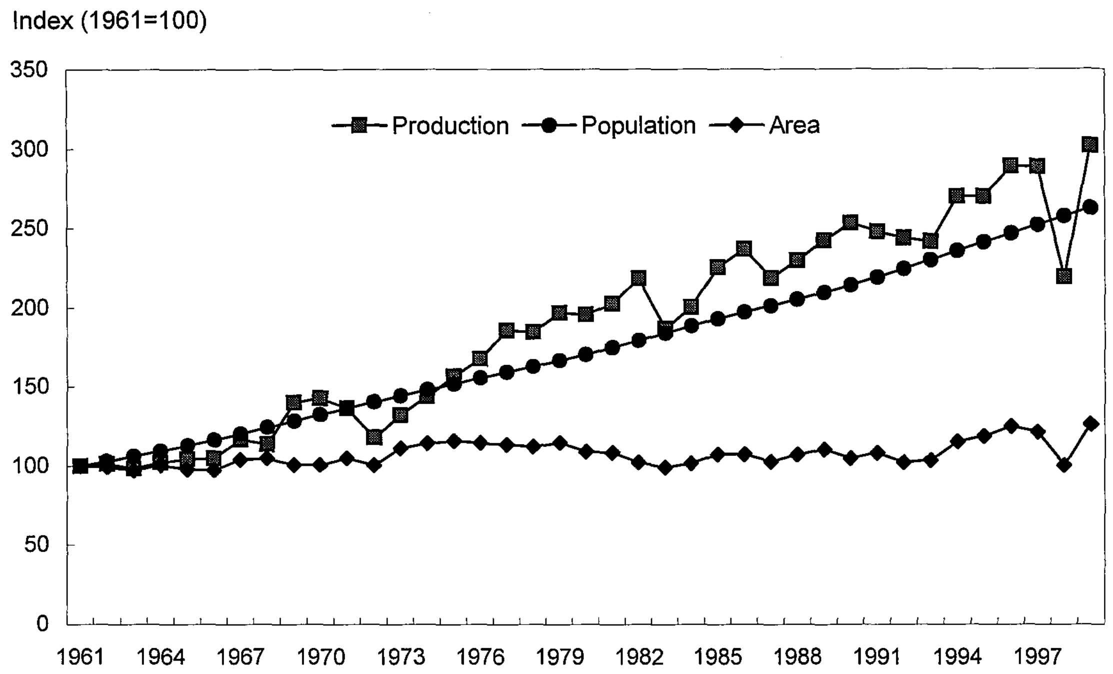
Figure 1.2 Rice area, yield and production in the Philippines, 1970-97.

Source of Data: IRRI (2003)

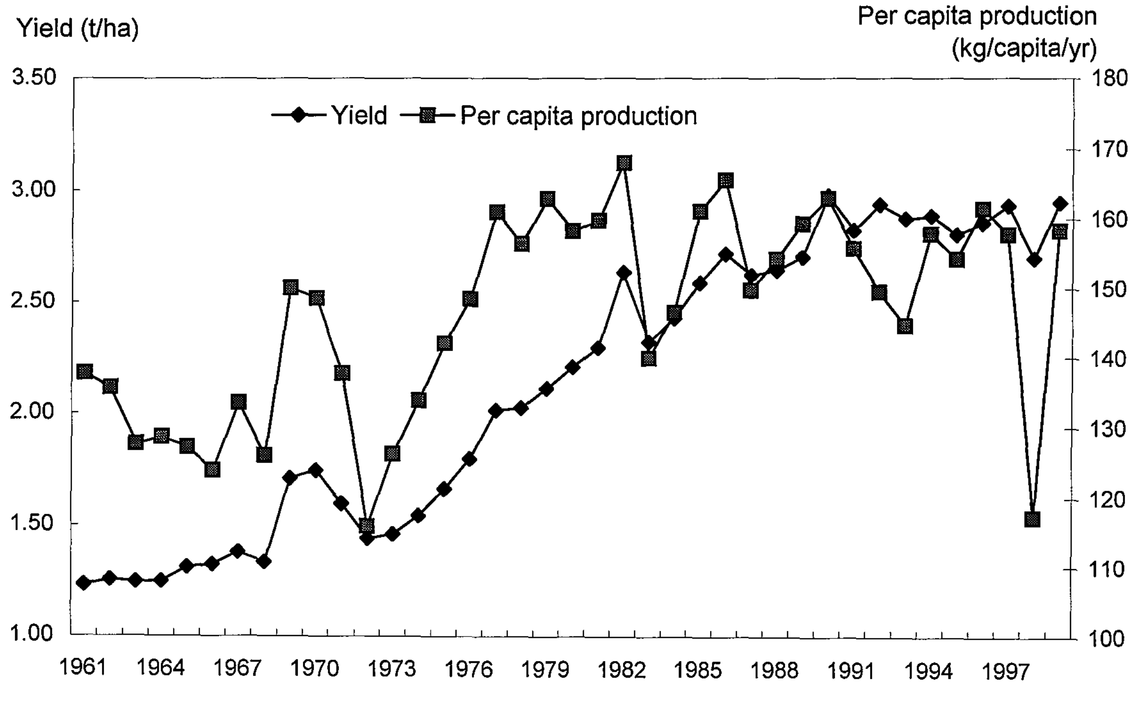
The relationship between rice production and population in the Philippines is presented in Figure 1.3. It can be seen that rice production kept pace with the growth in population over the last three decades. It outpaced population growth during the period of the Green Revolution, 1968-80. In the 1960s, rice production was unable to meet the demands of the population (Figure 1.3a). This was changed during the Green Revolution, where production of rice grew much faster than population growth. Growth of rice production slowed down during the late 1980s and during the 1990s when the per capita rice production was almost the same as in the 1960s (Figure 1.3b). This phenomenon poses a challenge to increase and sustain production in order to meet the needs of the booming population. In 1997, the country's population reached 71 million and is increasing at a rate of 2.2 per cent per year.

In 1995-98, the Philippines imported an average of 1.1 million tonnes of rice per year, with the highest being 2.4 million tonnes in 1998 (Department of Agriculture 2002). The high importation of rice in 1998 was the result of a sharp decline in total rice production brought about by the *El Niño* phenomenon.

According to the projections made by the International Food Policy Research Institute (IFPRI), the demand for rice will increase by about 1.8 per cent per year over the period 1990-2020 (Rosegrant, Agcaolli and Perez 1995). In the next three decades, the consumption of rice will increase by as much as 70 per cent. In order to meet this demand, Asian rice production must increase by about 840 million tonnes in 2020 from the present level of 490 million tonnes to feed the rapidly growing population. Despite the overwhelming importance of irrigated ecosystems, in generating the bulk of the rice supply in the country, there are indications that these ecosystems alone will not be able to generate the additional supplies needed by 2020 (Pandey 1997). The higher costs associated with developing new irrigation facilities and maintaining the existing ones, the trend toward diversification out of rice, environmental concerns associated with further intensification of irrigated rice production, and the lack of an economically exploitable "yield gap" are some of the major factors that limit the possibility for further increases in rice production from irrigated ecosystems (Rosegrant and Svendsen 1993; Pingali, Hossain and Gerpacio 1997).



a) Rice area, production and population, 1961-99



(b) Rice yields and per capita rice production, 1961-99

Figure 1.3: Relationship between population, rice production, area and yield in the Philippines, 1961-99.

Source of Data: IRRI (2003)

The current yield of rice in rainfed ecosystems averages 1.9 tonnes per hectare. Assuming that the area of rice in irrigated and rainfed environments remains unchanged, the average yield of irrigated rice would have to increase to 8.2 tonnes per hectare by 2020 if the average yield in rainfed ecosystems remains constant at the current level of 1.9 tonnes per hectare. Improved technology for rainfed rice can help reduce the intensification pressure in irrigated ecosystems. For example, if the yield of rainfed rice could be increased to three tonnes per hectare, the average yield of irrigated rice would need to be increased to 7.2 tonnes per hectare by 2020 (Pandey 1997). In addition to reducing the pressure to intensify irrigated ecosystems, technological improvements in rainfed ecosystems will help reduce poverty in these poorer areas and spur overall economic growth (Hossain 1995).

1.3 Rationale and Statement of the Research Problem

Rainfed lowland rice offers a substantial potential for increasing the total rice production, not only in the Philippines, but also in the rest of rice-growing countries in the world. The rainfed lowland rice ecosystems are defined as areas where rice is grown in unirrigated, levelled and bunded fields that are shallowly flooded with rain water (Mackill et al. 1996). They are characterised by lack of water control, with floods and droughts as the potential problems.

As in many other parts of Asia, the Green Revolution has helped most irrigated farmers in the Philippines to improve productivity of major food crops, such as rice. Farmers in the rainfed lowland environment, however, have drawn fewer benefits from the Green Revolution. While there are already available technologies for the rainfed lowland ecosystems, farmers are unable to achieve the full potential of these technologies. The adverse climatic conditions (the amount and frequency of rainfall) and poor soil conditions are just some of the major factors that prevent farmers from increasing their productivity.

Compared with irrigated rice environments, which have benefited from yield-increasing technologies of the Green Revolution, most rainfed lowland rice ecosystems currently have low and unstable yields due to a host of abiotic and biotic stresses (IRRI 2003). Land-use intensity is low, production systems are predominantly subsistence-orientated and farmers mostly practise rice monocropping in the wet season. As a result of these characteristics, the level of poverty among the rural households is high. Most of the countries where rainfed lowland rice ecosystems predominate also have low national income per capita, which is growing slowly although some countries in Southeast Asia have now achieved a higher rate of economic growth.

One can attribute the low and unstable productivity of rainfed rice to several socio-economic or biological factors. The unpredictable variations in yield and prices of inputs and outputs tend to be the major source of risk in the rainfed environment (Pandey, Singh and Villano 2000). Uncertainties arise most importantly from the natural environment, through unpredictable variations in precipitation, radiation, other atmospheric phenomena such as strong winds and extreme temperatures, and events such as flooding and submergence (Anderson 1995). The existence of risk in production environments affects decision making of farmers in terms of input allocation decisions, and, therefore, output supply. The degree of riskiness of an outcome or event depends on the farmers' (decision-makers') preferences and attitudes towards risk.

The risk faced by rainfed lowland rice farmers can be grouped into input price risk, production risk and output price risk. Of these categories, production risk is one of the major constraints encountered by farmers, causing them to under-invest in their farming activities. It is important to analyse how risk affects the decisions of farmers on input allocations and, likewise, how it affects their objectives to attain full economic efficiency.

Over recent decades, researchers have been concerned to study the causes of low productivity among low-income farmers and to understand the process of technology adoption. A number of studies of the adoption process in the context of risk provide empirical evidence on the ways farmers respond over time to new production technologies that are introduced in a risky environment. Considerable research has shown the importance of risk in decision-making by farmers. Attitudes toward risk are believed to be a major determinant of the rate of diffusion of new technologies among farmers. For new technologies to be effective they should be tailored to the needs and attitudes of farmers. Researchers need to identify the specific determinants of behaviour and preferences towards risk, and to quantify their impact on the decision-making process.

In order to meet the challenge, it is important to bring the perspectives of farmers into research planning, policy formulation and technology development. Improving policies requires an intimate understanding of the environment, production systems and problems of prospective users and beneficiaries of a given technology. This set of requirements indicates the need for information on the dynamics of the rural household economy and the farming systems. It is important to analyse the interactions of the agro-climatic and socio-economic environments and their impact on the efficiency of resource use. It is essential to have empirical evidence on the production behaviour of rainfed lowland rice farmers in their pursuit of food security under risk while pursuing economic efficiency.

The measurement of technical efficiency and production risk in the agricultural sector of developing and developed countries has been a central theme in a large number of empirical studies. This literature focuses on the specification of deviations from the deterministic portion of a production model to be used in a two-pronged analytical framework, i.e., risk analysis and technical efficiency analysis. Risk analysis, in a Just and Pope (1978, 1979) framework, involves recovering the residuals of the regression model and using them to investigate the marginal effects of inputs on production risk. The main focus of this specification is to allow inputs to be either risk-increasing or risk-decreasing. From a policy point of view, information on whether inputs are risk-increasing or risk-decreasing is quite useful, especially for risk management.

Technical efficiency analysis in a stochastic frontier production framework involves specifying a noise component and a one-sided inefficiency component in the model. There are no restrictions on the marginal inefficiency effects so that inputs can be either efficiency increasing or decreasing. Recent empirical applications have mostly focused on the inefficiency component to estimate technical efficiency and the marginal effects of inputs on inefficiency, hence ignoring the marginal effects on the risk component, despite the fact that the stochastic frontier model is consistent with the Just-Pope model.

While there have been several attempts to estimate production risk and technical efficiency in a single framework (Kumbhakar 1993; Battese, Rambaldi and Wan 1997; Jaenicke and Larson 2001), another stumbling block is the incorporation of the attitudes of producers towards risk in the model. The attitudes of producers towards risk are important in input-allocation decisions and, therefore, output supply (Kumbhakar 2002). Because of this, it is fundamental to consider a model that enables the examination, not only of production risk and technical inefficiency, but also the attitudes of producers towards risk.

In an attempt to estimate production risk and the risk preferences of producers simultaneously, Love and Buccola (1991, 1999), Chavas and Holt (1996) and Saha, Shumway and Talpaz (1994) have jointly analysed input allocations and output-supply decisions. Love and Buccola (1991) proposed a primal model, which allows a firm's preferences and technology to be estimated jointly in the presence of risk. Their study is an extension of the Just and Pope framework, which implicitly assumes that inputs are given. Saha, Shumway and Talpaz (1994), on the other hand, developed a method using the expo-power utility function, which imposes no restrictions on risk-preference structures. Their results showed that joint estimation of parameters of the production function and the utility function is more efficient than estimating them separately.

Some of the immediate problems of bringing attitudes of producers towards risk into empirical analysis are: an explicit form of the utility function has often to be assumed; it is necessary to impose distributional assumptions on the error term representing production risk; only a few utility functions and probability distributions can be used to derive the risk preference function analytically; and the associated empirical models become quite complicated and difficult to estimate. To address these limitations, Kumbhakar (2002) proposed a methodology that accounts for production risk, risk preferences and technical inefficiency simultaneously. An algebraic expression of the risk preference function is derived, without having to assume an explicit form of the utility function and a specific distribution on the error term representing production risk.

The present study is an attempt to provide empirical evidence on production risk, risk preferences and technical efficiency in the rainfed lowland rice environment in the Philippines. A heteroscedastic production model, which follows the Just and Pope (1978) technology specification, is estimated. Technical efficiency is estimated separately using the stochastic frontier production model. Joint estimation of production risk, technical efficiency and risk preferences is carried out using the model and methodology developed by Kumbhakar (2002). Thus, this study makes an empirical contribution to the literature on production risk, risk preferences and technical efficiency. Most importantly, it is envisaged that this study will provide reliable and precise estimates of technical efficiency and production risk. These will be useful for research managers and policy makers.

1.4 The Research Objectives

The main objective of this study is to investigate production risk, risk preferences and technical efficiency using farm-level data from the rainfed rice environments in the Philippines. The specific objectives of this study are:

- to examine the nature of production risk in rainfed rice environments;
- to estimate the technical efficiency levels of rainfed rice farmers;
- to estimate risk preferences simultaneously with production risk and technical efficiency using a generalised stochastic frontier model.

1.5 Research Approach

In order to address the research problem, an in-depth understanding of a whole range of issues is needed. This study employs the following approach:

1. A review of the importance of, and issues surrounding, the rainfed rice environment. This includes an examination of rainfed rice and a discussion of the opportunities facing the industry.

2. An evaluation of the production systems and their social and environmental characteristics. The main aim of this phase is to have a full understanding of the nature of agricultural production activities in the rainfed environments and to establish a data set needed for the empirical analysis.

3. A literature review is conducted of the concepts for estimating production risk and technical efficiency. This phase is essential to establish the theoretical foundation and conceptual framework.

4. A heteroscedastic production function is estimated to examine the nature of production risk in the rainfed rice environment. This analysis examines whether production inputs are risk-increasing or risk-decreasing.

5. A stochastic frontier production model is used to estimate the technical efficiencies of individual farmers. A review of related empirical studies is used to develop the econometric models used for this analysis.

6. Finally, risk preferences are estimated using a generalised stochastic frontier production model incorporating production risk and technical inefficiency.

1.6 Organisation of the Thesis

This thesis consists of eight chapters. This introductory chapter is followed by an overview and characterisation of the rainfed lowland rice environment. Chapter 3 is a discussion of the rice production systems in the study area. Chapter 4 is devoted to a review of the theoretical concepts for estimating production risk and technical efficiency. Chapter 5 presents the analysis of production risk using a heteroscedastic production model. Chapter 6 presents the analysis of technical efficiency using the stochastic frontier production model. Chapter 7 presents the simultaneous estimation of production risk, risk preferences and technical efficiency using the joint estimation approach. Finally, a summary and discussion of results and their implications are presented in Chapter 8.

Chapter 2
An Overview of Rainfed Rice Environments

2.1 Introduction

The rainfed lowland ecosystem covers 48 million hectares worldwide, about one-fourth of the total rice area. Most of the rainfed lowland rice is grown in South and Southeast Asia, in a belt stretching from eastern India through Nepal, Bangladesh, Myanmar, Thailand, Laos, Cambodia and Vietnam. Large areas of rainfed rice are also grown in Indonesia, the Philippines, Madagascar and Brazil (Ingram 1995). Despite the large area covered by rainfed lowland rice, land productivity in these areas is low. Only 17 per cent of the total world rice output being produced in rainfed lowlands, which are heterogeneous in any location, diverse across locations, and unpredictable everywhere.

Over the years, the rainfed rice areas have been the focus of several studies to understand the environment and cropping practices so as to encourage research into appropriate technological interventions. The literature reveals that rainfed rice environments have been characterised for various purposes at different scales using a large range of techniques (Singh, Tuong and Kam 2000). The research ranges from broad regional-scale characterisation to detailed farm-level studies.

Studies have been and are being carried out in different geographical areas by different institutions. An example is the formation of the Rainfed Lowland Rice Research Consortium (RLRRC) by the International Rice Research Institute (IRRI), in partnership with national agricultural research systems (NARS) in several Asian countries. It was established to identify, prioritise and execute strategic research activities that address the critical yield and productivity constraints in the rainfed lowland rice environments. The consortium has conducted strategic research on the complex issues related to productivity and sustainability, and the characterising and understanding of the heterogeneity of the ecosystem. Principal intervention points for achieving sustainable yield increases are in developing drought- and submergence-tolerant germplasm with good yield potential, improved nutrient management under stress conditions, efficient water use and crop establishment practices, and understanding farmers' approaches to risk management (Zeigler 1999).

The objective of this chapter is to present some of the salient features of the rainfed lowland rice environments. In doing so, section 2.2 provides a brief physical description of the different ecosystems. This section discusses the characteristics of the environments where rice is grown. Section 2.3 covers the basic characteristics and importance of the rainfed rice environments. This involves a discussion of the significance of the rainfed environments in terms of area, production and yield. Section 2.4 presents a specific case of the role of rice in the Philippine economy. This brief account of the Philippine rice industry demonstrates the importance of rainfed rice and the main research issues being addressed in this study. Section 2.5 presents some of the major issues surrounding the use of the yield-gap approach in identifying the constraints to production. This section includes a critique of the approach and an opportunity for a different methodology. This chapter ends with some concluding remarks in section 2.6.

2.2 Rice Environments

Rice is grown in a wide range of ecological environments involving different altitudes, climates and soil types. Several attempts have been made to classify the environments in which rice is grown, and relate them to the different terminologies to describe rice-farming systems (IRRI 1993; Greenland 1997). Most of the classifications use the water regime as a basis for the classification system. This classification may relate to topography and the ability of the soil to retain water. The general classification of rice production is grouped into the irrigated, rainfed lowland, upland and flood-prone environments (IRRI 1993; Greenland 1997). The classification of the different rice production environments is depicted in Figure 2.1. All of the rice ecosystems are characterised by the natural resources of water and land, and by the adaptation of rice plants to them. Irrigated rice may be found at any point in the toposequence if water delivery is available.

For the purpose of comparison, the characteristics of the different rice environments are presented in this section. The basis of classification is that being used by the International Rice Research Institute (IRRI 1993). An *irrigated environment* is where rice is grown in bunded, puddled fields with assured irrigation for one or more crops in one year. The irrigated ecosystem is divided into the irrigated wet season and the irrigated dry season with rainfall variability and supplementary irrigation as the basis for classification.

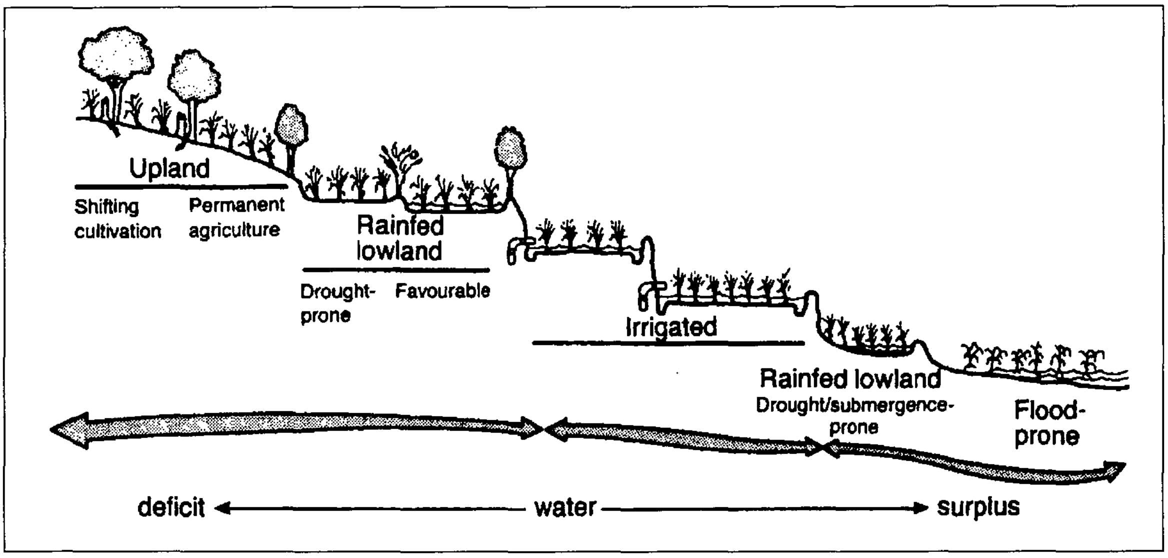


Figure 2.1: Rice ecosystem characteristics.

Source: IRRI (1993), adapted from Greenland (1997)

In an *upland environment*, rice is grown in areas where no effort is made to impound water and where there is no natural flooding of the land. Upland rice is planted in areas at higher slopes of an undulating landscape where the groundwater table is at least 50 cm below the surface although the soils may be classified as hydromorphic, as in West Africa. People who practise shifting cultivation grow a significant part of the upland rice. In shifting cultivation, rice is usually inter-cropped with maize, cassava and other crops.

Another important rice ecosystem is the *flood-prone environment*. The fields are slightly sloping or depressed. Rice may be submerged for 10 consecutive days during crop growth. It is usually seeded immediately before the arrival of the floodwaters, and little more is done until the time arrives for the crop to be harvested. In some areas, the rice may be transplanted once or twice as the floodwaters advance, in an attempt to save the young rice seedlings from drowning if the floods rise too rapidly for the seedlings to survive.

The major characteristics of farming systems of the major rice production environments are presented in Table 2.1. The features of the rainfed rice environment are discussed in the next section.

2.3 The Rainfed Lowland Rice Environments

2.3.1 Physical description

The rainfed lowland environments are where the water supply for rice plants is principally provided by rainfall, run-off water and underground water. The rainfed lowland rice fields are usually bunded. The bunds serve to retain floodwaters, as well as rainwater, which fall during the growing season. Rice fields, in general, are submerged or flooded with water that may exceed 50 cm for no more than 10 consecutive days (IRRI 2001).

Table 2.1: Characteristics of rice-farming systems in major rice production environments

Rice Environment	**Characteristics**
A. Irrigated rice, with assured year-round water	Continuous rice, with one or two crops per year, and occasionally a third rice crop or an upland crop.
B. Diversion irrigation and (favourable) rainfed lowland rice	Where the monsoon season is six months or more: Dry-seeded rice, followed by transplanted rice (irrigated when water is available), followed by an upland crop. Where the monsoon season is less than six months: Transplanted rice (irrigated when water is available), followed by upland rice.
C. In rainfed, drought-prone areas (mostly on alluvial terraces)	One dry- or wet-seeded rice crop. Upland crops may follow in good seasons.
D. In flood-prone (deepwater and floating rice) areas	One transplanted or wet-seeded rice crop. (In some deepwater areas, double transplanting is practised.)
E. In upland rice areas	Under shifting cultivation: Dry-seeded rice, often interplanted, e.g., with maize, and followed by another upland crop, e.g., cassava. Under mechanised cultivation: Sole crop dry-seeded rice, grown annually for several years, after which a grass pasture may be established.

Source: Greenland (1997)

Depending on environmental conditions, rainfed lowlands may be classified into favourable and unfavourable ecosystems (drought-prone, submergence-prone, drought and submergence-prone and medium-deep water). In favourable areas, which are intermediate between rainfed and irrigated ecosystems, field water cannot be completely controlled but rainfall is usually adequate and well distributed. The favourable rainfed areas account for 20 per cent of the total rainfed lowlands (Mackil et al. 1996) and the remaining 80 per cent of the rainfed lowland area is less favourable. Rice in the latter area suffers from varying degrees of drought, submergence and both drought and submergence (Pandey 1997).

Rainfed lowland rice crops may suffer from both drought and flood. At higher terraces, rainfed lowland environments may be drought-prone. In the back swamps, poor soil conditions due to poor drainage are typical causes of the problem. Farmers often cultivate rainfed lowland rice at several toposequence levels such that on one farm some fields may be drought-prone while others may be flood-prone in the same season.

The predominant cropping system in the rainfed environments is a single crop of rice although, in some areas, farmers are able to grow rice and a post-rice crop in the following season. For example, in the rainfed areas of eastern India and the northern provinces of the Philippines, farmers plant legumes, wheat, maize or vegetables as a second crop, but usually on a smaller area.

2.3.2 Distribution of rice area

Rainfed lowland rice is grown on more than 48 million hectares, with one-third of that in South and Southeast Asia (IRRI 2000). This is approximately 28 per cent of the total rice-growing area, and rainfed lowland rice forms about 18 per cent of the global rice supply (Pandey 1997). Areas where rainfed lowland rice is the predominant ecosystem are among the world's most densely populated rural regions. The rainfed lowlands must contribute to the production needed to feed expanding urban areas while preserving the natural resources and improving the well-being of farm families. The distribution of the rainfed lowland areas in selected Asian countries is presented in Table 2.2.

Table 2.2: Rainfed lowland rice area of selected Asian countries

Country	Area (million ha)	Percentage of total rice area	Yield (t/ha)
Bangladesh	5.17	47	2.5
India	13.93	35	2.4
Nepal	0.94	66	2.2
Sri Lanka	0.45	53	2.5
Cambodia	0.86	48	1.5
Indonesia	0.71	7	3.0
Laos	0.32	56	2.1
Malaysia	0.13	21	1.5
Myanmar	2.51	52	3.0
Philippines *	1.20	31	2.0
Thailand	8.57	85	1.8
Vietnam	1.76	28	2.0

Source: IRRI (1993, 2003)

* Data used are for 1997.

The classification of fields into different ecosystems may vary over time. The area classified as rainfed lowland may become an irrigated area with the expansion of the irrigation system. In the same way, the irrigated area may become a rainfed area if there is lack of irrigation. Overall, the rainfed rice area has declined by about 10 per cent since the late 1970s (Pandey 1997), although the rate and direction of the change are not uniform across the Asian countries. There has been a substantial increase in Cambodia, Laos, Vietnam, Myanmar and Thailand and a reduction in the Philippines, Nepal, Bangladesh, Malaysia, China and India (Huke and Huke 1996).

2.3.3 Productivity and rice yield

The yield of rainfed lowland rice is low compared with the yield of irrigated rice. It varies from 1.5 tonnes per hectare in Cambodia and Malaysia to 3.0 tonnes per hectare in Indonesia and Myanmar (Table 2.2). The overall average yield of rainfed rice in Asia is about 2.3 tonnes per hectare (Pandey 1997). Complete time-series data are not available for all countries, making it hard to examine the pattern of yield growth by ecosystem. Nevertheless, the data for India and the Philippines indicate that, as compared with the irrigated environment, yield growth in rainfed rice is not only low but also variable, as measured by the coefficient of variation (Table 2.3).

Table 2.3: Growth rates and coefficients of variation of rice yields by ecosystems

	Irrigated	Rainfed Lowland	Upland
For India (1956-87)			
Growth rate (%)	2.5	1.0	0.3
Coefficient of Variation (%)	10.0	12.0	16.0
For Philippines (1961-87)			
Growth rate (%)	3.2	2.4	1.4
Coefficient of Variation (%)	6.0	8.0	8.0

Source: Pandey (1997)

2.4 Rice in the Philippine Economy

2.4.1 Performance of the rice sector

Rice remains the most important economic and political commodity in the Philippines. It is cultivated in 2.7 million hectares or 30 per cent of the total crop area harvested (Maclean et al. 2002). The crop is harvested from about 3.9 million hectares, of which 2.5 million hectares are irrigated, 1.2 million hectares are of rainfed rice and less than 0.2 million hectares are of upland rice.

Rice contributes an average of 15.5 per cent of the country's gross value-added in agriculture, 13 per cent of the basis for the consumer price index, 3.5 per cent to the gross domestic product and 3.3 per cent to the gross national product (Gonzales 1999; Department of Agriculture 2002).

Rice is the staple food of Filipinos in most parts of the country. It accounts for 35 per cent of the average calorie intake of the population and 60 to 65 per cent of the calorie intake of households in the lower income quartile (David and Balisacan 1995). Rice also accounts for about 41 per cent of the total protein intake. Labour absorption by the rice industry is highest among the agriculture sub-sectors. There are about 11.5 million farmers and family members, and almost 75 per cent of farm household income is derived from rice farming and related activities.

In terms of production, the rice industry has been performing well, except for some years when the El Niño phenomenon and other calamities hit the country. The trend in rice output in the Philippines is presented in Figure 2.2. In 1988, the country harvested about 9.0 million tonnes. In 1995, the harvest reached 10.5 million tonnes, but dropped to about 8.6 million tonnes in 1998 in the wake of the El Niño phenomenon. The country's production has recovered since and it reached 13.3 million tonnes in 2002.

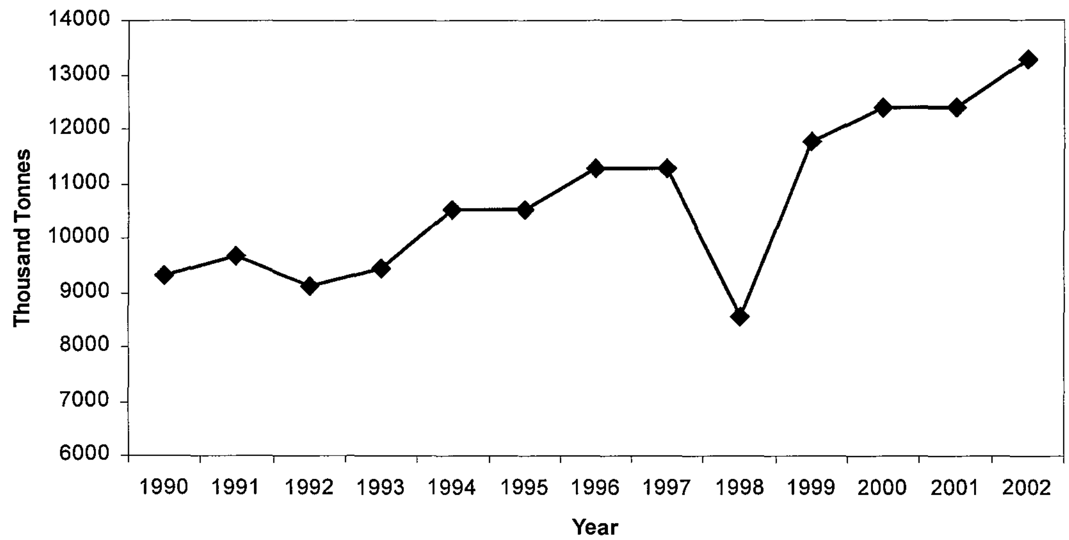


Figure 2.2: Rice production in the Philippines, 1990-2002.

Source of data: PhilRice-BAS (1998) and IRRI (2003)

Despite the steady increase in production, the Philippines remains a net importer of rice (Department of Agriculture 2002). This can be attributed to the rapid increase in the country's population. Records show that the population has more than doubled since the first high-yielding rice varieties were released in the mid-1960s. The population was then 32.7 million and it was recorded as 75.3 million in 2000 (NSO 2002).

2.4.2 Importance of rainfed rice

Rainfed lowland rice in the Philippines is grown in almost all parts of the country. It constitutes about 31 per cent of the total rice area (IRRI 2003) and 88 per cent of the total rainfed rice area (Cruz and Fabiosa 1997). While irrigated lowland rice is the dominant rice environment in the Philippines, the contribution of the rainfed lowland rice is unquestionably important. About 1.2 million hectares are harvested from rainfed lowland rice environments, with the largest areas in the Western Visayas and Central Luzon. The distribution of the rainfed rice areas is presented in Table 2.4. In terms of the national average, the area under rainfed rice decreased during the 1990s because of increased investment in irrigation infrastructure facilities. More farmers are also using supplemental irrigation facilities such as water pumps. In other areas, the insufficiency of irrigation infrastructure has limited the planting of rice to one season only.

Compared with other rice-growing countries, the adoption of modern varieties in the rainfed lowland rice environments is high in the Philippines. About 85 per cent of the land is planted to modern varieties during the wet season and almost 90 per cent during the dry season. The most common modern varieties are the IR and PSB[1] series varieties, while the traditional varieties that are currently planted include *Wag-wag*, *Sinandomeng* and *Biniding*.

[1] These varieties were released by IRRI and Philippine Seed Board (PSB), hence the names IR and PSB.

Table 2.4: Estimated area harvested (in hectares) under rainfed rice, by modern and traditional rice varieties in different regions of the Philippines, 1997

Region	January-June			July-December	
	Modern	Traditional		Modern	Traditional
I	32	---		123,611	8,279
II	34,171	8,368		13,071	390
III	520	180		105,234	642
IV	39,467	15,461		80,742	9,539
V	36,451	7,799		53,885	11,871
VI	96,602			150,289	598
VII	33,752	112		26,010	2,928
VIII	63,919	15,637		34,726	3,789
IX	9,131	5,962		19,106	5,400
X	1,144	289		2,149	
XI	7,494	3,935		8,898	3,264
XII	24,160			30,948	874
XIII	2,175	14,944		10,481	31,622
CAR	380	12		1,914	3,722
Total	375,127	75,543	450,670	668,257	89,138

Source: PhilRice-Bureau of Agricultural Statistics (1998)

Region I: Ilocos Norte, Ilocos Sur, La Union and Pangasinan. Region II: Cagayan, Isabela, Nueva Viscaya and Quirino; Region III: Tarlac, Nueva Ecija, Pampanga, Bataan and Bulacan; Region IV: Aurura, Laguna, Quezon, Palawan, Mindoro Occidental, Mindoro Oriental; Region V: Albay, Camarines Sur, Camarines Norte, Catanduanes, Masbate and Sorsogon; Region VI: Aklan, Iloilo, Capiz, Antique and Negros Occidental; Region VII: Negros Oriental and Bohol, Region VIII: Northern Samar and Leyte; Region IX: Zamboanga Del Sur; Region X: North Cotabato, Bukidnon, Agusan del Norte, Agusan del Sur and Surigao del Norte; Region XI: South Cotabato, Davao del Sur, Davao Oriental and Surigao del Sur; Region XII: Sultan Kudarat, Lanao del Norte; Region XIII (ARMM): Maguindanao, Lanao del Sur, Cordillera Autonomous Region (CAR): Ifugao and Kalinga Apayao.

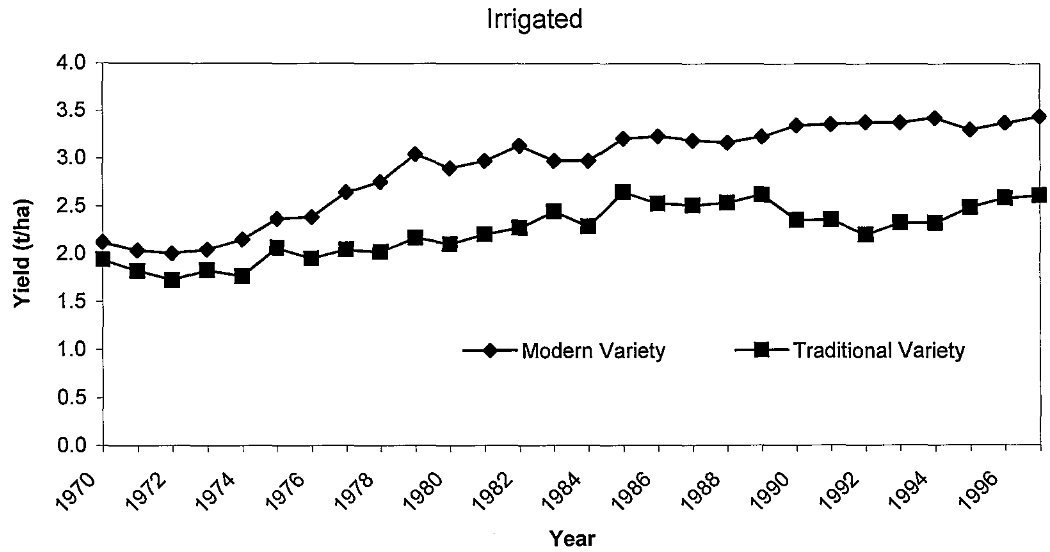
While the area under rice in the rainfed lowland environments is decreasing, the yield of the varieties planted increased from the mid-1980s to the 1990s. In Figure 2.3, the seasonal data for rainfed and irrigated conditions are plotted from 1970 to 1998. Since 1990, yields of modern and traditional varieties in rainfed conditions have been about one tonne per hectare lower than the yields in irrigated conditions. This could be attributed to the lower amounts of fertiliser used in rainfed conditions where there is greater risk of exposure to drought stress (PhilRice-BAS 1995). It can also be seen from Figure 2.3 that the yields of both modern and traditional varieties have increased over time. The increase in rice yield was greater during the period from 1974 to 1984 because of massive government intervention through supervised credit, fertiliser subsidies and greater use of technology (Balisacan 1990).

2.4.3 Production constraints

Despite technological breakthroughs in rice research, yields at the farm levels in the Philippines are still well below their maximum potential due to biological, technical, physical, socio-economic and policy constraints (Sebastian, Alviola and Francisco 2000). In the rainfed lowlands, rice suffers from uncertain timing of the arrival of rains, and droughts and submergence – often in the same fields over the course of a single season or in different fields within a farm over the same season. High costs of production, low and fluctuating prices of rice and inaccessible credit facilities are other factors that inhibit farmers from increasing their total output.

2.5 Issues and Opportunities

The expansion in area of rice cultivation, generation of improved rice technologies and the enthusiasm of rice farmers in adopting improved production technologies are some of the factors that increase rice production to meet the demand of the growing population. Although the yield of rice is increasing over time, the question is how to sustain the growth in order to meet future demands. In the case of the rainfed rice environments, the question is how to increase rice productivity.



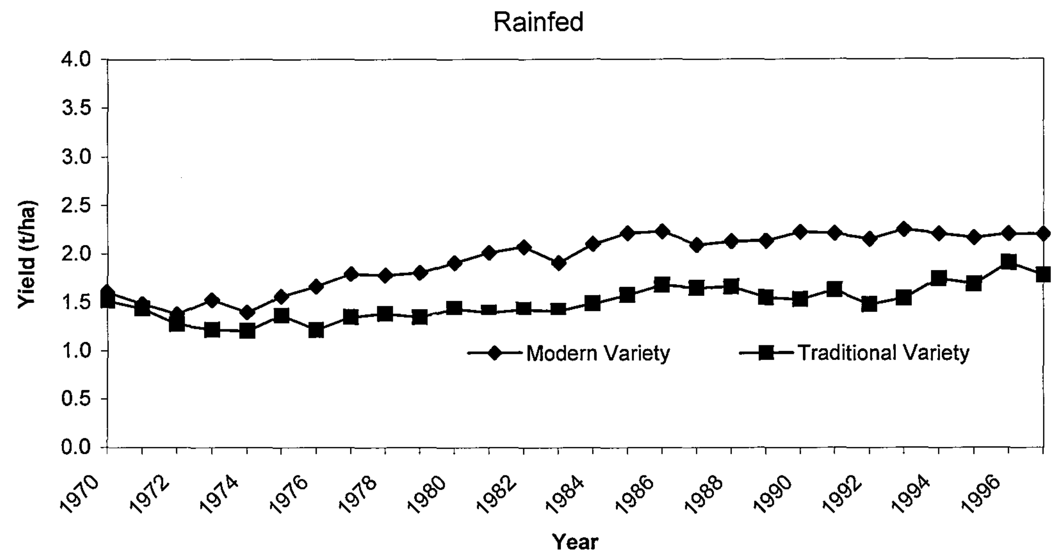


Figure 2.3: Average yields for irrigated and rainfed rice in the Philippines, 1970-97.

Source: IRRI (2003)

Approaches to bridging the gap between the projected demand and the current level of production include expanding the rice area, increasing yields, bridging the yield gap and reducing yield losses (Chaudhary 2000). The prospects for higher productivity in rice appear crucial in view of the fact that farmers' yields in the major rice environments, such as the irrigated environment, are about to reach the potential of existing technologies. A breakthrough is possible only by a revolution of another kind in rice production, such as hybridisation of varieties or by unfolding new frontiers of production technologies with biotechnology. Otherwise, increasing the productivity of the rainfed rice environments is vital.

Rainfed lowland farmers have started adopting the new varieties, but the yields have remained lower in the rainfed lowland environments than in more favourable environments. The major concerns are low soil fertility and fertiliser use, drought and flood problems, the lack of location-specific varieties and production technologies, poor weed management, inadequate availability and quality of inputs, inadequate and ineffective extension support to farmers, slow adoption of recommended technologies, and poor rural infrastructure.

The objective of this section is to discuss the issues surrounding the identification of constraints in rice production. In identifying the constraints to rice production, most studies in the literature have focused on the use of the yield-gap approach. The approach is to identify the nature of the yield gap between the potential maximum yield and what farmers actually achieve. Once the magnitude and nature of the yield gap are established, the second step is to identify biological, physical and socio-economic factors that explain the gap.

This section provides an overview of the concept of the yield gap, followed by some evidence derived from empirical studies. A critique of the approach is included which sets out the motivation for doing this research.

2.5.1 The yield-gap approach

By definition, a yield gap is the difference between the potential yield and the actual yields (Gomez et al. 1979). The potential yield for a particular variety is obtained from modelling with optimum growth conditions. The yield gap is divided into two parts. Yield gap 1 is the difference between research and average farmers' yields in any given location. Yield gap 2, in a given location, is the difference between the mean yield of large plot demonstrations, or the top 10 per cent of farmers, (using the presently available improved technologies and management practices in the best possible combination) and the average yield of all farmers for that location (FAO 2000). The yield gaps are described in Figure 2.4.

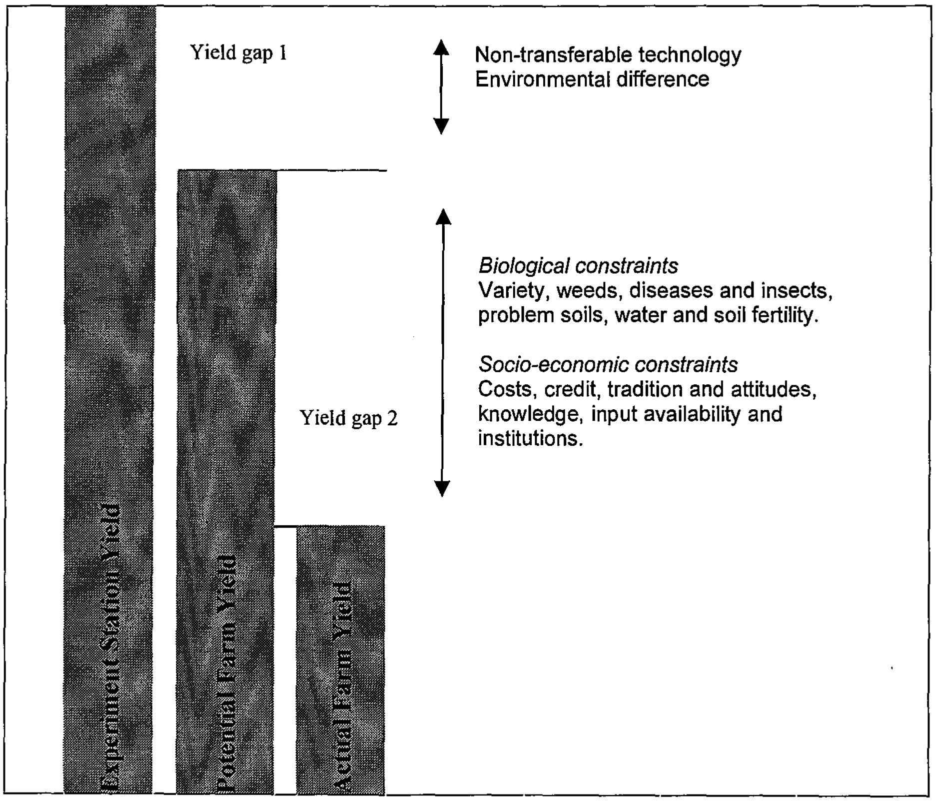


Figure 2.4: Yield gaps between the experimental station yield, potential farm yield and actual farm yield.

Source: Modified from Gomez (1977)

2.5.2 Empirical evidence

In an effort to quantify the yield gap, a number of analysts have estimated the value of the differences in yields from the experimental station, on-farm trials and farmers' fields. Hossain (1997) estimated the potential yields for the major rice-growing countries in Asia on the basis of the existing distribution of rice-growing areas under the different rice environments and compared them with the highest yield achieved at the national level (see Table 2.5). The results show that there is a large potential to increase rice yield in Asia in the medium term by developing appropriate rice varieties that are suitable for different local conditions and by disseminating these varieties through better extension services and better infrastructure. Although the data used are up to 1993 only, the point here is that there is a need to increase the production of rice in order to meet the growing populations and the demands projected to the year 2020.

Table 2.5: Maximum attainable yields and yield gaps in selected Asian countries

Country	% of rice under ecosystem				Maximum attainable yield (t/ha)	Current yield (1991-93)	Required yield to sustain food security (t/ha)
	Irrigated	Rainfed lowland	Flood prone	Upland			
Bangladesh	35	34	23	8	5.4	2.7	5.8
China	93	5	0	2	7.6	5.9	8.9
India	45	33	7	15	5.9	2.7	5.4
Indonesia	72	7	10	11	6.4	4.4	7.4
Philippines	61	35	2	2	6.3	2.9	5.4
Thailand	7	86	6	1	5.3	2.1	2.3
Vietnam	53	28	11	8	6.1	3.5	5.6
Myanmar	18	32	24	6	5.1	3.1	3.7

Source: Hossain (1997)

On more specific estimates of the yield gap, several analysts have indicated that the yield gap is high in the unfavourable environments, the rainfed environment being a case in point. In the Philippines, the difference between the actual farmers' yield is almost 70 per cent of the potential yield during the dry season period (Hossain, Gascon and Revilla 1996). The estimates of the yield gap also proved to be higher in the rainfed rice environments than those in the irrigated environments.

In most Asian countries, the average yields obtained in the farmers' fields are significantly lower than the maximum yields on experimental stations (Herdt 1996). This is supported by country studies of the estimation of yield gaps in various seasons and rice environments (Table 2.6). It can be seen that, in terms of the absolute value of the gap, the difference is higher in the less favourable environments. Although the data in this table are not strictly comparable, they nevertheless illustrate the importance of understanding the general picture of research opportunities.

Table 2.6: Estimated differences between maximum yields on experiment stations and potential farm yields (gap 1) and between potential and actual farm yields (gap 2) in the main rice seasons

Region	Yield gap 1 (kg/ha) in season			Yield gap 2 (kg/ha) in season		
	1	2	3	1	2	3
China [a]	4584	3628	6448	2564	2981	3391
Eastern India [b]	391	533	783	1887	2262	866
West Bengal [b]	284	700	141	1698	786	1561
Southern India [c]	813	939	1416	1147	591	544
Bangladesh [d]	*na*	*na*	*na*	575	762	1380
Thailand [e]	264	1637	1125	401	765	517
Nepal [f]	900	1400	900	300	900	1300
Philippines [g]	460	*na*	860	3480	2450	3050

[a] 1 is early season, 2 is late season, 3 is single season.
[b] 1 is rainfed lowland, 2 is irrigated wet season, 3 is irrigated dry season.
[c] 1 is Karnataka, 2 is Kerala, 3 is Tamil Nadu; all are rainfed.
[d] 1 is rainfed upland, 2 and 3 are as in West Bengal.
[e] 1 is rainfed upland, 2 is rainfed lowland, 3 is irrigated.
[f] 1 is upland, 2 rainfed lowland, 3 is irrigated; all are in *Tarai.*
[g] 1 is wet season rainfed, 2 is wet season irrigated, 3 is dry season irrigated.
Source: Adapted from Herdt (1996) in Evenson, Herdt and Hossain (1996)

In eastern India as a whole, Widawsky and O'Toole (1996) illustrated that there are considerable gaps among, and variation across, the different rice-growing environments. They found that the yield gap is smallest, in terms of percentages, in favourable areas. These areas are the ones with assured water control, planted modern varieties and high use of inputs. In absolute terms, the yield gap was found to be highest in the rainfed lowland and upland environments. Almost 70 per cent of the total rice area in eastern India is under a rainfed environment. Siddiq (2000) conducted a state-level analysis and confirmed these findings.

In a more recent study, Janaiah and Hossain (2001) calculated the yield gap for sampled rice farmers in India. They found that the highest yields obtained by the sampled farmers over a 10-year period were almost the same as those that researchers obtained in the experimental stations. Evidently, this study was conducted in an area with assured irrigation, high adoption of modern varieties and inputs where farmers have exploited almost 90 per cent of the potential yields with existing technologies.

Similarly, the estimated yield gaps in Bangladesh in 1999 were 1.63 tonnes per hectare for *boro* rice (irrigated), 2.32 tonnes per hectare for *aman* rice (rainfed first-season rice) and 1.69 tonnes per hectare for *aus* rice (rainfed second-season rice). According to Sattar (2002), such yield gaps can be attributed to the annual variations in weather conditions and the ability of the variety to withstand pressures from pests and diseases, which vary from season to season and year to year. Furthermore, physical and socio-economic factors responsible for the large yield gaps are low levels of management, lack of price stability, loss of farmers' interest in investments due to an unbalanced land tenure system and other socio-economic factors (Sattar 2000).

Overall, the present production of rainfed rice has remained low and it is apparent that there is still great potential to achieve higher and more stable yields. It is also important to understand the nature of constraints to production and identify the factors that contribute to yield gaps. From the foregoing empirical evidence, it can be gleaned that constraints to rice production in various rice-growing areas can be grouped into biological, socio-economic and technical constraints. The biological constraints encompass biotic and abiotic factors that limit rice yields and are distinct from the socio-economic constraints. Adverse climatic conditions, adverse soil types and diseases are some of the major factors in this group.

Socio-economic factors, including the farmers' social and economic statuses, traditions and knowledge, family sizes, household incomes, expenses and investment, contribute to the yield gap (FAO 2000). In the Philippines, the typical Filipino rice farmer is only 40 per cent as efficient as the best Filipino farmer (Department of Agriculture 2002). The limited management skills of farmers are major socio-economic constraints that are cited in the literature. On average, most rice farmers in the Philippines have limited skills in making rice farming an agribusiness venture. The relatively low fertiliser use and proper timing of application, accompanied by poor management practices, are major sources of inefficiency (Sebastian, Alviola and Francisco 2000). In addition, limited access to credit for processing and storage facilities forces farmers to sell their marketable surplus during harvest months when prices are low. Farmers are unable to wait for a good price because they do not have places to dry and store their rice. As a result, wholesalers dictate prices to retailers and consumers.

Institutional and policy constraints are also vital. They include government policies, rice price-setting mechanisms, credit and input supply, land tenure, marketing, development and extension.

Technical constraints are those factors that include varieties planted, resource-use efficiency (water, soil, nutrients, seed quality, pest and weed control), harvest and post-harvest activities. Considerable efforts have been expended in explaining the various factors that affect the differences in yields. Most of the available estimates are concentrated on the effects of biological constraints. The losses are noted to be due to the effects of adverse conditions, and biotic and abiotic factors.

The focus of most available analyses is to close the yield gap. Closing the yield gap means increasing productivity, thereby, ensuring food security. Attempts have been made on varietal improvement, particularly developing varieties that can withstand adverse soil and climatic conditions. This includes developing drought- and flood-prone tolerant varieties. Analysts have also looked at the impact of technology adoption and diffusion. There is still a need to identify and quantify the effects of other socio-economic and technical constraints.

Over the past decade, research organisations, policy makers, government and non-government agencies have struggled to come up with possible solutions to declining productivity and a persistently large yield gap. The institutions are, however, not immune from the need to achieve economic efficiency. Several attempts have been made to overcome the constraints in production. A forum organised by the Food and Agriculture Organization (FAO) of the United Nations, and attended by experts from the major rice-growing countries, outlined various strategies for bridging the yield gap in rice. Chaudhary (2000) summarised the examples of these strategies. One notable strategy is to have stable-performing varieties. Location-specific varieties that are tolerant to adverse conditions are required. IRRI developed a new variety (super rice) that has the ability to raise the present yield potential by 25 to 30 per cent (Khush 1995). The use of biotechnology may also provide an opportunity to increase yields in a more effective and sustainable manner.

In order to combat the effects of biotic and abiotic stresses, efforts have been directed to understanding the genetic basis of resistance of varieties to pests and diseases. Host-plant interaction and control measures reduce losses in proportion to their use, and this is one way of reducing the yield gap. Efforts have also been directed towards tackling problems with declining soil fertility and fertiliser management, water scarcity and unreliability, irrigation management, integrated crop management and post-harvest operations.

Overcoming the socio-economic and technical constraints is another difficult challenge for researchers, policy makers and other parties who have the mission to improve the welfare of rice farmers. A number of studies revealed the importance of providing timely delivery and availability of inputs, the need for institutions that provide affordable and timely credit, the need to stabilise and sustain production, and institutional support. It is believed that government and private institutions associated with credit, inputs and pricing have a direct influence on the adoption of improved inputs and the levels of their use, and, thereby, on the yield level (Chaudhary 2000).

2.5.3 A critique of the yield-gap approach

The concept of a yield gap has been widely used in order to examine the performance of a particular production unit by identifying the constraints to production. Research planners and managers have also used this approach as a guide to their research agenda. Experts have identified biophysical, socio-economic, technical, management, institutional and policy factors as the major causes of the difference between the yields that are obtained by farmers and the maximum attainable yield.

Most scientists believe that large yield gaps for rice still exist in both favourable and less favourable conditions in many countries and they could still be exploitable for further improvement in productivity (Duwayri, Tran and Nguyen 2000). This can be due to poor crop management and problems in institutional support, especially in input and farm credit facilities. However, Pingali, Hossain and Gerpacio (1997) argued that the yield gaps in favourable rice environments are not significant for increasing rice yields and production.

Bridging the yield gap is promising but, because of its complexity, there are different views concerning its value as a tool for increasing rice production (Duwayri, Tran and Nguyen 1998). It requires integrated and holistic approaches, including appropriate concepts and policy interventions. It should be aimed not only at increasing rice yields and production but also improving the efficiency of input use, thereby reducing the cost of production.

The extent by which the yield gap should be narrowed depends on the way in which the existing constraints to production are addressed. There are issues to be considered that go beyond yield maximisation. Farmers may not achieve the full yield potential of the technology because they opt not to. Farmers are influenced by several factors, including those that affect their ability to achieve the maximum attainable yield. First, the economically efficient yield is seldom the maximum yield attainable. Second, a risk-averse attitude might cause a farmer to rationally choose a yield lower than the economically efficient yield. Third, the technical efficiency of farmers should be considered.

Using the potential yield as the benchmark for increasing yields may be misleading. The concept of the yield gap only accounts for the differences in the experimental yield, potential yield and the farmers' actual yields. Consideration should be given also to the technically efficient yield, not to mention the economically attainable yield based upon the availability of farmers' resources. Because of the stochastic nature of rice production, the efforts of farmers should also focus on the reconciliation of the role of random shocks in the system to achieve risk-efficiency.

The maximum attainable yield is most unlikely to be the economically efficient yield. Yield gaps may be caused by technical deficiencies but also by economic considerations. For example, farmers who seek maximum profit may not apply fertiliser dosage to obtain maximum production. Assuming that a farmer's objective is to maximise the expected utility of profit, the maximum attainable yield would not necessarily be the point where marginal utility of profit is maximised. Hence, reducing the yield gap without considering the economic aspect may have a counter-productive effect (Duwayri, Tran and Nguyen 2000). Closing the yield gap may actually decrease a farmer's utility, especially if rice prices are low.

Furthermore, the maximum attainable yield may not be the risk-efficient yield. The yield-gap concept does not take into account the risk element associated with a given technology or new technologies. The maximum potential yield may not be achievable because of the risk attitudes of farmers. Farmers generally avoid situations which offer the potential for substantial gains but which also leave them even slightly vulnerable to losses below some critical level.

The application of the yield-gap approach for analysing the existing differences in yields between farmer's fields and the maximum attainable yield should take into account factors such as the technical efficiency of farmers and the factors that affect the levels of inefficiency. Moreover, consideration should be taken of the risk element associated with the technology and assessment of the attitudes of farmers towards risk.

2.5.4 Opportunities

The previous sections present the yield-gap approach and selected empirical evidence for understanding the current yield gaps in rice farming. In view of the issues raised in using the yield-gap approach, this study takes an alternative approach to understanding optimisation processes in the rice production system. We examine the technical efficiency of individual farmers and identify the factors that explain the levels of inefficiency. This approach allows us to examine the factors that influence the farmer's ability to maximise utility. Because of the stochastic nature of the production process, this methodology brings an opportunity to estimate the technical efficiency of farmers by taking into account simultaneously the production risk and risk preferences of individual farmers. This approach is discussed further in Chapter 4.

2.6 Concluding Remarks

This chapter provides an overview of the rainfed rice environments. There are four basic rice environments based on water regimes: the upland, rainfed, irrigated and flood-prone. The upland environment is where dry-seeded rice is produced under shifting cultivation. The irrigated environment is where there is continuous water supply and the land is usually planted with two rice crops in a year. In rainfed environments, rice is planted in levelled and bunded fields that are shallowly flooded with rainwater.

The rainfed rice environment is second to the irrigated rice environment in terms of area and production. Despite its importance, yield in the rainfed environments is still low. Rice suffers from drought and submergence - a typical occurrence in an environment that is susceptible to erratic rainfall and characterised by heterogeneous land and soil types.

This chapter highlights the importance of rice in the economy of the Philippines. Rice remains the most important economic and political agricultural commodity. Although the trend in total rice output is positive, the country remains a net importer of rice. The rainfed rice environments are important in the Philippines in terms of their share in area and production. They currently account for 35 per cent of the total area. But despite their importance, the productivity and full potential of these environments is not achieved due to many limiting factors. Other than the intrinsic nature of these environments, some socio-economic factors are constraining the productivity of the rainfed areas in the country.

According to the yield-gap approach, the major issue surrounding the rainfed environments is the wide gap between the actual and attainable yields. This gap can be attributed to biological, economic, institutional and technical factors. Increasing the production of rice and closing this gap remains a challenge for all researchers and policy makers.

Despite the widespread application of yield-gap approach, its validity is questionable because farmers seldom wish to achieve the maximum attainable yield. First, the economically efficient yield is seldom the maximum yield attainable. Narrowing the yield gap aims not only to increase rice yields and production but also to improve the efficiency of resource use. Second, a risk-averse attitude might cause a farmer rationally to choose a yield lower than the economically efficient yield. Third, the technical efficiency of farmers should be considered.

This thesis makes a contribution in research in this area by providing empirical analyses of the roles of risk and inefficiency in understanding the complexity of the rice production systems in the rainfed lowland rice environments.

Chapter 3

Rice Production in Tarlac, Philippines: Environmental and Socio-Economic Characteristics

3.1 Introduction

The main objective of this chapter is to explain the production system of rice in Tarlac, Central Luzon, Philippines. This area is a typical rainfed lowland rice environment in the country. It is important to understand the rice production system for the formulation of appropriate econometric models used in the empirical analyses in Chapters 5, 6 and 7. The chapter is organised as follows. The second section provides the general description of the study area and the survey design. This is followed by a section on the demographic and environmental characteristics in the region. The fifth section contains a discussion of the inputs used in the production of rice in the area. A concluding section summarises the information presented in this chapter.

3.2 The Study Area and Survey Design

This study involves data that were collected in the province of Tarlac, Philippines, which is the northwestern side of Central Luzon, bounded by the provinces of Pampanga in the south, Pangasinan in the north, Zambales in the west and Nueva Ecija in the east (Figure 3.1). The total land area of the province is 305,345 hectares. It has 18 municipalities that comprise 509 *barangays.*[1] The municipality of Tarlac is the capital of the province. Tarlac is the home province of several ethno-linguistic groups, including *Ilocanos, Pangasinenses, Tagalogs* and others.

[1] A *barangay* (village) is the smallest administrative and political unit in the Philippines.

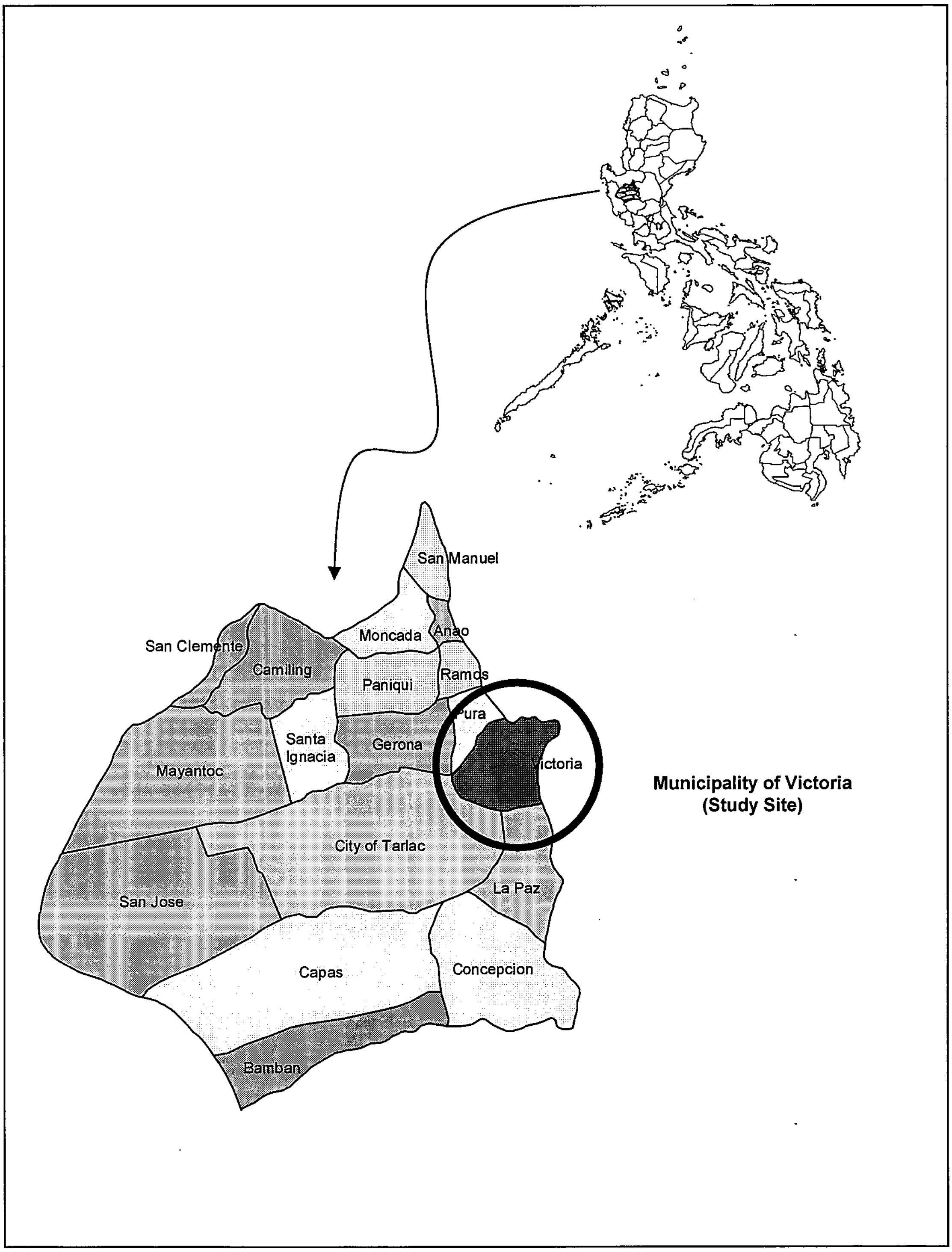


Figure 3.1: Map of the province of Tarlac.

The soils in the province are derived from consolidated and unconsolidated volcanic rock coming from the Zambales Mountains to the west. Tarlac has coarse-textured soils compared with those of the Central Luzon plains of Pangasinan and Nueva Ecija. The study site has different kinds of soils from silt loam to undifferentiated soil.

Like the rest of Central Luzon, the province has two distinct seasons: the dry season from November to April and the wet season for the rest of the year. The average annual rainfall is about 1,620 mm, with most of the rains falling in the months from June to October. With the rainfall not being pronounced in the remaining months of the year, a second cropping for most of the rainfed rice fields is not possible. Rice is grown in the rainy season and most of the land is left fallowed during the dry season.

The agricultural sector is dominant in the economy of Tarlac. Rice is the main crop planted during the wet season, accounting for almost 90 per cent of the total cropped area. In 1997, the total area planted to rice was approximately 103,000 hectares with a total production of 389,000 tonnes. Irrigated rice is by far the most important rice ecosystem, accounting for about 67 per cent of the rice area planted and 77 per cent of total rice production. Overall, the average yield of rice is about 3.8 tonnes per hectare. The trends in area, production and yield of rice in the province are presented in Figure 3.2. Although there is an increasing trend in the annual yields of rice, it is evident that there is some degree of instability in production. Production risk in the rainfed rice environment is mainly due to climatic variability.

In an effort to explain the variations in yield, IRRI initiated socio-economic monitoring of the rice production activities in the Municipality of Victoria in the Province of Tarlac in 1990. The municipality is located in the eastern part of the province, which has a common boundary with Nueva Ecija. It is about 10 kilometres northeast of the provincial capital of Tarlac City. The town is bounded on the north by the municipality of Guimba, Nueva Ecija, Tarlac City on the south, Gerona on the west, and Licab, Nueva Ecija on the east.

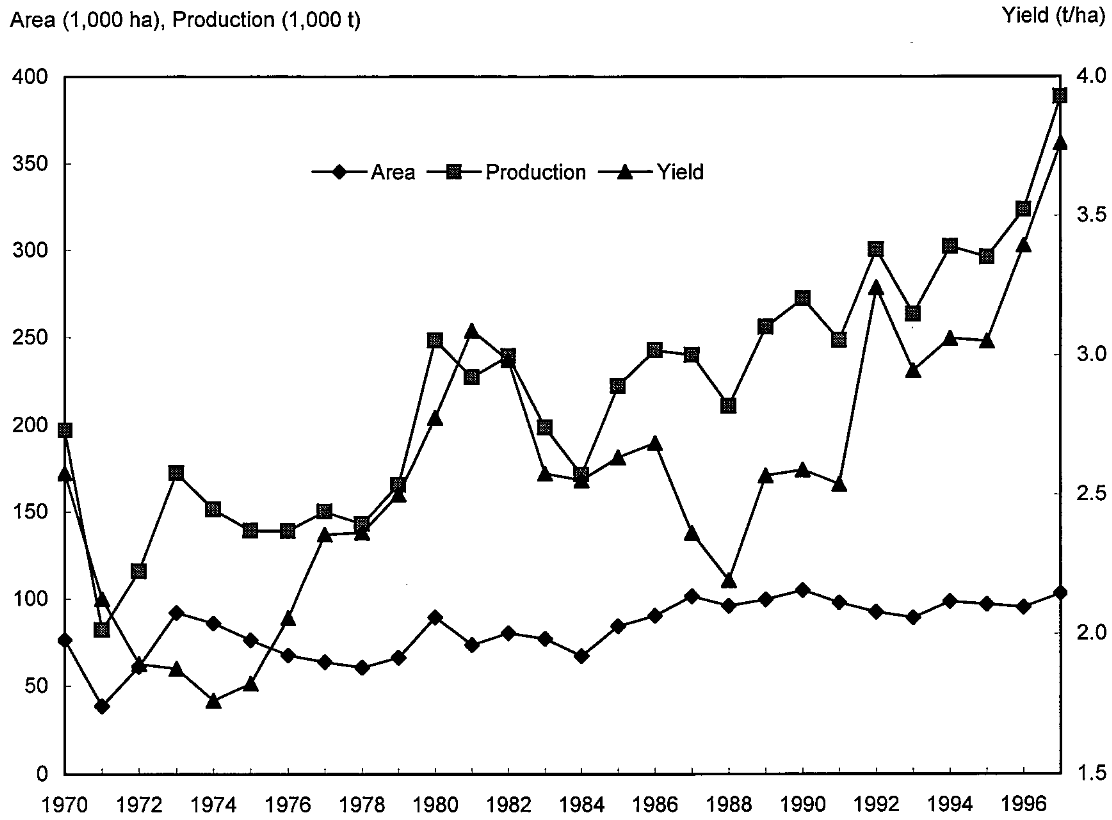


Figure 3.2: Area, production and yield of rice in the province of Tarlac, Philippines, 1970-97.

Source: PhilRice-Bureau of Agricultural Statistics (1998)

The municipality is composed of 26 villages, four of which were used as representative villages for the survey. The villages selected were Calibungan, Canarem, Mangolago and Masalasa. The selected villages are accessible via the provincial road leading to Guimba, Nueva Ecija. It is paved and concrete, and is often used for the solar drying of rice harvests. The available modes of transport are jeepneys, buses, private cars and tricycles. Farmers also use hand tractors with trailers to carry farm inputs and products to and from the village to the town of Victoria.

A total of 46 farmers were randomly selected from the population of 600 households in the four representative villages. Prior stratification of the population was not possible because of a lack of data on household and field characteristics for the overall population. After the random sampling, the identification of farmers was conducted.

Primary data were collected using a structured questionnaire. Information on the farmers' resource base, land-use patterns, rice production practices, labour allocation and non-farm incomes were collected during the interview. The collection of data was continued using the same group of farmers from 1990 to 1997. Rice production data were obtained for all the fields operated by the sample farmers. The interview process was conducted twice each year, the first after the crop establishment and the second after the rice harvest. Farmer and parcel-wise panel data were collected for all farm operations.

To reinforce the description of the study site, some secondary data were collected from the Bureau of Agricultural Statistics and from the National Statistics Office.

3.3 Demographic Characteristics

3.3.1 Household composition

The inhabitants of the surveyed villages are generally of *Ilocano, Pangasinenses* and *Tagalog* ethno-linguistic backgrounds. Most of them have lived in their respective villages for a long time. The households included in the study were grouped according to farm size. By Philippine standards, farmers who have less than 1.5 hectares are considered small farmers, those with 1.5 to 2.5 hectares are categorised as medium farmers and those with more than 2.5 hectares are considered large farmers. The general household characteristics of the surveyed area are presented in Table 3.1.

The average household size was 5.1, which is lower than the national and provincial average family sizes, which are both equal to 5.5 (NSO 2002). About 50 per cent of the total household composition is male. Household size is highest in the medium-sized farms. All the 46 sample households had male heads. This follows the dominant trend in the Philippines where the households are mostly patriarchal. The wife would be considered the head of the household only when the husband passed away or if the wife is separated from him legally or otherwise.

Table 3.1: Selected characteristics of farm households by farm size in Victoria, Tarlac, Philippines, 1992*

Item	Units	Size of Farms			All Farms
		Small	Medium	Large	
Number of respondents	Number	19	13	14	46
Average household size	Number	4.7	6.6	4.6	5.1
Average age of household head	Years	49.6	45.4	48.1	47.8
Average number of years of education of household head	Years	7.1	7.3	7.5	7.3
Household composition	(%)				
Sex					
Male		51	46	55	50
Education					
Primary		51	51	43	48
High school		29	39	28	32
University		6	6	18	10
Not in school		14	5	10	10
Age					
< 15 years old		28	33	22	28
15-50 years old		53	57	56	55
> 50 years old		19	11	22	17

* Demographic information was collected starting 1992 only.
Source: Survey data

The mean of the years of formal schooling of household heads is approximately 7 years. Of the other members of the household, 48 per cent were in primary school, 32 per cent were in high school or had completed high school and 10 per cent had either completed or reached the tertiary level. It can be seen that larger farmers have a higher proportion of members who had reached tertiary level. The average age of household heads was about

48 years. About 55 per cent of the total household members were between the ages of 15 and 50 years old.

3.3.2 Household asset ownership

It is generally believed that household asset ownership is a good proxy for the wealth of the farm households surveyed. Other than land operated, the most notable asset holdings of the farmers were the machinery and equipment, livestock and consumer durables. Table 3.2 provides a summary of the percentage of households in each farm-size category with respect to asset holdings. The ownership of machinery and equipment generally increased with farm size. Larger farm households could afford to purchase farm equipment. Tractors and *carabaos* were two of the most important assets for farmers. The ownership of these assets is critical, especially in the land preparation stage. About 64 per cent of the large farmers owned tractors, compared with about 42 per cent of all surveyed households. Farmers with no tractor rent one during the land preparation period.

About 73 per cent of the households had their own *carabao*. Ownership of other livestock such as cattle and goats were an integral component of the farming system in the area. Land fallowed during the second season was used as pasture for these animals, which was a source of additional income for the households. The share of livestock in total household income is discussed in the latter part of this chapter.

The values of these assets are used as a proxy for the initial wealth of farmers when estimating the risk aversion coefficients of farmers in Chapter 7.

Table 3.2: Percentages of households owning assets by farm size in Victoria, Tarlac, Philippines

Item	Size of Farms			All Farms
	Small	Medium	Large	
Tractor/Equipment				
Tractor	26	42	64	42
Irrigation Pump	11	42	43	29
Sprayer	11	25	57	29
Plough	47	58	71	58
Harrow	32	33	50	38
Other*	37	50	79	53
Animals				
Carabao	68	75	79	73
Cattle	47	58	71	58
Poultry**	53	67	71	62
Goat	32	33	21	29
Pig	11	8	7	9

* Other includes cart, trailer and sled. ** Poultry includes backyard chickens, ducks and geese.

Source: Survey data

3.4 Environmental Characteristics

To enable an appropriate analysis of the technical efficiency of rice production under risky conditions, it is essential to understand the nature of the environments where rice is grown. This section provides a brief description of some of the biophysical characteristics of the study area.

3.4.1 Landholding and tenure

The average operational holding of the sample farms during the period from 1990 to 1997 was about 2.2 hectares. Of this total area, 54 per cent was owner-operated, 24 per cent was under fixed-rent leasehold and 22 per cent was under share tenancy (see Table 3.3).

There are more leaseholders among small farms and, as expected, there are more owner-operators among large farms. Landholdings are also fragmented, with an average of 3.3 parcels per household and an average area per parcel of almost 0.8 hectare.

Table 3.3: Landholding and tenurial status by farm size in Victoria, Tarlac, Philippines

Item	Size of farms			All farms
	Small	Medium	Large	
Farm size (ha)	1.0	2.2	3.5	2.2
Number of parcels	2.1	3.2	4.1	3.3
Area of parcel (ha)	0.5	0.7	1.1	0.8
Distribution of landholding by tenure (percentage)				
Owned	54	35	62	54
Leasehold	31	19	24	24
Share tenant	16	47	13	22

Source: Survey data

The above operated area can be classified into different land and soil characteristics, which are presented in section 3.4.2.

3.4.2 Land and soil characteristics

Land classification can be done in two ways, the scientific method and the traditional method. The traditional method is the way the farmers classify their land. In general, the classification of land type is based on the position of the land in the toposequence. Farmer classification of field characteristics has been found to correspond well with the scientific classification (Talawar 1996). In this study, we use the farmers' classification of land type. In Tarlac, land type can be classified into upper *bantog* (upper fields), lower *bantog* (medium fields) and *lubog* (lower fields). The *bantog* fields are drought-prone fields on the upper part of the toposequence while the *lubog* fields are on the lower part of the toposequence and are generally prone to flood and submergence. Overall, the *bantog* is the most common land type because about 76 per cent of the total area under rice is from such fields (see Table 3.4).

Table 3.4: Percentages of area by land and soil type and farm size in Victoria, Tarlac, Philippines

Item	Size of Farms			All Farms
	Small	Medium	Large	
Land type				
Upper *Bantog*	23	9	18	17
Lower *Bantog*	58	63	58	59
Lubog	19	28	24	24
Soil type				
Panaratin (Sandy)	27	36	40	38
Kadagaan (Clay)	67	54	44	50
Pila (Heavy Clay)	6	9	16	12

Source: Survey data

Alternatively, soil types are classified as *Panaratin, Kadagaan* and *Pila,* which are sandy, clay and heavy clay soils, respectively. Of the total operational landholdings, clay soils cover about 50 per cent of the area monitored. Table 3.5 shows that sandy soils are most dominant in the upper fields while clay soils are dominant on the medium and lower fields.

Table 3.5: Percentages of area by soil and land type in Victoria, Tarlac, Philippines

Soil type	Upper *Bantog*	Lower *Bantog*	*Lubog*
Panaratin (Sandy)	74	38	7
Kadagaan (Clay)	17	51	75
Pila (Heavy Clay)	9	11	18

Source: Survey data

3.4.3 Rainfall pattern

There are two distinct seasons in the province. The wet season usually starts in late June and ends quite abruptly in mid-October. The average annual rainfall in the province of Tarlac from 1977 to 1997 was about 1,620 mm, with most of the rains during the months from July to September. Overall, the rainy season provides four months of more than 200 mm per month. The dry season occurs from November to April with an average rainfall of less than 100 mm per month. The average monthly rainfall pattern in Tarlac is graphed in Figure 3.3.

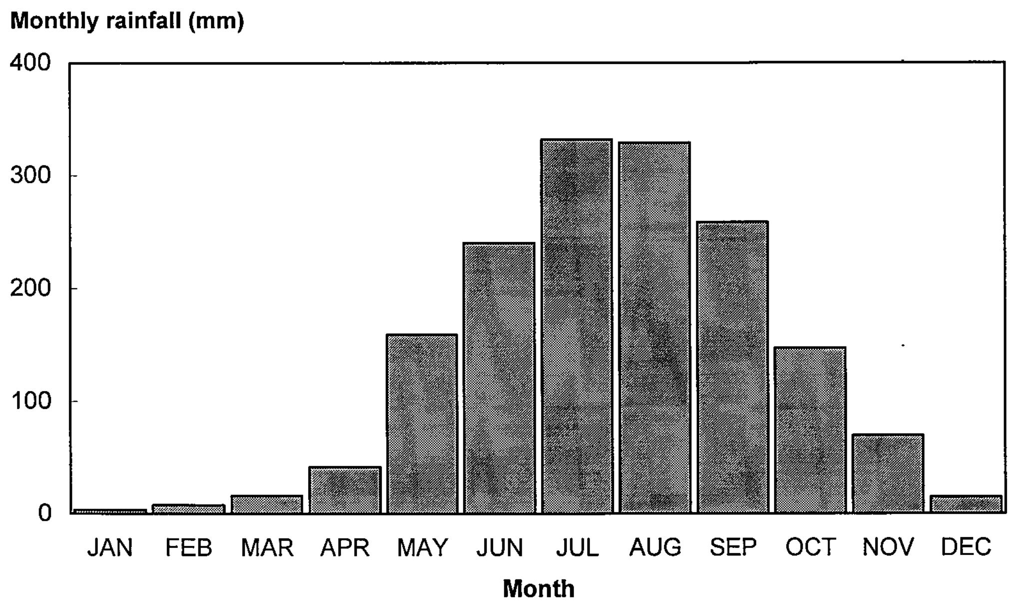


Figure 3.3: Average monthly rainfall in Tarlac, Philippines, during 1977-97.

The rice production environment of this province is subject to a high degree of variability, which is reflected by the relatively high coefficient of variation of annual rainfall of about 23 per cent (Table 3.6). The onset of rainfall is an important factor in rice production activities. This gives the signal to farmers when to start the land preparation activities, and, thereby, affects the timing of crop establishment. Rainfall at the commencement of the season (i.e., June) is characterised by a high degree of variability, as attested by its high coefficient of variation of 65 per cent. The rainfall data indicate that farmers in this province have to deal with the variability of moisture conditions, both at the initial stage of land preparation and rice establishment (June/July), as well as during the later stage of crop development (October). The coefficient of variation of rainfall for October is about 84 per cent. The rainfall data from 1990 to 1997 are plotted in Figure 3.4. It can be seen that the averages for 1994 and 1996 fell below the long-term average rainfall of 1620 mm in the area. In addition to the variability of rainfall, the province also experiences tropical depressions and typhoons.

Table 3.6. Wet season rainfall in Tarlac, Philippines, 1990-97

Year	Jun	Jul	Aug	Sept	Oct	Total (Wet season)	Total (Annual rainfall)
1990	559	710	427	367	63	2127	2434
1991	323	416	448	388	97	1671	1931
1992	271	315	402	312	138	1438	1635
1993	354	475	392	294	457	1973	2248
1994	238	326	228	320	49	1162	1465
1995	225	308	248	456	141	1380	1835
1996	64	292	198	149	62	764	1161
1997	348	171	452	185	36	1192	1519
Long-term average [a]	240	332	329	258	148	1307	1620
Long-term coefficient of variation (%)	65	45	35	38	84	28	23

[a] The long-term average and the coefficient of variation were computed using the data from 1977 to 1997.

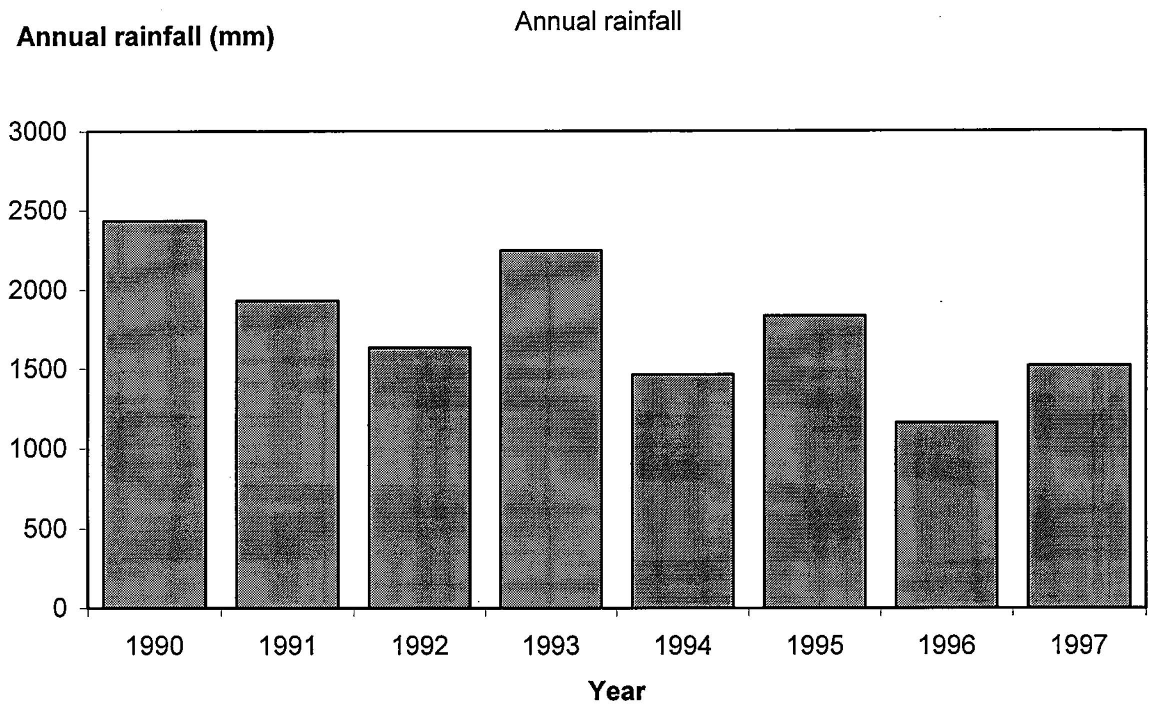


Figure 3.4: Average annual rainfall in Tarlac, Philippines, during 1990-97.

3.5 Agricultural Production Activities

3.5.1 Land use and cropping patterns

Over the eight years of cropping seasons, about 97 per cent of the total operational holdings were planted to rice during the wet season. Because rainfall is inadequate for a second crop of rice, rainfed fields are mostly left fallowed after the wet season rice is harvested. Following the rice-fallow rotation, the most dominant cropping patterns in the area are rice-mungbean and rice-corn (see Table 3.7). A small number of farmers who hade access to irrigation (tubewells) also grew vegetables in the dry season. There were instances where farmers practised rice-mungbean rotations because the mungbean can be grown in the presence of soil moisture obtained during the rainy season.

Table 3.7: Percentages of parcels planted to different crops in the dry season [a]

Pattern	1990	1991	1992	1993	1994	1995	1996
Rice-Corn	2	1	0	0	0	15	0
Rice-Fallow	78	75	63	59	72	80	80
Rice-Mungbean	16	20	34	38	25	2	14
Other [b]	4	4	3	3	3	3	6

[a] Data for 1997 were not collected.
[b] *Other* includes rice-vegetables and rice-rice patterns.

3.5.2 Rice yield and varieties

The eight-year average rice yield was 3.17 tonnes per hectare. In terms of the different land types, the average yields were 3.30 tonnes per hectare for the upper fields, 3.33 tonnes per hectare for the medium fields and 2.76 tonnes per hectare for the lower fields (see Table 3.8). The coefficient of variation of yields tended to be highest for the lower fields. The variations obtained for the survey data are the sum of the effects of the climatic variability, parcel effects and effects of the management practices by farmers.

There were 109 varieties of rice reported by the sample farmers. Of these, about 60 were improved varieties. The most popular varieties in the *bantog* fields were IR 64, IR 66, IR 68 and IR 36, which together occupied more than 50 per cent of the total cropped area. On the *lubog* fields, the most popular varieties were IR 64, IR 68 and IR 42. Over time, these improved varieties have replaced traditional varieties such as *Wag-Wag* and *Pagay Iloko*. Overall, IR 64 was the dominant variety (see Figure 3.5). IR 64 is better qualitatively (longer grain, intermediate amylose content, low gelatinisation temperature) and is increasingly popular (Pandey et al. 1999). Most farmers who used this variety indicated that it was high-yielding and had good taste. When farmers are to decide on what variety to use, some other factors that they consider are the previous year's performance of the variety, the availability of seeds, duration and the adaptability of the variety to adverse incidents, such as lodging and infestation by pests and diseases.

Table 3.8: Average yields of rice (t/ha) by land type, 1990-97*

Year	Upper Fields	Medium Fields	Lower Fields	All Fields
1990	3.34 (0.94)	3.27 (1.25)	2.00 (1.43)	2.95 (1.37)
1991	2.77 (1.10)	3.14 (1.35)	2.24 (1.23)	2.84 (1.33)
1992	3.50 (1.14)	3.64 (1.18)	3.01 (1.23)	3.46 (1.21)
1993	3.33 (1.12)	3.30 (1.32)	2.58 (1.51)	3.12 (1.37)
1994	3.26 (1.35)	3.05 (1.06)	2.26 (1.11)	2.88 (1.18)
1995	3.86 (1.76)	3.41 (1.22)	3.67 (1.98)	3.56 (1.57)
1996	2.50 (0.97)	2.85 (1.27)	2.42 (1.37)	2.67 (1.26)
1997	3.86 (1.04)	3.96 (1.50)	3.79 (1.84)	3.90 (1.52)
All Years	3.30 (1.26)	3.33 (1.31)	2.76 (1.61)	3.17 (1.41)

* Figures in parentheses are standard deviations. The numbers of plots were 164, 518, 249 for upland, medium and lower fields, respectively.
Source: Survey data

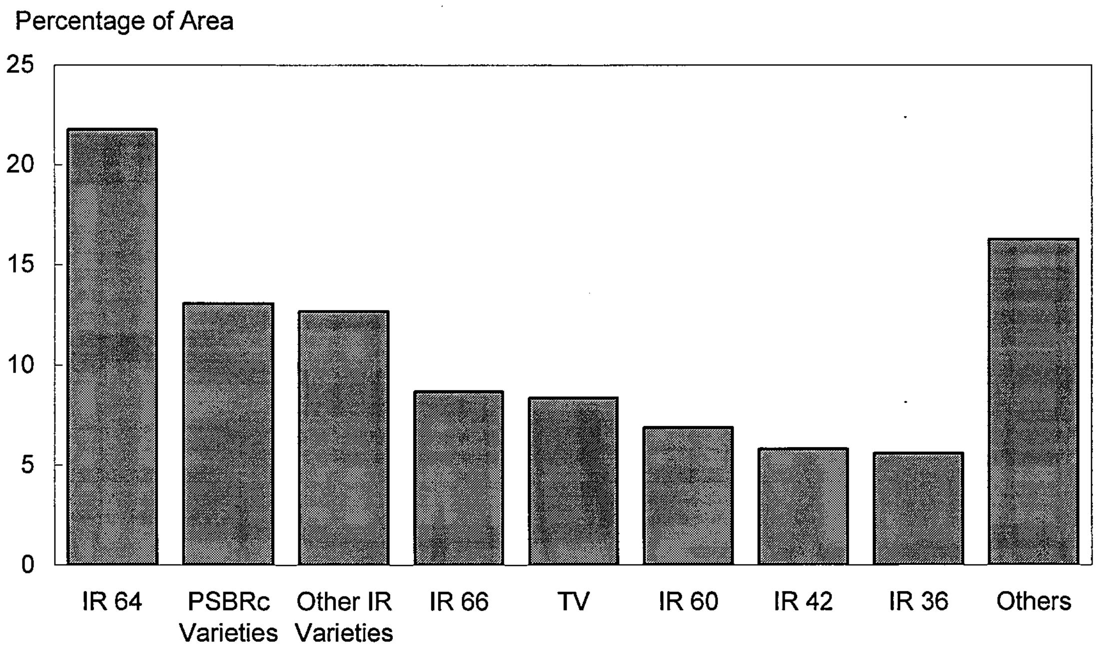


Figure 3.5: Varietal use in the rainfed lowlands of Victoria, Tarlac, Philippines, 1990-97.

3.5.3 Rice production practices and input usage

As mentioned earlier, almost all land is planted to rice during the wet season. Seedbed and land preparation is done after the first onset of rain towards the end of May or early June. Ground water is the source of supplemental irrigation if rainfall is not sufficient to cultivate the land. About 29 per cent of the farmers have their own water pumps.

Land preparation activities involve ploughing and harrowing using animal power (*carabao*) or hand-tractors. There is a trend towards farm mechanisation in the province and about 42 per cent of the surveyed farmers had hand-tractors. In recent years, almost all farmers had used hand-tractors in at least one of their parcels planted to rice. They used their own or rented tractors. From the survey data in 1990, only 36 per cent of the farmers used tractors while use had increased to 100 per cent in 1997. Carabaos, nevertheless, were still widely used by farmers. On average, ploughing and harrowing were done twice. Cleaning and repairing dykes and waterways are other basic activities.

If fields are to be transplanted, a separate plot is used as a seedbed. Seeds are pre-germinated, sown in a small plot and then transplanted in the main fields when they are four to five weeks old. In the case of direct seeding, seeds are directly sown in puddled soils. The average seeding rate is about 103 kilograms per hectare.

Crop establishment is basically done by hired labour, sometimes on a contract basis. The contractor determines the number of labourers, but the total labour-hours do not vary from those of labourers on a non-contract basis. On average the labour requirement for crop establishment is about 20 days per hectare.

Chemical fertilisers are applied on both the seedbed and main field at an average rate of 90 kilograms of NPK per hectare (see Table 3.9). The rates of application vary across land types, with those on the lower fields using lower rates. Fertilisers are applied in split doses. The first and second applications are made roughly 15 and 45 days after planting, respectively. The rates of application of insecticides do not vary much across different land types. The applications of herbicides, on the other hand, are higher on upper fields.

Table 3.9: Average levels of input use for rice cultivation by land type in Victoria, Tarlac, Philippines during 1990-97

Item	Units	Upper Fields	Medium Fields	Lower Fields	All Fields
Number of plots	Number	164	518	249	931
Seed	kg/ha	105	97	102	100
NPK	kg/ha	97	91	76	88
Insecticide	kgai/ha	0.08	0.08	0.11	0.09
Herbicide	kgai*/ha	0.26	0.19	0.13	0.19
Animal power	days/ha	5.2	4.0	2.7	3.9
Tractor power	days/ha	2.6	2.9	3.2	2.9
Labour	days/ha				
Land preparation		10	9	9	9
Crop establishment		21	20	18	19
Crop care *		2	1	1	1
Pre-harvest		33	30	28	29
Harvesting/Threshing		24	21	19	22
Total labour		56	51	46	51
Family and Exchange		43	38	34	38
Hired		13	13	12	13

* Kilograms of active ingredients (kgai) are converted using the international standards of active ingredients of chemicals, according to the conversion factors in Blondaz, Gavoret and Jourdain (1991).
** Crop care includes labour for fertiliser and chemical applications and hand weeding.
Source: Survey data

Weeds are perceived to be a problem in these fields because the water level is not stable. Hence, there is a greater probability of weed infestations. Herbicide use is about 0.17 kilogram of active ingredients per hectare, with the highest application in the upper fields. Farmers do manual weeding whenever necessary.

Rice is normally harvested in late October or early November. Harvesting and threshing are mostly done on a sharing basis. Threshing is normally carried out by using a mechanical thresher, and the rental market for these machines is well developed in the municipality. On average, the harvester gets about eight per cent of the total produce while the thresher gets 6.5 per cent.

Overall, the total labour requirements for rice production in the rainfed lowlands in Tarlac are approximately 51 days or 408 working-hours. The labour includes operations from land preparation to harvesting and threshing. About 25 per cent of the total labour requirement is based on the use of hired labour.

Input usage on a per farm basis is presented in Table 3.10. Larger farms have higher usage of fertiliser, chemicals and tractors in land preparation activities. Smaller farms use more animal power for their land preparation activities. This is an indication that farmers with smaller land areas to cultivate are cash-constrained.

Table 3.10: Average levels of input use per hectare in rice cultivation by farm size in Victoria, Tarlac, Philippines during 1990-97

Inputs	Units	Size of farms			
		Small	Medium	Large	All farms
Seed	kg/ha	94	102	102	100
NPK	kg/ha	81	79	95	88
Insecticide	kgai/ha	0.04	0.08	0.10	0.09
Herbicide	kgai/ha	0.09	0.17	0.23	0.19
Animal power	days/ha	6.2	4.6	2.8	3.9
Tractor power	days/ha	2.2	2.6	3.3	2.9
Total labour	days/ha	53	50	50	51

Source: Survey data

3.5.4 Costs and returns of rice production

The average costs and returns for rice production from 1990 to 1997 are presented in this section. Costs and returns analyses by land type are also available in Pandey et al. (1999) and Abedullah (1998) but these analyses were based on the data set for 1990 to 1995 only. The following estimates of costs and returns are based on the eight cropping years.

The gross returns are the total value of rice output multiplied by the output price. The real price of paddy rice was used to compute the gross returns. This price is estimated by dividing each year's actual price by the agricultural price index (with base year 1990). For farmers who did not sell output in the market, the opportunity value of the output is computed at the average market price.

The two components of costs are cash and non-cash costs, which are presented in real values with 1990 as the base period. The real wage rate and the real prices of inputs are used to compute the costs of labour and material inputs.

Most of the paid-out costs are for hired labour and the purchase of material inputs such as fertilisers, insecticides and herbicides. The non-cash costs are mainly composed of the value of planting materials, which are valued at the prevailing market price, the imputed value of the family labour and the value of the shares for harvesters and threshers. About 61 per cent of all costs accrue to labour. Further, the cost of labour was the dominant component of total cost in all land types. Seeds are considered non-cash costs because they are retained from the previous year's cropping season or sometimes exchanged with other farmers. The average costs and returns are presented in Table 3.11.

Overall, the average cost of rice production was about $222 per hectare.[2] The shares of cash and non-cash costs are equal, which suggests that farmers depend also on market-orientated resources for rice production in the province. The highest component of cash cost is fertiliser inputs, which is almost 48 per cent. The cost per hectare across land types shows that the cost incurred is lowest in the lower fields (*lubog*). This is mainly because of the lower use of fertiliser on these fields.

The output shares of harvesters and threshers were the dominant components of the non-cash costs, accounting for almost 69 per cent. The cost of family labour valued at the prevailing wage rates during the specific years was only about $14 per hectare, which was approximately 13 per cent of the total non-cash costs.

[2] All monetary figures are in US dollars, with base year 1990 when one US dollar is equivalent to 24 Philippines pesos.

Table 3.11: Average costs and returns for rainfed rice in Victoria, Tarlac, Philippines, 1990-97*

Item	Upper Fields	Medium Fields	Lower Fields	All
Cash Costs ($/ha)				
Material [a]	73	69	57	66
Insecticide and Herbicide	14	13	12	13
Fertiliser	59	56	45	53
Labour Costs	44	43	46	44
Total Cash Costs [b]	117 (51)	112 (49)	102 (50)	110 (50)
Non-Cash Costs ($/ha)				
Seed	21	21	20	21
Labour	90	97	80	91
Labour [c]	14	14	16	14
Harvesting/Threshing [d]	76	83	64	77
Total Non-Cash Costs [b]	111 (49)	118 (51)	100 (50)	112 (50)
Total Costs ($/ha) [e]	**228**	**230**	**202**	**222**
Material Costs	94 (41)	90 (39)	77 (38)	87 (39)
Labour Costs	134 (59)	140 (61)	126 (62)	135 (61)
Benefits ($/ha)				
Gross returns	702	687	567	658
Returns above paid-out costs	585	575	465	548
Net returns	474	457	365	435
Benefit per unit of cash costs	4.06	4.08	3.57	3.95

[a] Sum of fertiliser, insecticide and herbicide costs.
[b] Figures in parentheses indicate the shares of cash and non-cash costs in total costs.
[c] Value of family labour.
[d] The value of shares for harvesters and threshers.
[e] Figures in parentheses indicate the shares of material and labour costs in total costs.
Source: Survey data

The net returns to rice production were computed by deducting the costs from the gross returns. Similarly, the rate of return over the cash invested in rice production was calculated by dividing the net returns by the total cash costs. On average, the net returns per hectare were \$435. They were highest for the upper fields, at \$474 per hectare. The benefits per unit of cash cost (i.e., the returns over paid-out costs) were higher for the *bantog* (upper and medium fields) than the *lubog* (lower) fields. The average rate of return was \$3.95 for every dollar invested in rainfed rice production.

The returns per hectare were highest in 1997 and lowest in 1996 (see Table 3.12). However, returns to cash invested were highest in 1992. It is evident that there was some variability in the net returns that were achieved from rice production. Table 3.13 presents the mean and coefficient of variation of plot-level yield, gross returns and net returns. It can be seen that while the average yield and returns in the *bantog* fields were higher, the values of the coefficient of variation of these variables were lower than those of the *lubog* fields. This implies that rice production in the lower fields is more risky than in the *bantog* fields. The lower fields have a greater degree of variability than the upper and medium fields because they are flood-prone and some of them experienced submergence during the survey period.

Pandey et al. (1999) estimated the variability of yield, gross returns, net returns and nitrogen use in the survey area. They generated variability indicators by pooling time-series and cross-sectional data for three years. An attempt was made to segregate the effects of temporal and spatial variability of these variables. It was found that the values of the coefficient of variation of net income from rice at the farm level were lower than those of net income at the field level. This result indicates that field diversification has helped to reduce the variability of returns from rice. The plot-level yield variability was used as a proxy for environmental variability. The values of the coefficient of variation of use of NPK were regressed against the plot-level yields. There was an indication that there is a greater sensitivity of NPK usage to environmental conditions in the lower fields.

Table 3.12: Average costs and returns of rainfed rice production in Victoria, Tarlac, Philippines, 1990-97

Year	Gross returns ($/ha)	Total costs [a] ($/ha)	Net returns ($/ha)	Returns over cash cost ($)
1990	614	218	396	5.18
1991	591	227	364	4.74
1992	720	226	494	6.54
1993	657	233	424	5.10
1994	582	216	366	4.03
1995	755	171	584	4.96
1996	533	225	308	3.34
1997	805	264	541	6.25
All years	658	222	435	4.97

[a] Includes the imputed value of family labour and non-cash costs.
Source: Survey data

Table 3.13: Mean and coefficient of variation of plot-level yields, gross returns and net returns in Victoria, Tarlac, Philippines, 1990-97

Item	Upper Fields	Medium Fields	Lower Fields	All
Rice yield				
Mean (kg/ha)	3,303	3,332	2,757	3,173
CV (%)	38	39	58	44
Gross returns				
Mean ($/ha)	702	687	567	658
CV (%)	39	41	62	46
Net returns				
Mean ($/ha)	474	457	365	435
CV (%)	53	53	87	62

Source: Survey data

Other than the variations in yield and cost of production, another source of variation of net returns from rice is the output price. In real terms, the output price was variable over the eight-year period but had an increasing trend. A modest decrease in the real price occurred in 1991 but a sharp increase occurred in 1995, followed by a marked decrease in 1996 (see Figure 3.6). Analysis of the trends of real wage rates and prices of inputs shows that they were all increasing during the survey period. The increasing costs of production and the variable yields and prices of the outputs have all contributed to the variability of net returns from rice. Because rice is the major source of income, the variability of net returns affects the variability of the total household income.

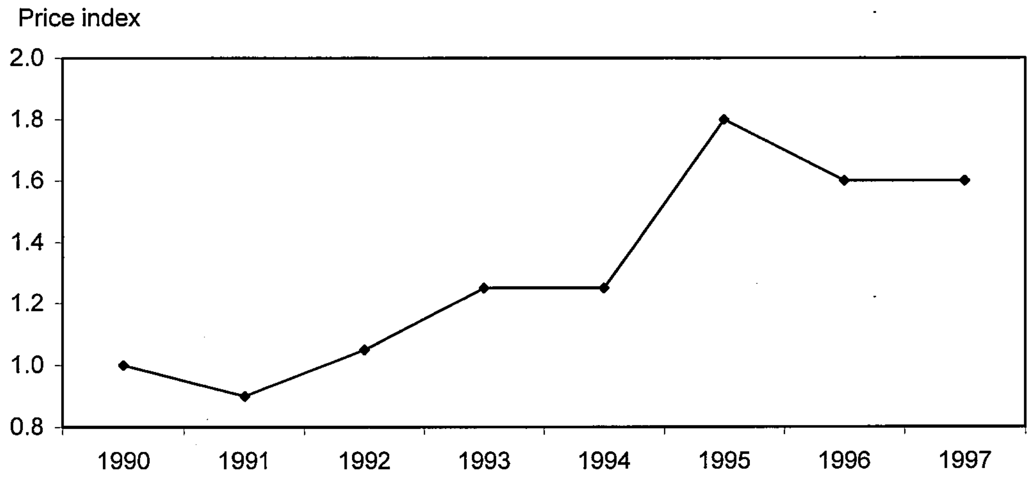


Figure 3.6: Real price of rice in Victoria, Tarlac, Philippines, 1990-97.

3.6 Sources of Household Income

Agriculture is the main source of income in the surveyed areas. While farming is the primary occupation of most farmers, off-farm and non-farm activities represent other sources of income.

The average real income per household (in constant 1990 prices) over the eight-year period was obtained by deflating the nominal values by the consumer price index (Table 3.14). The average household income was approximately $1339, of which rice contributed 70.5 per cent. This was the value of the total output minus the paid-out costs incurred. Of the 46 farmers in the study sample, the minimum share of rice income was 19.3 per cent. The maximum share of rice income in the total household income was 97.6 per cent, which reinforces the importance of examining the needs and circumstances of the rainfed lowland rice farmers.

Table 3.14: Total farm household income and percentage share of different activities in total income in Victoria, Tarlac, Philippines, 1990-97

Attributes	Mean	Minimum*	Maximum*
Total household income (US$)	1339	262	4549
Activities (% share)			
Rice	70.5	19.3	97.6
Other crops	3.7	0.3	23.3
Livestock	4.7	0	32.1
Non-farm and off-farm activities	21.1	0	78.2

* Denotes the average of the 'minimum' and 'maximum' shares over the whole sample period.

In a risky environment, one common method to stabilise household income is to have additional sources of income from other crops, sale of livestock and non-farm and off-farm activities. The other sources of household income of the sample farmers were mainly non-farm activities and the sale of livestock. Abedullah (1998) and Pandey et al. (1999) demonstrated that non-crop income had a stabilising effect on total income. However, income from other crops was minimal, owing to the fact that only a small proportion of the area was planted to non-rice crops during the dry season.

3.7 Conclusions

This chapter presents a description of the study area. The data used in the empirical analyses in the succeeding chapters are based on the survey data collected from the municipality of Victoria in the province of Tarlac in Central Luzon, Philippines. The characteristics of the rice-production system in this province represent a typical rainfed rice farming system in the country.

The demographic characteristics of the households are discussed. Farmers are classified into small, medium and large farmers based on their operational landholdings. In order to capture the importance of the heterogeneity of agricultural land, landholdings are further classified based on their toposequence. Various characteristics of the production system are classified according to these categories, thus capturing some of the differences in environmental features.

The economics of production includes a discussion of the production process, input usage, costs and returns analysis, and household income. It is noted that input usage varies with land topography. It is also shown that smaller farmers used fewer cash-based inputs such as fertiliser, chemicals and tractors. Rice is the major source of income, but non-farm activities also play an important role in the composition of household income.

The preceding discussion of the nature of the production system forms a basis for the specification of the econometric models and empirical analyses in Chapters 5, 6 and 7.

Chapter 4
Production Technology, Risk and Efficiency: Theoretical and Conceptual Review

4.1 Introduction

The measurement of risk and technical efficiency in the agricultural sector of developing and developed countries has been one of the central themes in a vast number of empirical studies. Risk and technical efficiency are important factors that need careful attention in agricultural development. Agricultural production is by nature a risky business (Anderson and Dillon 1992). The farming households have to contend with a variety of price, yield and resource risks due to environmental, institutional and economic factors. Risk under rainfed conditions is usually high because the variability of rainfall can lead to large fluctuations in yields and outputs. Farmers in the rainfed lowland rice environments face biophysical, socioeconomic and cultural constraints to increasing rice productivity. Technical inefficiency is believed to be one of the factors preventing farmers from reaching the full potential of the technology.

The objective of this chapter is to present a review of the theoretical frameworks for analysing production risk and technical efficiency in rainfed rice environments. This chapter is organised as follows. Section 4.2 contains a discussion of the basic properties of production functions. Section 4.3 deals with concepts useful for undertaking risk analysis in which the role, sources and measurement of risk in agricultural production are discussed. Section 4.4 examines concepts useful for efficiency measurement. Specifically, this section focuses on the methods for estimating technical efficiency. The topics discussed in sections 4.2 to 4.4 are reconciled in section 4.5, which forms the conceptual foundation used in the empirical application. A brief summary of the chapter is given in section 4.6.

4.2 Properties of Production Functions

For a simple production function, $Y = f(X)$, describing the set of feasible input-ouput vectors, the essential properties of $f(X)$ can be summarised as (Chambers 1988; Kumbhakar and Lovell 2000):

P1: Monotonicity and strict monotonicity

(a) If $X' \geq X$, then $f(X') \geq f(X)$ (monotonicity)

(b) If $X' > X$, then $f(X') > f(X)$ (strict monotonicity)

P2: Quasi-concavity and concavity

(a) $V(Y) = \{X: f(X) \geq Y\}$ is a convex set (quasi-concave)

(b) $f(\theta X^0 + (1 - \theta)X^*) \geq \theta f(X^0) + (1-\theta) f(X^*)$ for any 0
$0 \leq \theta \leq 1$ (concave)

P3: Weakly essential and strictly essential inputs

(a) $f(0_n) = 0$, where 0_n is the null vector (weakly essential)

(b) $f(X_1,\ldots,0, X_{i+1},\ldots, X_n) = 0$ for all X_i (strictly essential)

P4: The set $V(Y)$ is closed and nonempty for all $Y > 0$.

P5: $f(X)$ is finite, nonnegative, real-valued and single-valued for all nonnegative and finite X.

P6: Continuity

(a) $f(X)$ is everywhere continuous; and

(b) $f(X)$ is everywhere twice-continuously differentiable.

The properties of the production function have several implications for the technological relationships between the output and input factors. Properties P1.a and P1.b imply that additional units of input can never decrease the level of output. This means that the marginal products are non-negative. In essence, these assumptions rule out stage 3 of the production process. While this assumption is universally accepted in production analysis, there are a number of exceptions to it. For example, in the case of rice production, as the amount of insecticide increases, the corresponding effect on rice yield may not necessarily be positive. An increase in insecticide use may be an indication that there is a vast pest or insect infestation. The use of pesticide may reduce the loss of yields from the infestation, rather than cause production to decline.

Properties P2.a and P2.b revolve around the concept of isoquants or input requirement sets. Strictly speaking, P2.a implies that we observe a diminishing marginal rate of technical substitution while P2.b implies that the law of diminishing marginal productivity holds. This law states that increasing the amount of a variable input in the production process, while holding other inputs constant, causes the amount of output added per unit of that input eventually to decrease (Doll and Orazem 1984).

The idea of weakly and strictly essential inputs implies that a positive quantity of all resources must be used to produce positive quantities of outputs. The remaining properties are practically technical assumptions for analysis. The input requirement set must be closed and bounded. This implies that functional values for the input requirement set exist for all output levels. In other words, this property guarantees the existence of a technically efficient input and output vector. Finally, it is important that the production function be finite (bounded) and real-valued. The continuity constraints are imposed for mathematical refinement.

4.2.1 Optimising behaviour

The basic assumptions in most agricultural production analyses are that farmers (i) maximise utility, (ii) maximise profit or (iii) minimise cost. These assumptions apply to all business firms. Assuming a single output and multiple variable inputs, the utility-maximisation problem can be expressed as

$$G(P,W) = \max_{X,Y}\{U(P'f(X) - W'X)\} \tag{4.1}$$

where P is output price, W is a vector of input prices and $U(.)$ is a utility function that summarises the farmer's preferences. Equation (4.1) implies that the farmer chooses levels of output and variable inputs to maximise the utility of profits subject to the constraint that the chosen inputs and outputs are technically feasible. The function, $G(P,W)$, gives the maximum utility achievable at a given output price, input prices and levels of fixed inputs.

Another important optimising condition in production theory is that the firm maximises profit, where profit is defined as the excess of revenue over cost. To understand the profit-maximising behaviour of the firm, it is useful to emphasise that the farmer must operate in an environment where both market and technological constraints guide choices of inputs and outputs.

In this case, the farmer's optimisation problem is

$$\pi(P,W) = \max_{X,Y} Pf(X_1,...,X_k) - \sum_{i=1}^{n} X_i W_i . \qquad (4.2)$$

Equation (4.2) states that farmers choose inputs to maximise profits subject to a given technology that is defined by $f(.)$. The function, $\pi(P,W)$, defines the maximum profit achievable at given output and input prices. Thus, $\pi(P,W)$ provides a standard against which to measure the performance of producers for whom the profit maximisation objective is deemed appropriate.

If $f(.)$ satisfies the properties outlined in section 4.2, so does $\pi(P,W)$. In addition to the properties listed in section 4.2.1, we assume that $f(.)$ exhibits strict decreasing returns to scale, since constant returns to scale would imply that either $\pi(P,W)$ =0 or $\pi(P,W)$= +∞). With this in mind, the properties satisfied by $\pi(P,W)$ are (Kumbhakar and Lovell 2000, p. 39):

$\pi 1$: $\pi(P',W) \geq \pi(P,W)$ for $P' \geq P$

$\pi 2$: $\pi(P,W') \leq \pi(P,W)$ for $W' \geq W$

$\pi 3$: $\pi(\lambda P,\lambda W) \leq \lambda\pi(P,W)$ for $\lambda > 0$

$\pi 4$: $\pi(P,W)$ is a concex convex function in (P, W)

If $\pi(P,W)$ satisfies the conditions $\pi 1$ to $\pi 4$, then $\pi(P,W)$ and $f(.)$ are dual. In this case, $\pi(P,W)$ and $f(.)$ provide equal representations of the structure of the production technology under the assumption of profit-maximising behaviour in the presence of exogenously determined output price and input prices (Kumbhakar and Lovell 2000).

For a single-output case, such as a rice monocrop, it is convenient to work with a normalised profit function (Kumbhakar and Lovell 2000). Since the profit function $\pi(P,W)$ is homogeneous of degree +1 in (P,W), it is possible to divide maximum profit $\pi(P,W)$ by $P > 0$ to obtain

$$\pi^*(W/P) = \pi(P,W)/P = \max_{X_1,\dots,X_k} f(X_1,\dots,X_k) - \sum_{i=1}^{n} X_i W_i / P_i . \tag{4.3}$$

The normalised profit frontier, $\pi^*(W/P)$, is nonincreasing, convex and homogeneous of degree 0 in $(W;P)$.

Another optimising condition is cost minimisation. For a single-input case, the cost minimisation problem is given as

$$C(Y,W) = \min_{X_1,\dots,X_k} \{W'X : Y \leq f(X)\}. \tag{4.4}$$

The cost function, $C(Y,W)$, shows the minimum expenditure required to produce any scalar output, given input prices. It provides a standard against which to measure the performance of producers for whom the cost minimisation assumption is deemed appropriate. The properties of cost functions are outlined and discussed by Kumbhakar and Lovell (2000, p. 34).

In this thesis, we assume that farmers maximise the expected utility of profits from rice production. We focus on the functional relationship between inputs and output, inputs and the variance of outputs, and inputs and inefficiency levels. While it is acknowledged that farmers behave in such a way that cost of production is minimised, we do not estimate cost functions.[1]

In the following chapters, optimising conditions are derived under the assumption that farmers maximise the utility of expected profit. In these models, risk-averse farmers choose input vector, *X*, to maximise the expected utility of profit given output and input prices (*P*, *W*) and prior knowledge of the risky production technology. The optimisation problem is the indirect utility function, which is defined as

$$U = U(E\pi(X;P;W),\ Var\,\pi(X;P;W),\ \partial U/\partial E\pi(.) > 0,\ \partial U/\partial Var\pi(.) < 0 \qquad (4.5)$$

where $E\pi(.)$ is the expected profit $(E\pi = P.f(X) - W'X)$ and $Var\pi(.)$ is the variance of profit $(Var\pi = P^2 Var(Y))$. Equation (4.5) represents a farmer's subjective trade-off between the mean profit (or output) and the variance of profit (or output).

4.3 Review of Concepts for Risk Analysis

4.3.1 An overview

This section presents the basic concepts associated with decision-making under risk. Before considering in some detail the technical approaches for analysing risk, it is worth reviewing the definition of risk. The following are some definitions of risk:

> Knight (1972) defined risk as occurring when the decision maker is able to attach probabilities to future events.
>
> Diamond and Stiglitz (1974) defined risk as a change in the distribution of a random variable which keeps its mean constant and represents the movement of a probability density from the centre to the tails of the distribution.
>
> Hardaker, Huirne and Anderson (1997) defined risk as uncertain consequences, particularly exposure to unfavourable consequences.

[1] The profit-maximisation problem can be reduced to a cost-minimisation problem under conditions where the value of the output *Y* is fixed or known. When all inputs are fixed but some outputs are endogenous, the short-run profit function becomes the revenue function, a concept that was made popular by McFadden (1978).

The terms, risk and uncertainty, are often applied generically and interchangeably to an analysis of situations with unknown outcomes. One common distinction is that choices under risk occur when the probability distribution of the outcomes is known to the decision maker, while choices under uncertainty occur when no objective probability distribution is given to the agent. While Roumasset (1979) made no distinction between risk and uncertainty, Robison and Barry (1987) used the word uncertainty to describe the environment in which economic decisions are made, and the word risk to characterise the economically relevant implications of uncertainty but Hardaker, Huirne and Anderson (1997) regarded uncertainty as imperfect knowledge and risk as uncertain consequences, particularly unfavourable consequences, as stated above.

Risk happens in several aspects of the production process. Baquet, Hamleton and Jose (1997) and Hardaker, Huirne and Anderson (1997) outlined the common types and sources of risk as follows: production risk, price or market risk, institutional risk, human or personal risk, business risk and financial risk. *Production* or *yield risk* occurs because agriculture is affected by many uncontrollable events that are often related to weather, including excessive and insufficient rainfall, extreme temperatures, typhoons, insects and diseases. *Price* or *market* risk reflects associated changes in prices of output or inputs that may occur after the commitment to produce has begun. *Institutional risk* results from changes in policies and regulations that affect agriculture. *Human* or *personal risks* are those that result from events such as death or injury. This may also reflect changes in the objectives of individuals involved in the business. Finally, *financial risk* results from the way the firm's capital is obtained and financed.

Understanding risk in farming is important because most farmers are risk-averse when faced with risky outcomes. A person who is risk-averse is willing to forgo some expected return for a reduction in risk, the rate of acceptable tradeoff depending on how risk-averse that individual is (Hardaker, Huirne and Anderson 1997). The challenge is to define the importance of risk for decisions and the behaviour of farmers. One important distinction is the impact of risk on the choice set and decision criteria (Musser and Patrick 2002). The importance of risk indicates that risk does influence farmers' input and output decisions, hence, the challenge is to specify or to take into account risk in the choice set, farm management and policy analysis.

4.3.2 Risk attitudes

A number of studies have theoretically and empirically supported the view that most farmers in developing countries are risk-averse (Boussard and Petit 1967; Cancian 1972, Anderson 1974; Lin, Dean and Moore 1974; Roumasset 1976; Moscardi and de Janvry 1977; Binswanger 1978; Dillon and Scandizzo 1978; Ortiz 1979; Moscardi 1979; Anderson and Hamal 1983; Walker and Ryan 1990). Risk aversion is a characterisation of the decision-maker's attitude towards risk. Risk attitudes are implied by the shape of the utility function (Hardaker, Huirne and Anderson 1997). Arrow (1965) and Pratt (1964) introduced quantitative measures of risk aversion. The most important of these measures are the absolute and relative risk aversion coefficients. These coefficients are derived from the von Neumann-Morgenstern utility function. Arrow (1965) hypothesised that individuals would exhibit decreasing absolute risk aversion and increasing relative risk aversion under most circumstances. These hypotheses have critical implications for the empirical specification of utility functions.

Absolute risk aversion is defined as

$$r_a(\omega) = -\frac{U''(\omega)}{U'(\omega)} \tag{4.6}$$

where ω is wealth, $U''(\omega)$ and $U'(\omega)$ represent the second and first derivatives of the utility function, respectively (Pratt 1964; Arrow 1965). It is generally accepted that $r_a(\omega)$ will decrease with increases in ω.

Relative risk aversion is defined as

$$r_R(\omega) = \left(-\frac{U''(\omega)}{U'(\omega)}\right)\omega\,. \tag{4.7}$$

It is a measure of risk proportional to the level of wealth, and can be thought of as the elasticity of risk aversion.

Arrow (1965) put forward two hypotheses about the measure of absolute risk aversion: decreasing absolute risk aversion (DARA) and increasing relative risk aversion (IARA). DARA implies that the willingness of an individual to take small bets of fixed size increases with wealth. IARA implies that, as wealth increases, the proportion of wealth that an individual is willing to risk declines. Similarly, Eeckhoudt and Gollier (1995) hypothesised that relative risk aversion does not increase if wealth increases. On the other hand, Hamal and Anderson (1982) found that relative risk aversion could reach values as extreme as four or more in extremely resource-poor farming conditions.

Different approaches have been developed to elicit the required information from decision makers to be able to encode their preferences into a suitable utility function (Hardaker, Huirne and Anderson 1997). The elicited utility functions can be presented as a graph that may be drawn through the elicited points. The shape of the utility functions implies risk attitudes (for example, a concave utility function for a risk-averse farmer). Alternatively, the utility function can be represented algebraically by, for example, a negative exponential, power or logarithmic utility function.

The negative exponential utility function is:

$$U(\omega) = 1 - exp(-c\ \omega), \qquad c > 0 \tag{4.8}$$

The power utility function is:

$$U(\omega)= \omega^{c} \qquad 0 < c < 1 \tag{4.9}$$

$$U(\omega) = \{1/(1-r)\}\ \omega^{(1-r)} \tag{4.10}$$

where c is the coefficient of absolute risk aversion and r is the coefficient of relative risk aversion. Hardaker, Huirne and Anderson (1997) discussed the above specifications and what they imply for risk attitudes. Equation (4.8) implies constant absolute risk aversion (CARA), while equations (4.9) and (4.10) imply DARA and constant relative risk aversion (CRRA), respectively.

Because of difficulties associated with elicitation methods for measuring risk attitudes of individual producers, Hardaker, Huirne and Anderson (1997) indicated that more pragmatic approaches of assessing risk aversion may be used. For example, the approach outlined by Anderson, Dillon and Hardaker (1986) is based on the assumption that measures of risk aversion may be approximately constant over restricted ranges of risk.

They suggested using an approximate procedure based on the classification of risk attitudes. Using the relative risk aversion coefficient, $r_R(\omega)$, the degree of risk aversion of any individual producers may be characterised in terms of different coefficients as follows (Hardaker, Huirne and Anderson 1997, p. 102).

$r_R(\omega) = 0.5$: hardly risk-averse at all;

$r_R(\omega) = 1.0$: somewhat risk-averse (normal);

$r_R(\omega) = 2.0$: rather risk-averse;

$r_R(\omega) = 3.0$: very risk-averse; and

$r_R(\omega) = 4.0$: almost paranoid about risk.

Saha (1993) proposed the expo-power utility function to allow for flexibility in modelling risk preference structures and allow the data to reveal both the degree and structure of risk aversion. In this specification, no prior assumptions are needed about the risk preferences of the decision-makers. The function takes the form:

$$U(\omega) = \theta - exp\{-\beta\omega^{\alpha}\} \tag{4.11}$$

where $\theta > 1$, $\alpha \neq 0$, $\beta \neq 0$ and $\alpha\beta > 0$ are the determinants of the risk preference structure. The values of α and β imply different attitudes towards risk. If $\alpha < 1$, $\alpha = 1$ and $\alpha > 1$, there is DARA, CARA and IARA, respectively. If $\beta < 0$ and $\beta > 0$, there is DARA and IARA, respectively.

Several attempts have been made to estimate the risk preferences of individual decision makers. Love and Buccola (1991, 1999), Saha, Shumway and Talpaz (1994) and Chavas and Holt (1996) attempted to evaluate risk preferences in a joint analysis of input and output decisions. Analogous to previous studies, their approach was to assume explicit utility functions for individual producers. More recently, Kumbhakar (2002) proposed a different methodology to estimate the risk preferences of individual producers. A risk preference function is derived and allows testing for the different risk attitudes of farmers. In this thesis, the estimation of risk preferences of farmers is based on the specifications developed by Kumbhakar (2002), which are not based on any specific form of utility function. The details of this function are presented in Chapter 7.

4.3.3 Modelling issues

Moschini and Hennessy (2001) identified the two most important concepts in economic modelling as optimisation (rational behaviour by economic agents) and equilibrium (the balancing of individual claims in a market setting). The application of these concepts raises problematic issues when risk is involved. For example, if the optimisation problem is applied to individual choices under uncertainty, one needs to know what is to be optimised. The traditional approach to modelling behaviour under risk is through the use of the expected utility approach. The optimisation problem is to maximise expected utility, which was first introduced by Bernoulli (1738) and popularised by von-Neumann and Morgenstern (1944). Expected utility theory describes the relationship between an individual's scale of preferences for a set of acts and their associated consequences. Von-Neumann and Morgenstern (1944) developed a set of axioms about the ordering, continuity and independence of individual choice and used this as a base to derive the properties of the utility function. The axioms[2] describe the conditions under which an individual's preferences under random choices correspond to maximisation under the expected utility model.

Friedman and Savage (1948) were the first to use the expected utility approach to explain economic behaviour. They defined the utility function on wealth, and represented diversification and general risk aversion by the function's concavity.

Arrow (1971) and Pratt (1964) introduced measures of risk aversion – the coefficients of relative risk aversion and absolute risk aversion – that are functions of the second and first derivatives of the von-Neumann-Morgenstern utility function. They established that, under the expected utility hypothesis, there exists a one-to-one relationship between preferences over random income (or wealth) and measures of risk aversion. They claim that, as income grows, one cares less about "one" unit of risk – the measure of absolute risk aversion is declining.

---

[2] These axioms are summarised and discussed in Anderson, Dillon and Hardaker (1997, pp. 66-68).

Following the establishment and initial applications of the expected utility theory, the next step in the theory of decision-making under risk is the development of models and concepts for measuring risk. The initial efforts to measuring risk were based on the notion of the mean and variance of the random outcome as arguments of utility functions. Markowitz (1952, 1959) and Tobin (1958) revolutionised the field of finance with the introduction of the mean-variance approach.[3] They argued for the explicit recognition of risk and its quantification in terms of variance. The notion of a mean-variance efficient portfolio was introduced as one that provides (i) minimum variance for a given expected return and (ii) maximum expected return for a given variance. Recognising that variance is not always a good measure of risk, Rothschild and Stiglitz (1970), Hanoch and Levy (1969), and Hadar and Russell (1969) developed models and concepts that are useful for a more general comparisons of risky prospects. The concepts such as mean-preserving spread and stochastic dominance were developed. These approaches use probability distributions and are independent of the decision maker's utility function.

Maximisation of expected utility of profit is still the most commonly assumed goal for the agricultural firm (Meyer 2002). With this theoretical base in place, the expected utility concept began to be used as an applied risk analysis tool. Anderson, Dillon and Hardaker (1977) summarised the use of this theory, and promoted the use of the theory and its importance for examining the behaviour of the firm under risk. The Just and Pope (1978, 1979) representation of the production technology provided a foundation for analysing producer's responses to risk

There is a huge amount of literature on risk in agricultural economics. Meyer (2002) and Just and Pope (2002) provide excellent overviews of the use of the expected utility concept for addressing risk problems in agricultural research. Despite the normative appeal of the expected utility theory, the framework has recently come under intense scrutiny because of its inability to describe some features of individual behaviour under risk (Moschini and Hennessey 2001). In connection with this inability, an emerging approach entailing a generalisation of the expected utility model has been proposed using the state-contingent approach (Machina 1987; Quiggin 1993; Chambers and Quiggin 1998; Chambers and Quiggin 2000).

---

[3] The mean-variance approach and other methods used for risk analysis are described in detailed in section 4.3.5.

4.3.4 Production functions and specifications under risk

Production risk is generally modelled through alternative specifications of the production function. We begin by specifying a simple production technology

$$Y=f(X, \varepsilon) \tag{4.12}$$

where Y is output, X is a vector of inputs and ε is a random variable with a given subjective probability distribution reflecting production uncertainty. The following are special cases of some representations of the stochastic nature of the production function.

Model 1: Additive risk

$$Y = f(X) + \varepsilon, \qquad E(\varepsilon) = 0 \tag{4.13}$$

In this case, input use does not affect risk and the only type of risk considered is output risk. This simple specification implies that $Var(Y) = Var(\varepsilon)$ and $\partial Var(Y)/\partial X = 0$, Thus, this stochastic production function specification restricts input use to have no impact on the variance of output.

Model 2: Multiplicative risk

$$Y = f(X)\,\varepsilon, \qquad E(\varepsilon) = 1 \tag{4.14}$$

In this case, any input that increases mean yield also increases the risks associated with yields. We have $Var(Y) = Var(\varepsilon)f(X)^2$ and $\partial Var(Y)/\partial X = 2\ Var(\varepsilon)\ f(X)\partial Y/\partial X$. Given $f(X) > 0$ and $\partial Y/\partial X > 0$, it follows that $\partial Var(Y)/\partial X > 0$. Thus, this stochastic production function specification restricts inputs to be always variance-increasing.

Model 3: Linear risk

$$Y = f(X) + g(X)\varepsilon, \quad E(\varepsilon) = 0 \tag{4.15}$$

This representation of production technology is popularly known as a heteroscedastic production function, as proposed by Just and Pope (1978). Under this specification, impacts of inputs on yield and risk can be differentiated. For example, some inputs may be yield-increasing ($f' > 0$) and risk-reducing ($g' < 0$). Other inputs may increase both the yield and risk components; hence, $f' > 0$ and $g' > 0$. Further details of this method are presented in section 4.3.5.

4.3.5 Methods of risk analysis

4.3.5.1 Mean-variance approach

Tobin (1958) and Markowitz (1959) were the first to introduce the mean-variance approach, which plays a key role in finance – being used as a basis for capital-asset pricing. The basic idea of this model is that utility from random prospects can be described as a function of moments of the distribution around the mean outcome, $\bar{Y}$, through a Taylor's series expansion:

$$EU(Y) = \int U(Y) f(Y) \partial Y \tag{4.16}$$

$$U(Y) = U(\bar{Y}) + U'(\bar{Y})(Y - \bar{Y}) + U''(\bar{Y})\frac{(Y - \bar{Y})^2}{2} + \sum_{n=3}^{\infty} U^n \frac{(Y - \bar{Y})^n}{n!} \tag{4.17}$$

from which, by taking the expectations of both sides:

$$EU(Y) = U(\bar{Y}) + \sum_{n=2}^{\infty} \frac{U^n(\bar{Y})}{n!} E(Y - \bar{Y})^n = f(M_1, M_2, M_3.....) \tag{4.18}$$

If a distribution can be completely defined by n moments, then the expected utility is a function of these moments. If a distribution is defined by its first two moments, then the expected utility is a function of the distribution's mean and variance. Two restrictive conditions on the utility functions and the distribution of the random variable are required in order to be able to express expected utility as a function of the mean and variance. They are: (i) the utility function must be quadratic or exponential in form and (ii) the outcome variable should be normally distributed. Given these conditions, the expected utility can be expressed as

$$EU(Y) = \alpha\bar{Y} + \beta\frac{\sigma^2}{2}. \tag{4.19}$$

Freund (1956) proved the linearity of the expected utility function under the conditions of normality and exponential utility. The linear mean-variance approach has the advantage that it is easy to work with and allows the consideration of behaviour under risk with a large number of random variables. Some of the limitations of the models are: (i) quadratic utility implies IARA; (ii) exponential utility implies CARA; and (iii) normality of the outcome variable may be difficult to deal with.

In spite of the above limitations, the mean-variance approach has been extensively used. For example, in farm planning the mean-variance approach is used to construct an efficiency locus of mean-variance trade-offs. This can be done as a quadratic programming problem.

Programming models were prominent in early theoretical and empirical research on risk-efficient choices, beginning primarily with Freund's (1956) incorporation of risk into a quadratic programming (QP) model. Building on the QP formulation, subsequent model developments in agricultural economics generally dealt with introducing risk into a computationally feasible programming format, or dealt with introducing different types of risk-aversion assumptions, such as safety-first or mean-variance, into a programming format (Taylor and Zacharias 2002).

Some of the programming formulations include quadratic risk programming (QRP), mean absolute deviation (MAD), absolute negative total deviation (ANTD), minimisation of total absolute deviation (MOTAD) in a linear programming framework, target MOTAD, direct expected utility-maximising nonlinear programming and discrete stochastic programming, among others. Discussion of the various programming models as well as references to these models can be found in Kennedy (1986) and Hazell and Norton (1986). The efficient mean and variance set of farm plans are derived using the programming models, one of the criticisms of which is the inability to perform tests of hypotheses.

4.3.5.2 Mean-preserving spread

There have been many attempts to define good measures of the riskiness of a prospect. Several general measures were developed within the context of expected utility. Rothschild and Stiglitz (1970) provided a methodology for ranking prospects that have the same mean outcome but different levels of risk. In addition, their method provides comparative statics results describing the impact of risk on key parameters. These methods are set within the framework of expected utility, ranking prospects derived from a von Neumann-Morgenstern concave utility function, implying risk-averse behaviour.

Rothschild and Stiglitz (1970) developed important concepts in comparing prospects with like means. These concepts are:

- For any X, Y with $E(X) = E(Y)$, *if* $EU(X) \geq EU(Y)$ for every U with $U > 0$, $U''<0$, then Y is riskier than X. In other words, if every risk-averse individual prefers X to Y, then Y is riskier than X.

- If Y is equivalent in distribution to X plus Z, where Z is a random variable with $E(Z|X) = 0$, then Y is riskier than X. In other words, if Y is the sum of X and another random variable, Z, when the conditional expectation of Z for every X is zero, then Y is riskier than X.

- If Y can be constructed from X through the use of a mean-preserving spread, then Y is riskier than X. A mean-preserving spread is a modification of a distribution that increases the variance of a distribution without changing its mean.

4.3.5.3 Stochastic dominance

Hadar and Russell (1969) developed the concept of stochastic dominance, which allows for the comparison of outcomes with differing means. This method also allows for the ranking of uncertain prospects without assuming a specific utility function.

First-degree stochastic dominance (FSD)

First-degree stochastic dominance is based on a simple behavioural assumption that more is preferred to less. Let X denote the value of a variable (e.g., wealth, income, profit) that can assume values in the range $(-\infty,\infty)$. Let the function, $F_i^X(x)$, be defined recursively where:

$$F_i^X(x) = \int_{-\infty}^{x} F_{i-1}^X(Z)dZ \qquad (4.20)$$

and where $F_0^X(x)$ is the density function of *X*. Under this definition, $F_1^X(x)$ is the cumulative distribution of *X*. Consider two random prospects, *X* and *Y*, the first-degree stochastic dominance of *Y* by *X* holds if

$$F_1^X(Z) \leq F_1^Y(Z) \text{ for } -\infty < Z < \infty \quad (4.21)$$

X is first-degree stochastic dominant to Y if the cumulative distribution of *X* is below that of *Y* for every *Z*, such that Prob($X \geq Z$) > Prob (Prob($Y \geq Z$) for every *Z*. It is argued that if *X* FSD *Y*, then every individual with a positive marginal utility will prefer *X* to *Y*. That is, if *Z* represents income, then every individual will prefer *X* over *Y* since it represents a higher probability of achieving high income.

Second-degree stochastic dominance (SSD)

When there is crossover in the cumulative distribution of the two prospects, and, hence, first-degree stochastic dominance cannot be used, then second-degree stochastic dominance is used. *X* is SSD to *Y* if

$$\int_{-\infty}^{Z} F^Y(z) \geq \int_{-\infty}^{Z} F^X(z) \quad (4.22)$$

Other than the assumption of "more is preferred to less", SSD relies upon the condition that individuals are strictly risk-averse or have diminishing marginal utility, i.e., a concave utility function. Under this assumption, individuals will prefer *X* to *Y*.

Third-degree stochastic dominance (TSD)

If ordering risky prospects is not possible using SSD, then TSD can be used. Other than the previous two assumptions, TSD employs an additional assumption that states that decision makers become decreasingly averse to risk as they become more wealthy (Pratt 1964). Because of the restrictive assumptions beyond the second degree, stochastic dominance becomes less useful as a concept.

Stochastic dominance is useful when the tests are applicable. However, in some cases, they become less useful because of its restrictive assumptions. The choice between two prospects would depend on the degree of risk aversion and the magnitudes of the mean and variance of the two alternatives. Stochastic dominance does not capture the trade-offs between risks and returns. An alternative could have a higher mean, non-FSD with higher variance and be second-degree dominated. Finally, Anderson (1974) pointed out some difficulties of using stochastic dominance in the presence of an infinite number of risky prospects available to decision makers.

4.3.5.4 Sandmo's model

Sandmo (1971) developed a model of a competitive firm facing price uncertainty. He used a multiplicative risk specification. In his model, the only risk faced by farmers is output price risk; hence, price is random. Sandmo established that a risk-averse firm facing output price risk will produce less output than a risk-neutral firm. Furthermore, a risk-averse firm will reduce output when price risk increases. The optimal solution under certainty and perfect competition, equality between expected price and marginal cost, does not hold for the risk-averse firm when facing price uncertainty. Instead, the risk-averse firm will produce an optimal output characterised by marginal cost being less than expected price. The Sandmo result has often been used to explain why poor farmers produce less output than the level that maximises expected profits (Wik and Holden 1996).

Under Sandmo's model, the following relationships can be established (Zilberman 2002):

- Under uncertainty, less output will be produced.
- An increase in risk aversion will reduce output.
- Optimal resource allocation by a risk-averse firm requires that the value of the marginal product of a resource exceeds its rental value.
- If there is decreasing absolute risk aversion, reductions in fixed costs will increase output. Thus, financial conditions may affect production decisions.
- Expected profit will be higher for firms closest to being risk-neutral and having the highest output.

Sandmo's technique has been used in several areas to estimate the impact of risk. An example is the study by Feder, Just and Zilberman (1985) of the adoption of new technologies in developing countries. The main limitations of this model are: (i) the multiplicative assumption does not allow for the analysis of differential impacts of an input on output versus production risk, and (ii) it is only possible to handle one random variable at a time. The advantage of this model is its generalised form, allowing for the use of less restrictive utility forms, in contrast with specific functional forms (Zilberman 2002).

4.3.5.5 Econometric approach

In early literature, the two methods used to quantify the risk relationships in the production process were the analytical and gross approach (Anderson, Dillon and Hardaker 1977). In the analytical model, the process is conceptualised in terms of three-way categorisation of input variables. The three types of variables are classified as follows (Anderson, Dillon and Hardaker 1997, p. 174):

- Input variables that are under the producer's control, i.e. decision variables (say denoted by X_i, $i = 1,2,....,k$);
- Input variables that are outside the producers' control and are stochastic and whose values are unknown at the time of decisions about X_i (say denoted by S_j, $j = 1,2,....,l$); and
- Input variables that are outside the producers control but whose values are known at decision time (say denoted by Q_f, $f = 1,2,..., m$). This may include variables that are fixed and stochastic variables that are realised and known at decision time.

Using the above notation, the production function can be specified as

$$Y = f(X_1, \ldots\ldots\ldots, X_k; S_1, \ldots\ldots\ldots, S_l; Q_1, \ldots\ldots\ldots, Q_m) \tag{4.23}$$

where Q_m variables serve merely to condition the response of Y to the X_i and S_j variables. The uncertainty associated with Y arises from the influence of the S_j variables. Estimation of equation (4.23) is done using a two-step procedure. The two steps are, first, describing the effect of the X_i and S_j variables in the production process and, second, assessing the joint probability distribution associated with the S_j variables.

In the gross approach, production risk is treated as a black box, without any attempt to identify the stochastic nature of risk. A problem with this method is that the exclusion of the measurable stochastic variables that contribute to production risk inhibits understanding of the causal factors underlying yield variability and limits generalisation of results to different environments (Rosegrant and Roumasset 1985). In the analytical approach, the functional relationship between the moments of the yield distribution and the level of managed input are estimated (Antle 1983; Antle and Goodger 1984). One of the drawbacks of the analytical approach is the restriction placed on the interaction between the managed inputs and stochastic elements of production.

Alternatively, Just and Pope (1978, 1979) developed general models for analysing cases of production risk econometrically. Traditionally, risk was analysed using the specification in equations (4.13) and (4.14), where risk was included in the production function in an additive or multiplicative manner. Risk in the production function causes complexities in the use of linear programming estimation procedures because it requires an examination of the properties of the random variables.

The drawbacks of the common additive and multiplicative specifications of production risk, as in equations (4.13) and (4.14), are outlined by Just and Pope (1978). The additive specification does not allow the uncertainty effect to be correlated with the input mix. Likewise, the multiplicative specification does not allow us to examine the differential impacts of inputs on mean and variance.

Since production specifications in common use fail to satisfy many of the risk assumptions, Just and Pope (1978, 1979) put forward an alternative stochastic specification of the production function. In the process of generalisation, a variance function is introduced into the model that allows investigation of the relationship of inputs to the variability of output. The representation of the production technology presented in equation (4.15) is reproduced below:

$$Y = f(X) + g(X)\varepsilon, \qquad E(\varepsilon) = 0 \qquad \mathrm{Var}(\varepsilon) = \sigma \tag{4.24}$$

where $f(.)$ is a mean function (the deterministic part), $g(.)$ is a variance function (the risk part) and ε is the exogenous production shock.

The above specifications of the stochastic production function are based on the following postulates that reflect stochastic and technical input-output relationships.

1. Positive production expectations ($E(Y) > 0$) prevail.

2. Positive marginal product expectations ($\partial E(Y)/\partial X_i > 0$) prevail.

3. Diminishing marginal product expectations ($\partial^2 E(Y)/\partial X_i^2 > 0$) prevail.

4. A change in the variance of random components in production should not necessarily imply a change in expected output when all production factors are held fixed ($\partial E(Y)/\partial V(\varepsilon) = 0$ is possible).

5. Increasing, decreasing or constant marginal risk should all be possibilities ($\partial V(Y)/\partial X_i <=> 0$ where $V(Y) = E[Y - E(Y)]^2$).

6. A change in risk should not necessarily lead to a change in factor use for a risk-neutral (profit-maximising) producer ($\partial X^*_i/\partial V(\varepsilon) = 0$ possible where X^*_i is the optimal input level).

7. A change in the variance of marginal product with respect to a factor change should not be constrained in sign *a priori* without regard to the nature of the input ($\partial V(\partial Y/\partial X_{i/})/\partial X_j <=> 0$ is possible).

8. Constant stochastic returns to scale should be possible.

By using the above postulates, the specifications of Just and Pope offer greater flexibility in describing stochastic production processes and related behaviour. By using the mean function and the variance function, this model allows for the differential impacts of an input to mean output and risk. The model also allows for the specification of testable hypotheses to determine whether inputs are risk-increasing or risk-reducing. Two disadvantages of this model are that it only allows the consideration of one random variable and is computationally demanding.

The specification of the stochastic technology developed by Just and Pope (1978, 1979) laid the foundation for subsequent theoretical and empirical research in production analysis. Various techniques are available in the literature to estimate the nonlinear model described in equation (4.24). Studies have employed different techniques to obtain consistent and asymptotically efficient estimators. Some of the common estimation techniques include (i) the Just and Pope (1979) estimation procedures, (ii) a flexible moment-based approach (Antle 1983), and (iii) the error decomposition model to estimate the above heteroscedastic production function on the same data set.

In this study, we employ the estimation procedures suggested by Just and Pope, which are discussed in Chapter 5. Our main task is to examine the marginal effects of inputs on the mean output and variance of output.

4.3.5.6 The state-contingent approach

The expected utility model has been widely embraced by economists for modelling decisions under risk because of its ease of use, normative appeal and reasonable accuracy in predicting behaviour under risk for many economic activities (Zilberman 2002). One of the criticisms of expected utility theory is that it does not explain individual behaviour regarding extreme probability alternatives (Just 2003). In response to this criticism Machina (1987) and Quiggin (1993) developed generalisations of the expected utility hypothesis. Accordingly, Chambers and Quiggin (1998) have exploited state-contingent utility models to explore implications for agricultural production under risk.

The recent developments of the use of the state-contingent approach are outlined by Chambers and Quiggin (2000). The "state-contingent" approach to uncertainty was initially introduced by Arrow (1953) and further detailed by Debreu (1959). It was made famous in the late 1960s by Hirshleifer (1965, 1966) in his theory of investment, and was advanced in the 1970s by the work of Radner (1968). Further development was proposed by Hirshleifer and Riley (1992).

The basic principle is that choices under uncertainty can be reduced to a conventional choice problem by changing the commodity structure appropriately. The state-contingent approach is thus distinct from the conventional "microeconomic" treatment of choice under uncertainty, such as that of von Neumann and Morgenstern (1944), in that preferences are not formed over "lotteries" directly but over state-contingent commodity bundles.

The basic proposition of the state-preference approach to uncertainty is that commodities can be differentiated not only by their physical properties and location in space and time but also by their location in "state". For example, with this approach Chambers and Quiggin (1998) developed an alternative way of characterising cost functions, such that they characterise risk by the set of all possible states of nature that have the appropriate probabilities. They define the revenue path that maps every possible state of nature into revenue realised by the firm for each possible decision. Then they define a cost function that specifies the minimum cost of obtaining each revenue path, hence, maximising the utility over all possible decisions.

The state-contingent approach, in effect, replaces the dependence on stochastic moments with a dependence on the outcome in every state of nature (Just 2003). This means that a revenue path identifies the outcome in every state of nature. According to Just (2003), knowing the revenue outcome in every state of nature is equivalent to completely characterising the distribution of revenue as well as the distribution of the states of nature upon which it is based.

To make the state-contingent approach operational requires a manageable number of states of nature. Due to insufficiency of data collected for this study, this method is not used in the empirical analysis reported in this thesis.

4.3.5.7 Summary

Agricultural production is inherently risky. Risk is the farmer's perennial problem. In the study area, risk is a major factor that the farm-household has to contend with. The analysis of risk has been one of the central themes of a number of empirical and theoretical studies in production analysis. The areas of concern are the elicitation of risk preferences, measurement of risk and ordering of risky alternatives. Some of the approaches used for measuring risk are discussed in this section. They include the mean-variance approach, the econometric approach and the state-contingent approach. This study uses the econometric approach, following the heteroscedastic model specification outlined by Just and Pope (1978). The empirical application is presented in Chapter 5.

4.4 Review of Concepts for Efficiency Measurement

4.4.1 Overview

The purpose of this section is to review the literature on efficiency measurement, with particular emphasis on the frontier methodology. Definitions of measures of efficiency are presented in section 4.4.2, followed by a discussion of the methods for efficiency measurement in section 4.4.3. Section 4.4.4 discusses the parametric methods of estimating technical efficiency, with emphasis on the deterministic and stochastic frontier methodologies. The discussion of the stochastic frontier methodology forms the basis for the empirical analysis in Chapter 6.

The usual definition of a production function involves the maximum amount of output from a specified set of inputs for a given technology. In this definition, the idea of "maximum" is important to satisfy certain economic questions such as the level of efficiency of a firm, which is usually given as a ratio of the actual output obtained to the maximum possible output that could be obtained for a given set of inputs. Traditionally, production functions were estimated with the use of ordinary least squares (OLS) regression analysis, which implies that the production function is an average function.

Attempts have been made to define and estimate a function that is consistent with the definition of a production function. This function is referred to as the *frontier production function*. The word frontier implies the condition of maximum output. The production frontier provides the upper boundary of production possibilities, and the input-output combinations of each producer are located on or beneath the production frontier. The development of the frontier production function paved the way for estimating efficiency. The challenge is to measure the distance from the input-output combination of each producer to the production frontier, enabling the measurement of the efficiency level of each firm.

4.4.2 Definitions and measures of efficiency

Efficiency is a fundamental economic concept and it is essential for estimating and evaluating the performance of producers. Efficiency scores are success indicators, or performance measure by which production units are evaluated. Lovell (1995) pointed out that only by measuring efficiency and separating their effects from the effects of the production environment could we explore the hypotheses concerning sources of efficiency differentials. Likewise, it allows us to quantify differentials that are predicted qualitatively by theory.

The components of economic efficiency are (i) technical efficiency, and (ii) allocative efficiency. Technical efficiency requires the firm to produce maximum output with given inputs. Allocative efficiency requires the firm to select the mix of inputs that produces a given quantity of output at minimum cost. Technical and allocative efficiencies thereby provide an overall measure of economic efficiency.

4.4.2.1 Technical efficiency

The technical efficiency of any production unit is defined as a comparison between observed and optimal values of its output and inputs (Lovell 1993). This implies certain benchmarks against which individual units are assessed. In the context of production, it is defined as the ratio of the observed output to the maximum attainable output from given levels of the inputs. The formal definitions and measures of technical efficiency originated from Koopmans (1951), Debreu (1951) and Farrell (1957). According to Koopmans (1951), a producer is technically efficient if an increase in any output requires a reduction in at least one other output or an increase in at least one input, and if a reduction in at least one input requires an increase in at least one other input or reduction in at least one output.

Given the available technical knowledge, the production function of a firm signifies the maximum output of the firm's product in terms of the variable factors of production it can utilise. Farrell (1957) introduced a framework for measuring the efficiency of a firm directly from observed data in a single-output case in the presence of multiple inputs. He hypothesised that productive efficiency can be partitioned into two-sub components: technical efficiency and price or allocative efficiency. He used a unit isoquant of fully efficient firms to define technical efficiency of individual firms by the distance that represents the amount by which all inputs could be proportionally reduced without a reduction in ouput, expressed in percentage terms. This can be illustrated by the following exposition. Let the production technology be represented by a single-output and two-input case, say,

$$Y=f(X_1, X_2). \tag{4.25}$$

Constant returns to scale implies that $1 = f(X_1/Y, X_2/Y)$.

The assumption of constant returns to scale further implies that the factor combinations, which give the same level of output, can be represented in a production indifference curve Farrell (1957). The input-output combinations of a given firm with the above given technology is shown in Figure 4.1. In this figure, the unit isoquant II′ represents the technically efficient combination of inputs. Points below this line are infeasible, while those above it are regarded as inefficient. Points A and B represent two different firms using the same ratio of inputs, X_1 and X_2. The firm located at point A (firm A) uses input quantities,
$X^A = (X_1^A, X_2^A)$, and is considered technically efficient.

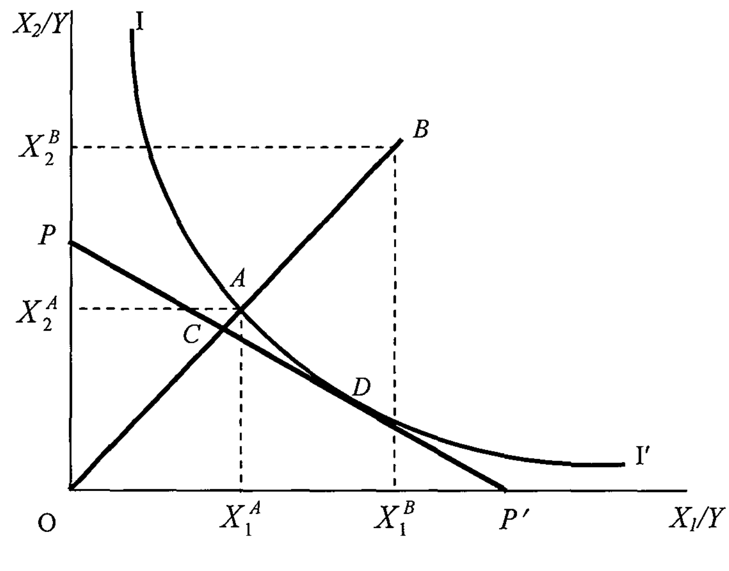


Figure 4.1: Concepts of efficiency.

The second firm at point B uses input quantities, $X^B = (X_1^B, X_2^B)$, and is considered technically inefficient. This firm is using more inputs but produces the same output as firm A. The distance, AB, which actually represents the amount by which both inputs can be proportionally reduced by firm B without a reduction in output, shows the technical inefficiency of firm B. This can be denoted by the ratio, BA/OB. Consequently, technical efficiency is expressed as:

$$TE_B = 1 - BA/OB = OA/OB \tag{4.26}$$

where TE varies from 0 to 1, with $TE = 1$ indicating that the firm is fully efficient.

4.4.2.2 Allocative efficiency

Allocative efficiency refers to the ability of the producer to use inputs in optimal proportions given relative input prices and technology. The measurement of allocative efficiency can be illustrated using Figure 4.1. The line PP' depicts the isocost line, which represents the input price ratio. The technically efficient point that minimises the cost of production is the point of tangency between the isocost line and the unit isoquant, which is at point D. The allocative efficiency of the firm operating at point B is defined as $AE_B = OC/OA$, because the distance AC represents the reduction in the cost of production that would occur if production were to occur at the allocatively (and technically) efficient point D instead of at the technically efficient but allocatively inefficient point A.

4.4.2.3 Economic efficiency

Economic efficiency (EE) is defined as the product of technical efficiency and allocative efficiency, i.e., $EE = TE \times AE$. Using Figure 4.1, it is $(OA/OB) \times (OC/OA) = OC/OB$. Again, $0 < EE \leq 1$ holds. When $EE = 1$, the firm is both technically and allocatively efficient.

4.4.3 Efficiency measurement

There are two principal types of methods that are used to estimate frontier functions, parametric and non-parametric methods. In broad terms, the parametric methods can be classified into two categories, namely, deterministic frontier models and stochastic frontier models. The most common non-parametric method is data envelopment analysis (DEA).

The parametric method of estimation of efficiency involves econometric modelling of production frontiers. In the deterministic frontier framework, any deviation of firms from the frontier is identified as inefficiency, while a stochastic frontier framework assumes that any deviation of firms from the frontier can be attributed to two parts, stochastic elements outside the control of firms and inefficiency elements within the control of firm management. Battese (1992), Bravo-Ureta and Pinheiro (1993) and Coelli (1995) reviewed some of the empirical applications of parametric methods.

One of the advantages of the parametric method is that it takes into account measurement error in the output and stochastic elements of production, thereby distinguishing the effect of noise from the effect of inefficiency. In addition, it allows us to perform conventional statistical tests. On the other hand, one of the criticisms of parametric methods is that it is more difficult to handle multiple-output cases. Also, the functional form needs to be specified, which puts restrictions on the production function and the analysis of technical inefficiency requires some distributional assumptions on the error term.

DEA is the most popular non-parametric method used for efficiency measurement. It enables the analyst to compare efficiency across firms without needing price data, but allocative efficiency can also be calculated if price data are available. In addition, total factor productivity indices can be calculated and decomposed into efficiency change and technical change. This approach was initiated by the seminal work of Charnes, Cooper and Rhodes (1978). Since then, DEA has been used in a wide variety of areas such as agriculture, hospitals, electricity utilities, educational institutions and manufacturing industries. Some of the empirical applications of this method are by Banker, Charnes and Cooper (1984), Färe, Grosskopf and Lovell (1985), Färe, Graboswki and Grosskopf (1985), Byrnes *et al.* (1987), Färe and Hunsaker (1986), Färe and Grosskopf (1994) and Umetsu, Lekprichakul and Chakravorty (2003).

There are two principal approaches in non-parametric methods, the input-oriented method and the output-oriented method. The output-oriented approach is applied when outputs can be increased subject to a given level of inputs, whereas the input-oriented approach is used to reduce inputs subject to given levels of outputs.

The main advantages of the non-parametric approach are that it does not require a functional form to specify the relationship between the inputs and outputs, and it can easily accommodate multiple-input and multiple-output technologies. The disadvantages are that it does not account for measurement error and other noise that can influence the frontier, and it does not permit statistical tests of hypotheses. Likewise, it does not consider the examination of the impacts of inputs on the mean, variance and inefficiency of the firm.

Further details of the concepts of efficiency measurement are found in Førsund, Lovell and Schmidt (1980), Schmidt (1986), Bauer (1990), Seiford and Thrall (1990), Lovell (1993), Greene (1993), Ali and Seiford (1993), Coelli, Rao and Battese (1998) and Kumbhakar and Lovell (2000). The parametric approach is chosen for the empirical analysis of technical efficiency in rice production in a rainfed lowland environment in the Philippines. The purpose of the succeeding sections is to draw a general picture of the methods used for efficiency measurement, with emphasis on the parametric approach.

4.4.4 Deterministic production frontiers

In the deterministic production frontier, output is assumed to be bounded from above by a deterministic quantity for each combination of inputs. The general form of the deterministic model can be expressed by:

$$Y_i = f(X_i, \alpha)\exp(-U_i) \qquad i = 1,2,\ldots,N \qquad (4.27)$$

where Y_i is the level of output produced by the i-th sample firm; X_i is a vector of inputs for the i-th firm; β is a vector of unknown parameters; $f(.)$ is a suitable functional form; U_i is a non-negative random variable associated with the inefficiency of the i-th firm; and N is the number of firms.

The inefficiency term, U_i, being non-negative restricts the individual unit's output to be less than or equal to the deterministic frontier, $f(X_i, \alpha)$:

$$Y_i \leq f(X_i, \alpha) \qquad (4.28)$$

The model specified in equation (4.28) was first proposed by Aigner and Chu (1968). They specified a homogeneous production function without the assumption of constant returns to scale, as was the case in the Farrell (1957) model. Given a Cobb-Douglas specification expressed in logarithmic form, we can write

$$\ln Y_i = \alpha_0 + \sum_{k=1}^{K} \alpha_k \ln X_{ki} - U_i \tag{4.29}$$

where $U_i \geq 0$ guarantees that $Y_i \leq f(X_i, \alpha)$. The objective is to obtain estimates of the α-parameters, which describe the production structure, and the U_is, which are used to estimate the technical efficiencies of the producers involved. The methods proposed to estimate technical efficiency are mathematical programming, corrected ordinary least squares (COLS) and modified ordinary least squares (MOLS).

Aigner and Chu (1968) suggested mathematical programming models for the estimation of the αs based on a cross-section of firms in the industry. The first model is a linear programming model, which takes the form:

$$\text{minimise} \sum_{i=1}^{N} \left| Y_i - f(X_i, \alpha) \right|$$

$$\text{subject to } Y_i \leq f(X_i, \alpha) \qquad i = 1, \ldots, N \tag{4.30}$$

In the linear model, the aim is to calculate a parameter vector, α, for which the sum of the proportionate deviations of the observed outputs of the producers beneath the maximum feasible outputs is minimised. Consequently, the technical efficiency for each producer is computed based on these proportionate deviations. The second model is the quadratic programming model. In quadratic programming, the goal is to calculate the parameter vector α for which the sum of the squared proportionate deviations of the observed outputs of the producers beneath the maximum feasible outputs is minimised. In this model, the problem can be expressed as:

$$\text{Minimise} \sum_{i=1}^{N} \left[Y_i - f(X_i, \alpha) \right]^2$$

subject to $Y_i \leq f(X_i, \alpha)$ $\qquad i = 1, ..., N$ (4.36)

Accordingly, technical efficiency can be calculated from the slacks in the functional constraints:

$$TE_i = exp(-U_i) \tag{4.31}$$

where $U_i = f(X_i, \alpha) - Y_i$.

The advantage of this approach is that it relaxes the constant returns-to-scale assumption of the original Farrell approach and also has the advantage of robustness to specification errors of inefficiency (Greene 1993). One of the difficulties of using programming models is the sensitivity of parameter estimates to outliers. Furthermore, because the estimators do not have any statistical properties, one is never sure how reliable they are (Førsund, Lovell and Schmidt 1980). Aigner and Chu (1968) suggested the investigation of the frontier without constraining all error terms to be negative. Timmer (1971) addressed this suggestion and calculated a probabilistic frontier. The frontier model was re-estimated using a reduced sample, by discarding the most efficient observations in order to stabilise the parameter estimates. The deficiencies of this approach are its arbitrary nature in selecting observations to be omitted from the sample and a lack of statistical and economic justification.

Schmidt (1976) pointed out that goal programming models can be given statistical justification if a distributional assumption is imposed on U_i. If the U_is follow an exponential distribution, then the estimates from the linear programming are maximum-likelihood estimates of the parameters of the deterministic production frontier. If the U_is follow a half-normal distribution, then the estimates of the quadratic programming model are maximum-likelihood estimates of the parameters of the deterministic production frontier. Greene (1980) suggested an alternative model in which the U_is follow a gamma distribution, which satisfies regularity conditions for obtaining asymptotic properties of the maximum-likelihood estimators.

COLS was first introduced by Winsten in 1957 (Lovell 1993; Kumbhakar and Lovell 2000). The procedure works in two steps. In the first step, the model is estimated using OLS and then the intercept is shifted upward until all the residuals are non-positive and at least one equals zero. In the second step, the corrected residuals are then used to obtain the technical efficiencies of individual firms. This method is easy to implement and does not assume any functional form for the efficiency distribution.

MOLS, introduced by Afriat (1972) and Richmond (1974), is based on distributional assumptions about the inefficiency terms, U_i, such as half-normal and exponential. The MOLS method is similar to the two-step COLS procedure. The estimated intercept from the OLS procedure is corrected by the mean of the assumed one-sided distribution.

The deterministic frontier models have been criticised because they lack statistical properties and fail to take into account the effects of random shocks beyond the control of the firm. With OLS, all variation in output not associated with variations in inputs is attributed to random shocks, while, in the deterministic approach, all variations in output not associated with variations in inputs are due to technical inefficiency. These drawbacks of the deterministic models are addressed in the stochastic production frontier models.

4.4.5 Stochastic production frontiers

The stochastic production frontier model was first introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). Using the stochastic production frontier model, equation (4.32), can be expressed as

$$Y_i = f(X_i, \alpha)\exp(V_i - U_i) \tag{4.32}$$

where V_i is a symmetric error term and U_i is the nonnegative technical inefficiency effect. The V_i are assumed to be identically and independently distributed normal random variables with mean zero and constant variance. The inefficiency components, U_i, are assumed to be derived from a half-normal distribution with mean zero and variance, σ_U^2. Equation (4.32) implies that possible production, Y_i, is bounded above by the stochastic quantity, $f(X_i, \alpha)\exp(V_i)$, hence the term stochastic frontier.

Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) suggested use of the maximum-likelihood method to estimate the parameters of the model. In obtaining the maximum-likelihood estimators, they suggested the parameterisation, $\sigma_S^2 = \sigma_U^2 + \sigma_V^2$ and $\lambda = \sigma_U / \sigma_V$, so that λ could be interpreted as an indicator of the relative variability of the two sources of random error that distinguish firms from one another (Aigner, Lovell and Schmidt 1977, p. 27). Battese and Corra (1977) used the parameterisation, $\sigma_S^2 \equiv \sigma_V^2 + \sigma_U^2$ and $\gamma \equiv \sigma_U^2 / \sigma_S^2$, so that γ is bounded between zero and one.

Using cross-sectional data, the firm's technical efficiency can be defined by the ratio of the observed output to the corresponding stochastic frontier output; i.e.,

$$TE_i = \frac{Y_i}{f(X_i;\alpha)\exp(V_i)} = \exp(-U_i)\,. \tag{4.33}$$

Jondrow et al. (1982) derived the conditional distribution, $(U_i|V_i\text{-}U_i)$, assuming a half-normal distribution for the inefficiency term, U_i. Once the point estimates of U_i are obtained, the estimates of technical efficiency for each producer can be obtained from

$$T\hat{E}_i = \exp[-E(U_i \mid V_i - U_i)]\,. \tag{4.34}$$

Battese and Coelli (1988) proposed an alternative point estimator for TE_i:

$$T\hat{E}_i = E(\exp\{-U_i\} \mid V_i - U_i)\,. \tag{4.35}$$

The point estimators given in equations (4.34) and (4.35) can give different results. The estimator in equation (4.35) is preferred, particularly when U_i is not close to zero (Kumbhakar and Lovell 2000).

4.4.5.1 Panel data models

So far, the discussion in section 4.4.5 assumes cross-sectional data for N firms. There are some difficulties associated with the use of cross-sectional data, as outlined by Schmidt and Sickles (1984). The use of panel data has many advantages over a single cross-sectional data set. Coelli (1995), Coelli, Rao and Battese (1998) and Kumbhakar and Lovell (2000) outlined some of these advantages. Repeated observations on a sample of producers can serve as a substitute for the strong distributional assumptions; relax the assumption that the inefficiency terms, U_is, are not correlated with regressor; delete the independence assumption; provide consistent estimators of firm efficiency; and simultaneously estimate technical change and efficiency change over time.

Pitt and Lee (1981) specified a panel version of the model developed by Aigner, Lovell and Schmidt (1977). In the panel data context, equation (4.38) can be expressed as

$$\ln Y_{it} = f(X_{it}, \alpha) + (V_{it} - U_{it}) \tag{4.36}$$

where Y_{it} is the output of the i-th firm ($i = 1,2,\ldots, N$) in the t-th time period ($t = 1,2,\ldots, T$). Pitt and Lee (1981) assumed a half-normal distribution for the inefficiency components, U_{it}, and estimated models that assume that the U_{it}s are time-invariant and not correlated over time or between firms.

The time-invariant model of Pitt and Lee (1981) takes the form:

$$Y_{it} = f(X_{it}, \alpha)\exp(V_{it} - U_i) \tag{4.37}$$

Battese and Coelli (1988) defined a stochastic frontier production function for panel data on sample firms such that the inefficiency effects, U_{it}, in equation (4.37) were time-invariant. They generalised the cross-sectional technical efficiency predictor of Jondrow et al. (1982) into the panel data case, presented in equation (4.40). Battese, Coelli and Colby (1989) further extended the model to account for unbalanced panel data.

Kumbhakar (1990) suggested a stochastic frontier model for panel data, in which the U_{it}s are allowed to change over time, such that

$$U_{it} = [1 + \exp(bt + ct^2)^{-1} U_i \tag{4.38}$$

where the individual firm effects, U_{it}, are functions of an exponential variable and a firm-specific random variable, U_i, which was assumed to have half-normal distribution and b and c are unknown parameters to be estimated. Battese and Coelli (1992) proposed an alternative model to equation (4.44), defined as

$$U_{it} = \{\exp[-\eta(t - T)]\} U_i \qquad (4..39)$$

where η is an unknown parameter to be estimated, and the U_is are independently and identically distributed non-negative random variables obtained by truncation (at zero) of a normal distribution with unknown mean, μ, and variance, σ^2. The value of the parameter, η, indicates the trend in the inefficiency effects. For $\eta > 0$, $\eta < 0$ and $\eta = 0$, as t increases, inefficiency decreases, increases and remains constant, respectively.

Further extensions of the panel data models are suggested by Lee and Schmidt (1993), Heshmati and Kumbhakar (1994) and Heshmati, Kumbhakar and Hjalmarsson (1995).

4.4.5.2 Explaining technical inefficiency

Kumbhakar and Lovell (2000, pp. 261-278) summarised the early and most recent approaches for incorporating exogenous influences on inefficiency. The first approach was to incorporate the exogenous variable into the production frontier directly:

$$Y_{it} = f(X_{it}, z_i; \alpha)\exp(V_{it} - U_{it}). \tag{4.40}$$

In this case, the z_i exogenous variables explain inefficiency effects. This approach cannot distinguish the influence of exogenous variables on the production frontier from the influence of those variables on technical inefficiency.

The second approach was to regress the technical efficiency indices on firm-specific explanatory variables after the estimation of the production frontier. Kalirajan (1991) and Parikh and Shah (1995) provide empirical applications of this approach. It is criticised because of its inconsistent assumptions regarding the independence of the inefficiency effects in the two estimation stages. Further, it requires that the variables used to explain inefficiency must be uncorrelated with the exogenous variables in the production frontier. Deprins and Simar (1989) extended the formulations in the above two approaches.

In the same vein, Kumbhakar, Ghosh and McGuckin (1991), Huang and Liu (1994) and Battese and Coelli (1995) proposed alternative approaches for examining the sources of technical inefficiency. These approaches specified that the technical inefficiency effects in the stochastic frontier are a function of variables that are considered relevant in explaining the inefficiencies of production.

Battese and Coelli (1995) proposed a model in which the non-negative inefficiency effects for panel data are modelled in terms of other explanatory variables, which can also include the time of observation. The U_{it}s were assumed to be independent non-negative random variables defined by a truncation of the normal distribution with mean, $\mu_{it} = \delta_0 + \sum_j^J \delta_j Z_{jit}$, and variance, σ^2, where Z_{jit} is the value of the j-th explanatory variable associated with the technical inefficiency effects of the i-th firm in year t.

Most recent studies explaining technical inefficiency follow the one-step procedure. The Monte Carlo results presented by Schmidt and Wang (2002) give evidence in favour of the one-step procedure. In this thesis, we follow the model specification of Battese and Coelli (1995), which is presented in Chapter 6.

4.4.5.3 Stochastic frontier production model and risk

In explaining inefficiency, the issue is to parameterise the mean of the pre-truncated distribution in order to study the influences of exogenous variables on inefficiency. A number of authors have addressed the problem of heteroscedasticity by parameterising the variance of the pre-truncated distribution. Caudill and Ford (1993), Caudill, Ford and Gropper (1995), Hadri (1999), Bera and Sharma (1999) and Hadri, Guermat and Whittaker (2003) proposed models in order to address the problem of heteroscedasticity in the stochastic production frontier models. Heteroscedasticity can appear in the error term component, and it can affect inferences concerning production technology parameters as well as parameters of the error component.

Wan and Battese (1992) and Battese, Rambaldi and Wan (1997) considered a model that permits the marginal production risk of inputs to be negative and positive and the technical efficiency of firms to be a function of the levels of the factor inputs. Battese, Rambaldi and Wan (1997) proposed a frontier model that incorporated the production risk structure suggested by Just and Pope (1978) and was consistent with the stochastic frontier models introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977).

Recently, Kumbhakar (2002) generalised the stochastic frontier model to accommodate production risk, risk preferences and technical inefficiency of individual farmers. The papers by Battese, Rambaldi and Wan (1997) and Kumbhakar (2002) form the basis of the empirical analysis in Chapter 7.

4.4.5.4 Estimation methods

Stochastic production frontier models are estimated using different functional forms and different methodologies. The Cobb-Douglas functional form has been the most common functional form used in empirical estimation of frontier models despite its restrictiveness in that returns to scale have the same values across all firms, output elasticities of inputs are constant and elasticities of substitution are equal to one. Other functional forms used in empirical analyses have been the translog production function and the Zellner and Revankar (1969) generalised production function. Empirical studies examining different functional forms include Gong and Sickles (1992), Zhu, Ellinger and Shumway (1995), Ahmad and Bravo-Ureta (1996), Battese and Broca (1997) and Giannakas, Tran and Tzouvelekas (2003).

The estimation of frontier models can be performed using the maximum-likelihood method or a variant of the COLS method suggested by Richmond (1974). Stochastic frontiers can be estimated using a different range of multi-purpose econometric software that can be adapted for the desired estimation procedure. This software includes statistical packages such as LIMDEP, TSP, SHAZAM, GAUSS and SAS. The two most commonly used packages for estimating stochastic production frontiers and inefficiency are FRONTIER 4.1 (Coelli 1996) and LIMDEP (Greene 1995). Sena (1999) and Herrero and Pascoe (2002) conducted reviews of both packages.

4.5 Conceptual Framework for Analysing Production Risk and Technical Efficiency

The purpose of this section is to summarise and outline the general analytical framework used in the empirical analyses presented in Chapters 5, 6 and 7. Following the preceding discussions of the concepts associated with production technology, risk estimation and efficiency estimation, this study uses the econometric approach to understand the nature of risk and efficiency in the rainfed rice environments. A general representation of the framework is presented in Figure 4.2. The discussion is supported by a presentation of the general forms of the econometric models.

In the econometric estimation of a deterministic production function, the specification of residuals from the deterministic portion of a production model is used in two-pronged analytical frameworks, i.e., risk analysis and technical efficiency analysis. The risk analysis in a Just-Pope framework (1978, 1979) involves recovering the residuals and using them to investigate the marginal effects of inputs on production risk. A heteroscedastic production function allows the examination of inputs on the mean output and the variance of output. The simple equation, $Y = f(X)$, with an additive heteroscedastic error structure represented in equation (4.14), allows an examination whether an input is risk-increasing or risk-reducing. In Chapter 5, the Just and Pope methodology is employed to estimate a heteroscedastic production function using farm-level panel data.

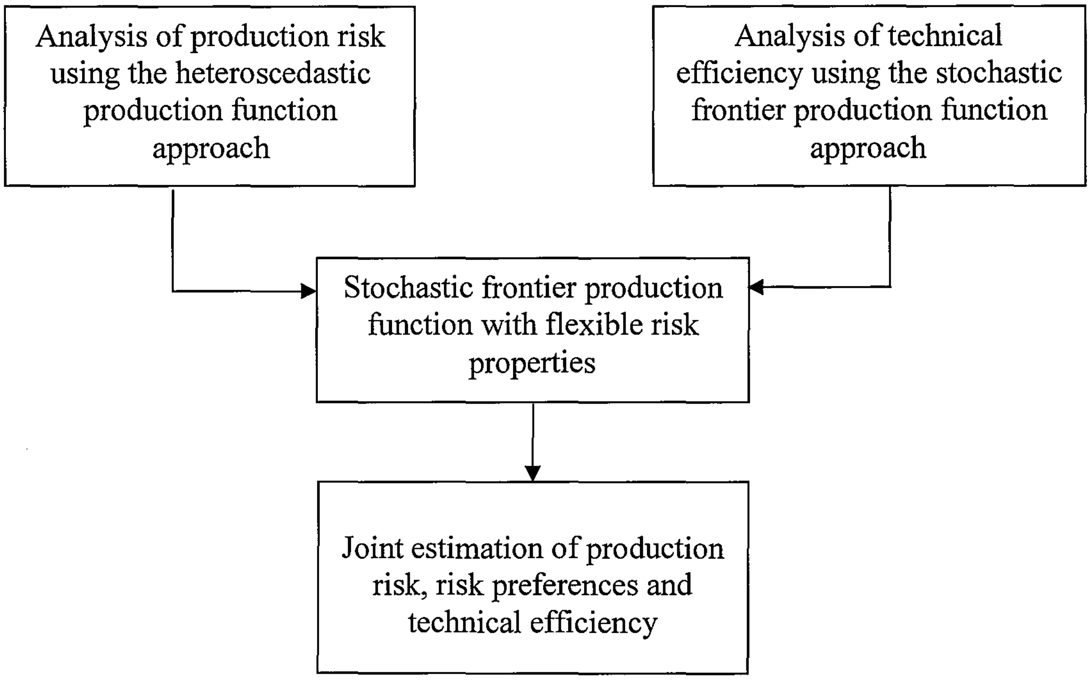


Figure 4.2: A diagrammatic representation of the framework for analysing production risk and technical efficiency in the rainfed lowland rice environment.

The second analytical framework is on technical efficiency analysis. Inefficiency analysis in a stochastic frontier production framework involves specifying a noise component and one-sided inefficiency component in the residuals. An analysis of technical efficiency in the rainfed rice environments using the stochastic frontier framework is presented in Chapter 6.

The two analytical frameworks are reconciled such that a stochastic frontier production function with flexible risk properties is specified. This model is consistent with the model proposed by Battese, Rambaldi and Wan (1997) which considered a stochastic frontier production function with an additive heteroscedastic error structure. The model allows for negative or positive marginal production risks of inputs, consistent with the Just and Pope (1978) framework. The technical efficiencies of individual firms are measured as a function of the levels of inputs in the stochastic frontier models.

The stochastic frontier production model with flexible risk properties is generalised to accommodate risk preferences of individual farmers using the method of analysis proposed by Kumbhakar (2002). This method allows for the joint estimation of production risk, risk preferences and technical efficiency in a model that is consistent with the stochastic frontier approach and the heteroscedastic approach proposed by Just and Pope (1978). An algebraic expression of the risk preference function is derived without having to assume an explicit form of the utility function and a specific distribution on the error term representing production risk. The details of the model and empirical analysis are presented in Chapter 7.

4.6 Conclusions

The present study is an attempt to provide empirical evidence of the estimation of production risk, risk preferences and technical efficiency in the rainfed lowland rice environment in the Philippines. In order to take account of production risk, the Just and Pope's heteroscedastic model is estimated in Chapter 5. The estimation of technical efficiency using the stochastic frontier model is presented in Chapter 6. Finally, an investigation of production risk and technical efficiency is undertaken in Chapter 7 by incorporating risk preferences using the model and methodology developed by Kumbhakar (2002).

This chapter is devoted to a review of the theoretical and conceptual aspects for analysing risk and technical efficiency. First, this chapter focuses on the aspects of production technology by highlighting the properties of a production function and the optimising behaviour of individual producers. Basic concepts for risk analysis are discussed, along with different approaches for measuring risk. The fourth section of this chapter is devoted to a discussion of major concepts related to efficiency measurement. This section highlights the methods for estimating technical efficiency with emphasis on the use of parametric methods.

The concepts and approaches for estimating risk and technical efficiency are summarised in section 4.5, which forms the foundation of the conceptual framework of this thesis. The econometric approach follows the Just and Pope (1978) model for analysing production risk in the rainfed rice environments, and the stochastic production frontier model is chosen for the empirical analysis of technical efficiency in the study area. These two approaches are reconciled in a single framework for simultaneously estimating production risk, technical efficiency and risk preferences.

Chapter 5

Analysis of Production Risk Using Farm-Level Panel Data: A Heteroscedastic Production Function Approach

5.1 Introduction

Risk has been identified as a major impediment to the adoption of technological innovations in agriculture (Feder 1980; Feder, Just and Zilberman 1985; Antle and Crissman 1990; Anderson and Hazell 1994; Kalirajan and Shand 1994). It is also seen as an important factor influencing the optimising behaviour of firms adjusting to disequilibria in agriculture (Schultz 1975). Risk affects the level of output by influencing the levels of inputs used (market or allocative risk) and constrains the firm from realising the full potential of a technology by influencing it not to follow the best practice in applying inputs (production or technical risk) (Kalirajan and Shand 1994).

Production risk is the most widely recognised risk element in agriculture. Crop yields, crop qualities and costs of production are inherently uncertain because of the vagaries of weather, diseases, pests and other factors. One important characteristic of production risk is that levels of inputs influence the level of output risk – some inputs increase the level of risk while others reduce risk.

In the context of empirical analysis of the behaviour of the firm, it is important to take production risk into account. Considerable evidence exists to suggest that farmers in low-income environments behave in risk-averse ways (eg., Dillon and Anderson 1971; Francisco and Anderson 1972; Binswanger, Jodha, and Barah 1979; Binswanger 1980; Sillers 1980; Antle 1988; Anderson and Dillon 1992). Farmers always operate in an uncertain environment and, thus, face difficulties in deciding about their farming activities. Risk-averse producers choose input levels that differ from the optimal levels of risk-neutral producers, and they are concerned about risk properties when they consider whether to adopt new technologies (Tveterås 2000).

Econometric studies of production risk have entailed the use of a number of different methodologies and approaches. As mentioned in Chapter 4, one of the early methods for analysing production risk is the so-called "gross" or "analytical" approach (Roumasset 1979; Anderson, Dillon and Hardaker 1977).

Alternatively, heteroscedastic production functions have been specified that allow the variance of the stochastic term to vary with the levels of managed inputs. Most studies dealing with production risk are based on the model of Just and Pope (1978, 1979). This model permits the analyst to estimate both positive and negative marginal effects of inputs on the mean output and the variance of output.

In this chapter, a heteroscedastic production function model is estimated using the farm level panel data described in Chapter 3. The aim is to examine the nature of production risk in rainfed rice environments. Although the importance of risk has been widely recognised by researchers and policy makers, there is a dearth of quantitative information on the effect of risk on rice production systems in rainfed rice environments (Pandey et al. 2000). In rainfed rice environments, farmers face considerable challenges in dealing with risk. They have to carry out production activities in an inherently uncertain production environment and adapt their cropping practices to the complex risks, potentials and problems they face. Most analytical work has been to quantify risk at a more aggregative level than the farm level. In contrast, the aim of the analysis in this chapter is to provide a quantitative measurement on the nature of production risk using farm-level data.

This chapter is organised as follows. Section 5.2 presents a review of relevant empirical studies. Section 5.3 discusses the heteroscedastic model that is used to estimate production risk. Section 5.4 presents the specifications of the empirical models, to be followed by a presentation of empirical results in section 5.5. Finally, a summary and conclusions are provided in section 5.6.

5.2 Review of Selected Empirical Studies

Just and Pope (1978, 1979) laid the foundation for theoretical and empirical research on production risk. They proposed a production function that allows inputs to influence both the mean and the variance of output. Several subsequent empirical studies of production risk using the Just and Pope approach have provided evidence of output risk in the agricultural production sector. Some of these empirical studies are reviewed in this section.

Anderson and Griffiths (1981), Anderson and Griffiths (1982) and Griffiths and Anderson (1982) used the multistage estimation approach, which was proposed by Just and Pope (1978), to quantify the impact of selected factors of production on the riskiness of production. They applied their model to the pastoral zone of the sheep industry in Australia. The study used a 10-year panel data set collected for 38 farms for the period from 1964/65 to 1973/74. Two production function models were estimated with error components for time and farms and a heteroscedastic disturbance. These models allowed the determination of both positive and negative marginal risks. Their results indicated that labour, water and fencing were likely to reduce the variance of wool production, but that sheep, buildings and land were likely to increase the variance.

Smith et al. (1983) examined the effect of risk on the optimal level of nitrogen use in the rainfed area of Bicol region in the Philippines. The data used in their study were based on the three-season experimental data collected by IRRI in three rainfed villages in the province of Camarines Sur. The period covered was the second season of 1980/81 and both seasons of 1981/82, with 668 total observations. Smith et al. (1983) applied the Just and Pope (1978) three-stage estimation technique to a quadratic production function. A constant partial risk-averse (CPRA) utility function, which was developed by Binswanger (1981), was used to compute the optimal nitrogen rates, under the assumption that farmers act as if they maximise the expected utility of profit. The optimal risk-averse nitrogen rates in the first and second seasons were 49 and 48 kilograms per hectare, respectively. The optimal risk-neutral nitrogen rates were 51 and 52 kilograms per hectare in the first and second seasons, respectively. It was found that risk appeared to have a small effect on the level of fertiliser use, which was only about four and eight per cent lower than the risk-neutral optimum levels in the first and second seasons, respectively. Smith et al. (1983) concluded that since profit variability did not have a significant effect on fertiliser decisions, risk-reducing policies such as crop insurance would be expected to have very little effect on fertiliser use.

Kalirajan and Huysman (1984) formulated a production risk equation to measure the effects of stochastic variables on yield, given the levels of decision and context variables, using a variant of the random coefficients model that was popularised by Swamy (1970). The effects of sampling variability were removed from estimates to obtain the true variability that influenced the decisions made by producers. The random coefficients model was estimated using panel data from farmers in a rainfed rice environment in the Philippines, covering the period 1979 to 1982. The data were obtained using a system of daily record-keeping of production activities for 25 farmers from the same village. The study area was a typical rainfed environment that was characterised by a highly diverse land resource base and dependency on rainfall.

Kalirajan and Huysman (1984) assumed a quadratic production function between rice yield and fertiliser. The variables they included in the model were nitrogen applied, interactions between nitrogen and solar radiation and between nitrogen and phosphorus, water stress days and a weed infestation index. The results of the GLS and OLS estimates were compared for pooled data. GLS estimates were found to be somewhat higher than the corresponding OLS estimates. The empirical results indicated a strong responsiveness of output to the inter-season and intra-season environmental variabilities, which implies that technology should be location-specific.

After finding out that inter-season environmental variabilities played a major role in the level of technology adoption, Kalirajan and Huysman (1984) concluded that blanket policies are inappropriate where technology adoption is not uniform. Once the desirable components and the scale of a relatively flexible policy element were identified, the policy could encourage the adoption of practices that are typical of farming strata in which particular inputs continued to contribute a significant marginal product (Kalirajan and Huysman 1984).

Smith and Umali (1985) estimated a random coefficients model by using data from nitrogen trials that were conducted by IRRI for a period of five years, 1976-79 and 1981, under rainfed conditions. Five nitrogen rates, from zero to 120 kilograms per hectare, were applied in several plots planted to different varieties.[1] A quadratic nitrogen response function was estimated by OLS and GLS for each of the sample years. A rice variety dummy was included in the model to take account for the variety that used nitrogen efficiently. The CPRA utility function that was specified by Binswanger (1981) was used to estimate the optimal nitrogen rates for risk-neutral and risk-averse preferences of the decision maker. Accordingly, the effect of risk aversion on fertiliser use was quantified. The results showed only a slight effect of risk aversion on fertiliser use. The optimal level of nitrogen for the risk-averse model was estimated to be 35 kilograms per hectare, compared with the estimated risk-neutral optimum of 42 kilograms per hectare. Therefore, the risk-neutral and risk-averse decision-making models predicted that moderately risk-averse farmers would apply only seven kilograms less than the risk-neutral, profit-maximising nitrogen rate. Smith and Umali (1985) acknowledged that these results must be interpreted cautiously because the analysis used data from experimental stations in a relatively favourable rainfed environment, which may not reflect the true conditions of the fields of farmers. They noted, however, that their results were consistent with the findings of risk studies conducted in irrigated areas of the Philippines by Roumasset (1976) and Rosegrant and Herdt (1981).

Rosegrant and Roumasset (1985) measured the effect of fertiliser on risk by employing the Just and Pope (1979) heteroscedastic production function. The estimation technique was applied to a pooled data set comprising a total of 3617 observations that were obtained from a series of yield response experiments for modern varieties in the fields of rice farmers in Central Luzon in the Philippines. The experiments were conducted by

[1] A split-plot design, replicated three times, was used with fertiliser, which was the variable of research interest in the main plot, and rice varieties, which was the variable of interest in the subplots. The varieties planted were IR36 and IR42.

IRRI, beginning with the 1973 wet season and ending during the 1977 dry season, giving a total of four crop years and eight seasons.

Rosegrant and Roumasset (1985) used GLS to estimate a quadratic production function that included managed inputs, fixed factors and measurable stochastic variables. The managed inputs (nitrogen, phosphorus, cost of insect control and cost of weed control) all had a positive impact on yield. The marginal product of nitrogen was found to decline as the level of nitrogen increased. Pest damage, disease, moisture stress, typhoon, age of seedlings and the clay content reduced yields, while solar radiation and organic matter increased yields. The analysis of the effect of nitrogen on the error term component of the variance of yield indicated that, at mean levels of the other variables, the error term variance first decreased and then increased as the nitrogen level increased.

The impact of nitrogen on the variance of yield also takes into account the variability of stochastic variables that interact with nitrogen. Rosegrant and Roumasset (1985) estimated the parameters of the probability distributions of yield to assess this impact and the impact of other variables on yields. The parameters of the yield distributions were estimated for four environments, ranging from the wet season rainfed environment to the dry season with good irrigation. These estimates were used together with an expected utility-maximising model of farmer behaviour to assess optimal nitrogen levels under various risk preferences. From this analysis, it was concluded that unless farmers are severely risk-averse, production risk did not cause large reductions in nitrogen use from risk-neutral or profit-maximizing levels. For moderately risk-averse farmers, the reduction in optimal nitrogen from risk-neutral levels was from 6.7 per cent to 16.7 per cent, depending on the environment (Rosegrant and Roumasset 1985).

Wan and Anderson (1990) used panel data and a production function with composite error structure and a heteroscedastic disturbance to explore the sources of increased variability in China's food grain production. They observed that the variance of output was positively related to most of the inputs included in the model (area, fertiliser and irrigation) but these variables did not contribute significantly to the changes in the variability of Chinese food grain production. These inputs nevertheless explained most of the changes in the mean output level. Electricity was the only input that had a negative effect on the variance of output. From these results, Wan and Anderson (1990) argued that other variables such as weather and policy factors were likely to influence the variability of food grain output, but such effects were not estimated due to the unavailability of the required data.

Sasmal (1993) studied the impact of extensive inputs on the mean yield and variability of output of modern varieties in both the rainy and the dry seasons in India. The results showed that fertiliser had no significant effect on production risk in either season. Pesticide was found to be risk-increasing in the dry season, although its effect on production risk in the rainy season was negligible. As usually expected, seed was observed as a risk-reducing input in both seasons but the effect was weak. The effect of labour was risk-reducing in normal situations, but production risk increased with an increase in labour employment in the case of uncertainty in the labour supply or when unskilled labourers were employed in large numbers. Mean output was higher and the variance of output was lower in the dry season than in the rainy season because the physical environment and the weather conditions in the dry season were more appropriate for the cultivation of modern varieties.

Other findings from the literature on risk analysis relate to the importance of risk in technology adoption and variability of total output. A common method used to study technology adoption is the variance decomposition method that was proposed by Hazell (1984). Flinn and Hazell (1988) analysed the effect of modern technology on the instability of the production of rice in the Philippines using time-series data from 1948 to 1983. Two intervals, 1948-68 and 1969-83, were selected as the time periods for the analysis. These intervals roughly corresponded with the periods before and after the introduction of modern varieties. The decomposition method of Hazell (1984) was employed to identify components and sources of change in production instability in the Philippines in the aggregate and in each of seven regions.

An interesting result of the regional analysis of rice production was observed in Central Luzon and Bicol where yield and production variances increased significantly from the first to the second period. An increase in interregional covariance accounted for about 50 per cent of the increase in the variance of Philippine rice production, much less than in Hazell's (1984) analysis of the increase in variability of India's rice production between 1954-64 and 1967-77, where changes in interregional covariance accounted for approximately 81 per cent of the change in the total variability.

At the aggregate level, relative production variability changed little while absolute production variability increased significantly with the introduction of modern rice technology in the Philippines.[2] Changes in rice production variability that occurred were equally due to changes in production variance within, and an increase in the positive covariance between, regions. Increases in area-yield covariance between regions also contributed to increased variability in total rice production from the pre-modern variety era to the post-modern variety era. An analogous study was conducted in eastern India.

Traxler et al. (1995) employed a heteroscedastic production function to examine the effect of improvement in varietal technology on the first two moments of wheat yield for the period 1950-86. The experimental data used in this study included 10 wheat varieties released in Mexico from 1950 to 1986 and were collected by the International Center for Improvement of Wheat and Maize (CIMMY). The data were gathered during three crop cycles (1987, 1988 and 1989) at five different nitrogen levels.

Traxler et al. (1995) interpreted the results of their analysis to mean that yield potential increased steadily between 1950 and 1980 and reached a plateau in the 1980s. The variance of output was estimated to have peaked around 1970, but it decreased after that time. The period after the Green Revolution exhibited slower mean yield growth but relatively rapid improvement in yield stability. In general, Traxler et al. (1995) reported a

[2] A similar result was obtained in a more recent study in India that shows yield variability declined in areas where the adoption of high-yielding varieties and the use of fertiliser occurred (Pal, Pandey and Abedullah 2000). This study was a district-level analysis that involved diverse agro-climatic conditions for the period 1969-94 and investigated the changing pattern of production variability and its primary causes. The data were used to show that the growth in yield of rice in eastern India accelerated in the early 1980s. Yield growth mainly contributed to growth in rice production in the eastern region. Almost 60 per cent of the rice area showed higher growth with a greater degree of stability in rice yields.

steady progress in producing "better" varieties; successive releases decreased yield variability or increased mean yields or both.

Abedullah (1998) and Abedullah and Pandey (2004) employed the Just and Pope technique, flexible-moment-based approach by Antle (1983) and error-decomposition model by Wallace and Hussain (1969), to estimate the effect of risk on fertiliser use and on the risk-neutral optimum level of fertiliser use. The empirical results showed that the effect of risk on fertiliser use in terms of percentage of the risk-neutral optimum level is small. The optimal fertiliser dose under risk aversion varied from zero to 20 per cent of the risk-neutral level, depending on the extent of risk aversion and the estimation technique

Other recent empirical applications of the Just and Pope specification include Smale et al. (1998), Tveterås (1999, 2000) and Asche and Tveterås (1999).

5.3 A Heteroscedastic Production Model

The general form of the Just and Pope (1978, 1979) specification is

$$Y_i = f(X_i;\alpha) + g(X_i;\beta)^{1/2}\varepsilon_i \tag{5.1}$$

where $f(X_i;\alpha)$ is the mean function; $g(X_i;\beta)$ is a suitable variance or risk function; Y_i is yield or output of individual i; X_i is a vector of explanatory variables; and α and β are unknown parameter vectors. The exogenous stochastic disturbance (or production shock) is represented by ε_i, where:

$$E(\varepsilon_i) = 0 \text{ and } Var\ (\varepsilon_i) = \sigma_\varepsilon^2. \tag{5.2}$$

An advantage of the above formulation is the separation of the mean effect and the variance effect of changes in input levels. With this formulation, the input vector X_i influences the mean output, which is defined as

$$E(Y_i) = f(X_i;\alpha), \tag{5.3}$$

and the variance of output, which is given by

$$Var\ (Y_i) = g(X_i;\beta)\sigma_\varepsilon^2 . \tag{5.4}$$

From an econometric viewpoint, this formulation is useful[3] because the variance function can be interpreted as a heteroscedastic disturbance term (Asche and Tveterås 1999). This can be seen by reformulating the Just and Pope specification as

$$Y_i = f(X_i;\alpha_i) + u_i \tag{5.5}$$

where $u_i = g(X_i, \beta)^{½}\varepsilon_i$ is an error term with variance

$$Var\ (u_i) = g(X_i;\beta)\sigma_\varepsilon^2 . \tag{5.6}$$

One of the requirements of the above specification is that there should be no a priori restrictions on the risk effects of inputs – it should be possible for inputs to be risk-decreasing, risk-neutral or risk-increasing:

$$\frac{\partial Var(Y_i)}{\partial X_{ij}} = \sigma_\varepsilon^2 \frac{\partial g(X_i;\beta)}{X_{ij}} <=> 0 \tag{5.7}$$

where X_{ij} is the j-th element of X_i. Because production risk may be modelled as heteroscedastic, the parameters in the mean production function cannot be efficiently

[3] A criticism of this formulation is that it does not accommodate the potential effects of input-level changes on third and higher moments of the output distribution (Antle 1983). This criticism was addressed in other empirical studies by Nelson and Preckel (1989) and Saha, Havenner and Talpaz (1997).

estimated if the production risk is not accounted for. In the empirical literature, this is done by estimating the production function and the variance function together using a generalised least squares (GLS) estimator.[4]

Estimation of equation (5.1) can be accomplished in two stages. First, a least squares estimate of α in the mean function is obtained by regressing output on a parameterised form of $f(X_i;\alpha)$. This will lead to a consistent estimator of α. If there were interest in the estimation of $f(X_i;\alpha)$ only, there would be no need to continue after this first stage.

However, there are two reasons why estimation beyond this point is important. First, one is not in a position to examine the effect of input use on risk after only the first stage of estimation. Second, even if risk is not important, the efficiency of the estimator (at least asymptotically) can be improved after accounting for the problem of heteroscedasticity.

The second stage involves estimating β in the variance function, $g(X_i;\beta)$. In most cases, this can be done by applying OLS to a model where the dependent variable is the natural logarithm of the squared residuals from the first stage (i.e., an estimate of the logarithm of the variance of u_i) and the right-hand side is a parameterised form of $g(X_i;\beta)$. Finally, after obtaining estimates of the variance of u_i, equation (5.5) can be re-estimated using GLS to obtain a consistent and asymptotically efficient estimator of α.

5.4 Econometric Model Specification

5.4.1 Mean and variance functions

In this section, we specify the econometric panel data models of production risk used in this chapter. The specification used is consistent with the general form used by Just and Pope (1978, 1979) and is given by

[4] The heteroscedastic production model can also be estimated using the maximum likelihood estimator, proposed by Harvey (1976), see Tveterås (1999, 2000) for details.

$$Y_{it} = f(X_{it}, t, \alpha) + u_{it} \tag{5.8}$$

where Y_{it} is the output of farm i (i=1, 2, …, N) in year t (t = 1, 2, …, T); X_{it} is the corresponding matrix of inputs; α is a vector of parameters to be estimated; and u_{it} is the random error, which is defined by

$$u_{it} = g(X_{it}, t, \beta)^{1/2}\varepsilon_{it} \tag{5.9}$$

where ε_{it} is a random variable with zero mean and unit variance. Thus

$$Var(u_{it}) = g(X_{it}; t, \beta) \tag{5.10}$$

The inclusion of the time trend t in (5.8) and (5.9) allows us to examine the rate of technical change (TC) for the mean and variance functions.

The Cobb-Douglas form has been used in most econometric specifications, both in the deterministic mean function, $f(.)$, and the risk part, $g(.)$, of the Just and Pope models, despite its strong restrictions on the production technology. Log-linearisation of the Cobb-Douglas or more flexible translog model cannot be undertaken under the Just and Pope model framework since the error term is not specified in the usual multiplicative form, $Y = f(.)e^{u}$, but in the additive manner, $Y = f(.) + u$ (Asche and Tveterås 1999; Tveterås 2000).[5]

In the present analysis, we use quadratic mean and variance functions for the estimation of the econometric model with Just and Pope specification. The quadratic specifications

[5] The Cobb-Douglas and translog models can be estimated using non-linear estimation procedures. However, convergence of non-linear estimators may be a problem in the estimation of these models.

are more flexible in that both input and scale elasticities are allowed to vary with input levels in both the mean function and the variance function.

The quadratic mean function is defined as

$$f(X_{it},t;\alpha)=\alpha_0+\sum_{j=1}^{5}\alpha_j X_{jit}+0.5\sum_{j\leq}^{5}\sum_{k}^{5}\alpha_{jk}X_{jit}X_{kit} \tag{5.11}$$

and the variance function is given by

$$g(X_{it},t;\beta)=\exp\left[\beta_0+\sum_{j=1}^{5}\beta_j X_{jit}+0.5\sum_{j\leq}^{5}\sum_{k}^{5}\beta_{jk}X_{jit}X_{kit}\right] \tag{5.12}$$

where the subscripts, j (and k), i and t refer to the j-th (and k-th) input(s) ($j,\ k = 1,2\ldots5$), i-th farmer ($i = 1,2,..,46$) and t-th year ($t = 1,2,\ldots,8$), respectively; and the αs and βs are unknown parameters to be estimated.

The elasticity of mean output with respect to the j-th input is given by

$$\eta_j=\frac{\partial E(Y_{it})}{\partial X_{jit}}\frac{X_{jit}}{E(Y_{it})}=\left(\alpha_j+\sum_{k=1}^{5}\alpha_{jk}X_{kit}\right)\frac{X_{jit}}{E(Y_{it})}. \tag{5.13}$$

The marginal output risk is defined by

$$\begin{aligned}\frac{\partial Var(Y_{it})}{\partial X_{jit}}=\frac{\partial Var(u_{it})}{\partial X_{jit}}&=\exp\left(\beta_0+\sum_{j=1}^{5}\beta_j X_{jit}+0.5\sum_{j\leq}^{5}\sum_{k}^{5}\beta_{jk}X_{jit}X_{kit}\right)\\&\times\left(\beta_j+\sum_{k=1}^{5}\beta_{jk}X_{kit}\right)\end{aligned} \tag{5.14}$$

and the output variance elasticity with respect to the j-th input is given by

$$\phi_j = \frac{\partial Var(u_{it})}{\partial X_{jit}} \frac{X_{jit}}{Var(u_{it})} = \left(\beta_j + \sum_{k}^{5} \beta_{kit} X_{kit} \right) X_{jit} . \tag{5.15}$$

The returns-to-scale (RTS) parameter is defined as the sum of the output elasticities for the four inputs (not including time, t). That is:

$$RTS = \sum_{j=1}^{4} \eta_j \tag{5.15}$$

Decreasing, constant or increasing returns to scale prevail if RTS is less than, equal to or greater than unity, respectively. Similarly, the total variance elasticity can also be measured by $\sum_{j}^{4} \phi_j$, which is defined as the total level of output risk due to a change in the scale of operation.

Cobb-Douglas and translog functions are also estimated to compare with the elasticities derived from the estimation of the quadratic production function. The Cobb-Douglas production function is given as

$$\ln Y_{it} = \alpha_0 + \sum_{j=1}^{4} \alpha_j \ln X_{jit} + \alpha_5 t + \varphi_1 D_{1it} + \varepsilon_{it} \tag{5.16}$$

and the translog mean production function is defined as

$$\begin{aligned} \ln Y_{it} = \alpha_0 + \sum_{j=1}^{4} \alpha_j \ln X_{jit} + 0.5 \sum_{j\le}^{4} \sum_{k}^{4} \alpha_{jk} \ln X_{jit} \ln X_{kit} + \alpha_5 X_{5it} \\ +0.5 \sum_{j\le}^{4} \sum_{k}^{4} \alpha_{jk} \ln X_{jit} X_{5it} + \varphi_{it} D_{1it} + \varepsilon_{it} . \end{aligned} \tag{5.17}$$

The elasticity of mean output with respect to the j-th input is given as $\eta_j = \frac{\partial \ln E(Y)}{\partial \ln X_j} = \alpha_j$.

The observations in the translog model are scaled so that the means of the logarithms are zero.

5.4.2 Data and variables

The models presented in the previous sections are estimated using farm-level panel data from one of the representative rainfed rice environments in the Philippines. The data set is presented and described in Chapter 3. For the purpose of our analysis in this chapter, the data used are annual totals for each farm for each year rather than plot-level data. A total of 352 observations are used for the eight-year study period.

As already mentioned, the production system in the rainfed environment is inherently risky, which is reflected by a high degree of variability in yield, gross returns and net returns, as presented in Chapter 3. In order to capture the effects of different input levels on the mean and variance of yield, the following variables are included in the estimation (farm and year subscripts are omitted for notational convenience):

Y represents the quantity of freshly threshed rice paddy (in tonnes);

X_1 is the total area planted to rice (in hectares);

X_2 is the amount of fertiliser applied (as nitrogen, phosphorus and potassium, or NPK) (in kilograms);

X_3 is the amount of herbicide applied (in grams of active ingredients);

X_4 is the total labour input by family, exchanged and hired labourers (in person-days) in the growing, harvesting and threshing of rice; and

X_5 denotes the year in which the observation on rice production was obtained.

The area planted to rice is included in the model as one of the factors that affects total rice production and the variability of rice output. Labour, fertiliser and herbicide are three important inputs in the rice production process. Herbicide is important in the rainfed environment because weeds are considered to be a major problem; hence, it is useful to examine the effects of herbicide on the mean and the variance of output. A time trend variable, t, is also included in the model to capture technical change in the mean production function and the variance function.[6] The specification of time in the variance function accounts for the effect of technical change on production risk over time. A summary of the variables included in the model is presented in Table 5.1.

Table 5.1: Descriptive statistics of the parameters included in the mean and variance functions

Variable	Mean	Standard Deviation	Minimum	Maximum
Rice harvested (t)	6.5	5.1	0.09	31.1
Area (ha)	2.1	1.5	0.2	7.0
Fertiliser (kg)	187	169	4	1031
Herbicide (grams)	0.39	0.62	0	4.41
Labour (person-days)	107	77	9	434

The average total production of rice per farm over the eight-year period was about 6.5 tonnes. A high degree of variability was observed among the total production at the farm level, with a minimum production of 90 kilograms for one household in a particular year. A check of the survey records indicated that this household was severely affected by drought. The average area planted to rice is 2.1 hectares per household, with a minimum area planted of 0.2 hectares. All households applied fertilisers in the main field, with an

[6] Rainfall was initially included in the model. However, this variable was highly correlated with the variable, t, because only one value of rainfall is recorded for all farms in each year. It is acknowledged that the onset and amount of rainfall during the productive stage of rice is an important factor to consider in explaining the variability of rice production. The treatment of rainfall, as an important factor in a heterogeneous production environment, can be addressed using another method of analysis such as the state-contingent approach (Chambers and Quiggin 2000), which is a potential topic for further study.

average application of 187 kilograms, which was about 90 kilograms per hectare. Not all farms used herbicides. The average amount of 0.39 grams was used, which was about 0.18 grams of active ingredients per hectare. An average of 107 person-days of labour was devoted to rice production.

There is evidence from previous studies that the level of fertiliser use increases the variance of yield; hence, fertiliser was expected to have a risk-increasing effect. However, Antle and Crissman (1990) found that fertiliser (nitrogen) was risk-reducing when used by experienced farmers who planted modern varieties. Labour may have a risk-reducing or risk-increasing effect. More labour can be an indication that the production process is labour-intensive (transplanting and manual weeding, rather than herbicide applications, were involved). Herbicide can also be a risk-reducing or risk-increasing input.

5.5 Empirical Results

5.5.1 Testing for production risk

The models were estimated using the software package, SHAZAM Version 8. The quadratic mean production function was first estimated using OLS.[7] The estimated model was subjected to two tests for the existence of homoscedasticity. The Breusch-Pagan test[8] (Breusch and Pagan 1979) and the Harvey (1976) test are presented in Table 5.2. The null hypothesis of homoscedasticity is rejected in both cases. These tests provide significant evidence of output heteroscedasticity in input levels. Accordingly, they indicate that production risk is present in the rainfed rice production system. Hence, the quadratic production model was estimated using GLS regression in order to account for the presence of heteroscedasticity of the outputs.

[7] OLS estimates are presented in Appendix 5.1.

[8] This is an alternative method if the error term is related to more than one explanatory variable. To perform the Breusch-Pagan test, the test statistic is given as: $BP=SSR/2\sigma^4$, which has approximately χ^2_S distribution, where the number of degrees of freedom, S, is equal to the number of variables in the model. The hypothesis of homoscedasticity is rejected if BP is greater than $\chi^2(c)$, the critical value from the χ^2_S-distribution for a given significance level (Griffiths, Hill and Judge 1993, p. 496).

Table 5.2: Tests for homoscedasticity using the Breusch-Pagan and Harvey tests

Item	**Values**
Breusch-Pagan Test Statistic	231.2
Degrees of Freedom	20
p-value	0.000
Harvey Test Statistic	92.2
p-value	0.000

5.5.2 Parameter estimates

The GLS estimates of the parameters of the mean and variance functions for the quadratic model are presented in Table 5.3. The parameter estimates are reasonable and were found to be consistent with the previous studies on rice farming. Fertiliser and labour were expected to be the major inputs needed in the production of rice. In the mean function, only fertiliser was found to be significant among the first-order coefficients, but six of the second-order coefficients were found to be significant.

It is difficult to provide a meaningful interpretation of the parameter estimates in the case of the quadratic functional specification. Hence, the values of elasticities at the mean input levels are computed and discussed in the next section.

The variance function was estimated using the residuals from the estimated mean function. The interaction between fertiliser and labour was found to affect the variability of rice production significantly, as shown in Table 5.3. Moreover, the joint effect of herbicide and labour had a significant negative effect on the variability of rice output.

Table 5.3: Generalised least-squares estimates of the parameters of the quadratic production model

Variable	Mean function		Variance function	
	Coefficient	Standard Error	Coefficient	Standard Error
Constant	0.29	0.43	-1.82**	0.84
Area	0.66	0.66	0.40	0.89
Fertiliser	0.0194**	0.0045	0.0094	0.0059
Herbicide	0.5	1.0	0.2	1.2
Labour	0.012	0.013	-0.003	0.017
Year	-0.18	0.16	-0.30	0.30
$(\text{Area})^2$	-1.77**	0.62	0.55	0.63
(Area) (Fertiliser)	-0.0002	0.0027	-0.0087**	0.0029
(Area) (Herbicide)	-1.43**	0.56	0.88	0.53
(Area) (Labour)	0.0428**	0.0085	-0.0010	0.0088
(Area) (Year)	0.121	0.093	-0.02	0.11
$(\text{Fertiliser})^2$	-0.000003	0.000011	-0.000007	0.000013
(Fertiliser) (Herbicide)	0.0096**	0.0040	-0.0017	0.0035
(Fertiliser) (Labour)	-0.000081	0.000054	0.000164**	0.000055
(Fertiliser) (Year)	-0.00151**	0.00071	-0.00063	0.00089
$(\text{Herbicide})^2$	1.5	1.4	1.7	1.1
(Herbicide) (Labour)	0.0036	0.0095	-0.0215**	0.0087
(Herbicide) (Year)	0.02	0.15	-0.12	0.17
$(\text{Labour})^2$	-0.00068**	0.00016	-0.00020	0.00018
(Labour) (Year)	0.0005	0.0018	0.0032	0.0021
$(\text{Year})^2$	0.045	0.031	0.040	0.059
Adjusted-R^2	0.89		0.22	
Log-likelihood function	-624.26		-772.71	

** denotes significant at the one per cent level.

Several tests of hypotheses were conducted on the structure of the variance component of the production technology and these are presented in Table 5.4. The first null hypothesis is that there are no marginal effects of inputs. This hypothesis was rejected at the one per cent level with a Wald test statistic of 62.79. This result implies that the joint effects of inputs on marginal risk are significant. The second hypothesis that the second-order risk effects of inputs are zero ($\beta_{jk} = 0$ for all j and k) was rejected at the five per cent level of significance. In individually testing the marginal effects of inputs on risk, the Wald test indicated that fertiliser and labour were significant at the one per cent level, with the test statistics of 12.93 and 18.87, respectively. The marginal effect of area on risk was found to be significant at the 10 per cent level. The test that there was no marginal effect of herbicide on risk was found to be not significant. The null hypothesis, that time had no effect on output risk, was not rejected. Therefore, there were no significant marginal changes in output risk over time.

Table 5.4: Results of tests of hypotheses on the risk structure of the production technology

Hypothesis	**Wald Test Statistic**	**Degrees of Freedom**	***p*-value**
No marginal risk effects of inputs ($\beta_j=\beta_{jk}=0$)	62.79	19	0.000
No second-order risk effects of inputs ($\beta_{jk}=0$)	23.19	10	0.010
No area effects on output risk ($\beta_1=\beta_{1k}=0$)	18.87	6	0.065
No fertiliser effects on output risk ($\beta_2=\beta_{2k}=0$)	12.93	6	0.044
No herbicide effects on output risk ($\beta_3=\beta_{3k}=0$)	7.51	6	0.27
No labour effects on output risk ($\beta_4=\beta_{4k}=0$)	18.87	6	0.016
No time effects on output risk ($\beta_5=\beta_{5k}=0$)	3.65	6	0.72

The results of the above tests of hypotheses illustrate the importance of the risk part of the technology in the rainfed rice farming system. To further examine the effects of inputs on the variance of output, the output variance elasticities of each input were computed and are presented in Table 5.5. According to the estimated variance elasticities, area, fertiliser and labour all have risk-increasing effects, while herbicide was found to be a risk-reducing input. As expected, fertiliser had the largest and most significant effect on the total variance of output, with an elasticity of 61 per cent at the mean input levels. The variance elasticities of fertiliser and labour were found to be significant at the five per cent level.

The total variance elasticity was also computed. The concept of total variance elasticity (TVE) is similar to that of RTS. If TVE is greater than zero, a factor-neutral expansion of input levels leads to an increase in total output risks (Tveterås 1999). For average input levels, the estimated TVE was 1.04. This implies that an expansion in the scale of operation would lead to an increase in total output risk. However, this estimate is not significantly different from unity.

Table 5.5: Variance function elasticity estimates of inputs and technical change for the quadratic model

Input	Elasticity	Standard Error
Area	0.27	0.59
Fertiliser	0.61*	0.35
Labour	0.20*	0.11
Herbicide	-0.04	0.15
TVE	1.04*	0.26
TC	0.12	0.72

* denotes significant at the five per cent level.

5.5.3 Elasticity estimates

The output elasticity estimates for the quadratic model are reported in the first two columns of Table 5.6. Area had the largest effect on mean output, followed by labour and fertiliser, with values of 0.477, 0.314 and 0.202, respectively. The estimated elasticities for area, labour and fertiliser are all highly significant at the one per cent level. The elasticity of herbicide was positive but not significant.

The derived elasticities of the quadratic functional forms using the heteroscedastic model are compared with the estimates of the mean function using the traditional Cobb-Douglas and translog models.[9] The results are presented in Table 5.6. According to all specifications, area has the largest effect on mean output, followed by labour and fertiliser. The estimated output elasticity of herbicide was found to be insignificant. The output elasticity estimates with respect to area, fertiliser and labour are all positive and highly significant at the one per cent significance level. In all three model specifications, the impact of herbicide on mean output is found to be positive but not significant.

Table 5.6: Output elasticity estimates of inputs and technical change using different functional forms

Input	Quadratic		Cobb-Douglas		Translog	
	Elasticity	Standard Error	Elasticity	Standard Error	Elasticity	Standard Error
Area	0.477*	0.067	0.360*	0.064	0.479*	0.072
Fertiliser	0.202*	0.045	0.192*	0.040	0.204*	0.044
Herbicide	0.021	0.021	0.014	0.022	0.042	0.030
Labour	0.314*	0.061	0.439*	0.070	0.275*	0.072
RTS	1.014*	0.051	1.005*	0.025	1.023*	0.032
TC	0.056	0.051	0.017	0.013	0.014	0.012

* denotes significant at the five per cent level.

The estimated RTS parameter is greater than one for all of the specifications. However, a test that the RTS parameter is unity was not rejected in all models, indicating constant returns to scale at mean input levels.

Finally, using the quadratic model specification, the average annual technical change for the mean and the variance functions were estimated to be 5.6 and 12 per cent, respectively. This implies that the mean output and variance of output increased over the eight-year period. However, the effect of time in the mean and variance functions was not significant. This is also supported by the earlier test of the hypothesis on the effect of time on total output risk. It was noted that it was earlier stated that year was also used to capture the effect year-to-year variation in rainfall to account for risk, but our result reinforce the argument that output risk is more than the incidence of variable rainfall, but also in other factors that were not captured in our model specification.

5.6 Conclusions

In this chapter, a heteroscedastic production function was applied to a farm-level panel data set collected from a rainfed rice environment in the Philippines. Rainfed rice environments are risky because crop yields, crop quality and costs of production are inherently uncertain because of the vagaries of weather, diseases, pests and other factors.

One important characteristic of production risk is that the levels of inputs influence the level of output risk. Some inputs increase the level of risk while others reduce it. In this chapter, we examine the risk properties of inputs on both the mean (deterministic) part and variance (risk) part of the production technology. A simple measure of technical change was also obtained by calculating the effects of a time trend in the model.

The mean and variance functions are assumed to have quadratic representation. The parameters of these models were estimated by taking into account the heteroscedastic

[9] OLS estimates of the Cobb-Douglas and translog mean production functions are presented in Appendices 5.2 and 5.3.

nature of the production technology. The presence of heteroscedasticity was indicated by the results of two different testing procedures.

All inputs had significant positive effects on the mean output of rice. Although its coefficient has the expected positive sign, herbicide was found not to affect mean output significantly. The estimate of returns to scale using the quadratic function indicates that there were slightly increasing returns to scale but constant returns to scale would not be rejected at the mean input levels. The estimates of elasticities of output using the quadratic models are comparable with those from the mean production functions that involve the traditional Cobb-Douglas and translog specifications.

The impact of each input on the variance of output was also analysed. The results of the test of hypotheses on the risk structure of the production technology indicated that there were significant marginal effects of inputs on output risk. As expected, fertiliser and labour significantly and positively affected the variance of output, indicating that they are risk-increasing inputs. Although the empirical results indicated that herbicide is a risk-reducing input, its coefficient was not statistically significant. The total impact of inputs on production risk was measured using the total variance elasticity, which is analogous to the concept of total returns to scale. As the scale of operation increases, the total output risk was estimated to increase.

The finding in this analysis supports the arguments put forward in earlier literature that the major inputs of production significantly affect both the mean and the variance of output. By using farm-level data for a panel of farmers, we have confirmed that risk is an important element that needs careful attention in rainfed rice environments.

Chapter 6

Analysis of Technical Efficiency in Rainfed Rice: A Stochastic Frontier Production Function Approach

6.1 Introduction

This chapter estimates a stochastic frontier production function based on the farm-level panel data set and estimates the sources of inefficiency in the rainfed lowland rice environment. This study makes a contribution by obtaining technical efficiency and output elasticity estimates for rainfed rice farmers at the farm level. In addition, this chapter presents elasticity estimates obtained using different functional specifications with the same data set and retains the same assumptions about the underlying technology and structure of farm efficiencies.

This chapter is organised as follows. Section 6.2 reviews some of the literature on efficiency studies in rice farming. Section 6.3 outlines the stochastic frontier model and the specification of the functional forms, and contains a definition of the variables involved. The empirical results are presented in section 6.4. Some conclusions are drawn in section 6.5.

6.2 Review of Efficiency Studies on Rice Farming

In studies of technical efficiency, rice production has frequently been the focus of attention, reflecting the importance of rice in agricultural development in the developing world. The purpose of this section is to identify and review related studies which illustrate the use of frontier techniques in analysing the efficiency of rice farming. Most of these studies have been reviewed by Battese (1992), Bravo-Ureta and Pinheiro (1993) and

Coelli (1995). The papers mentioned in these studies are reviewed in this section, along with selected recent studies using frontier methodologies in rice production.

In Chapter 4, we note that frontier methodologies are classified into parametric and non-parametric approaches. The parametric frontiers can be deterministic or stochastic. The frontier models are applied to either cross-sectional or panel data. A summary of selected empirical studies in rice farming is presented in Table 6.1. The following discussion focuses first on the studies pertaining to Philippine rice farms; the second half of the discussion focuses on the literature for other countries. A brief concluding paragraph is included in this section to summarise the major issues raised in the empirical studies.

6.2.1 Philippine studies

Some of the early applications of frontier studies in rice farming are in the Philippines (Kalirajan and Flinn 1983; Lingard, Castillo and Jayasuria 1983; Kalirajan 1984; Färe, Grabowski and Grosskopf 1985; Dawson and Lingard 1989).

Kalirajan and Flinn (1983) applied the methodology proposed by Jondrow et al. (1982) to the data of 79 rice farmers in the Bicol region. A translog stochastic frontier production function was assumed to explain the variations in rice output in terms of several input variables. The parameters of the model were estimated using the maximum-likelihood method. The Cobb-Douglas model was found to be an inadequate representation of the farm-level data. The average technical efficiencies ranged from 0.38 to 0.91. In order to determine the factors that affect the levels of technical efficiency, the predicted technical efficiencies were regressed on several farm-level variables and farm-specific characteristics. Several variables, including the practice of transplanting rice seedlings, the incidence of fertilisation, years of farming and number of extension contacts, were found to have significant effects on the variation of estimated technical efficiencies.

Table 6.1: Selected efficiency studies in rice farming in the Philippines

Author(s)	Year of publication	Location	Model
Kalirajan and Flinn	1983	Bicol	Stochastic
Lingard, Castillo and Jayasuriya	1983	Central Luzon	Covariance Analysis
Färe, Grabowski and Grosskopf	1985	Philippines	Deterministic
Dawson and Lingard	1989	Central Luzon	Stochastic
Dawson, Lingard and Woodford	1991	Central Luzon	Stochastic-panel
Rola and Quintana-Alejandrino	1993	Selected regions	Stochastic
Larson and Plessman	2002	Bicol	Stochastic
Gragasin, Maruyama and Kikuchi	2002	Mindoro and Cavite	Stochastic
Umetsu, Lekprichakul and Chakravorty	2003	All Regions	Malmquist Index

Lingard, Castillo and Jayasuriya (1983) measured the farm-specific technical efficiency of rice farmers in Central Luzon, using IRRI's "Loop Survey" data. They estimated a production function for 32 farmers from panel data for 1970, 1974 and 1979 using covariance analysis. Measures of technical efficiency were calculated from the farm-specific dummy variables. The results showed that the least efficient farm achieved only 29 per cent of the maximum possible output for the given input levels.

Dawson and Lingard (1989) extended the analysis of Lingard, Castillo and Jayasuriya (1983) and estimated the farm-specific technical efficiency from a stochastic frontier production function using data for 1970, 1974, 1979 and 1982. For each year, a stochastic frontier production function was estimated using the composed error model of Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). By using the methodology of Jondrow et al. (1982) and a Cobb-Douglas functional form, the technical efficiencies were calculated for each farm in each year. The results showed an even greater efficiency range, between 0.10 and 0.99. The mean technical efficiency for the four years ranged between 0.60 and 0.70.

Dawson, Lingard and Woodford (1991) used a Cobb-Douglas stochastic frontier production function to estimate the technical efficiency of rice farmers in Central Luzon. The data used in this study were similar to those of Dawson and Lingard (1989), with the addition of a one-year data set collected in 1984. Because they used a panel-data approach, the data for only 22 farmers were available. The stochastic frontier production function method was used to calculate a single measure of technical efficiency for each farm over the whole fifteen-year period. The results showed a narrow range of efficiency estimates – between 0.84 and 0.95 – across the 22 farms, which implies that increases in rice production in the future must come from further technological progress (Dawson, Lingard and Woodford 1991).

Rola and Quintana-Alejandrino (1993) used a stochastic frontier production function approach in order to estimate the technical efficiency of rice farmers in different rice environments in selected regions of the Philippines. The study used a Cobb-Douglas production frontier and estimated the model by the maximum-likelihood method. Input variables in the production frontier included farm size, fertiliser (nitrogen), insecticide, herbicide and labour. In addition, variables such as education of the household head, tenurial status and water source were used in the production function. Input-output data and other demographic information of farmers from irrigated, rainfed and upland environments in five rice-producing regions of the Philippines were gathered. The data were collected for 1987 in Central Luzon, Western Visayas and Central Mindanao, 1988 in Bicol and 1990 in the Cagayan Valley.

The results obtained by Rola and Quintana-Alejandrino (1993) showed that there was high variability in the technical efficiency estimates among the different rice environments. The estimates of technical efficiency revealed that farmers in the irrigated environment were more efficient than rainfed and upland farmers. The mean technical efficiencies were 0.72, 0.65 and 0.57 for irrigated, rainfed and upland environments, respectively. Education, access to capital and tenurial status were some factors that affected the levels of technical efficiencies of farmers in different environments.

Larson and Plessman (2002) used data collected in the Bicol region in the years 1978, 1983, and 1994. The study used a balanced panel data set comprising 144 observations in order to estimate a translog stochastic frontier production function. The variables included in the model were irrigated area, rainfed area, upland area, fertiliser and labour. A model that takes into account the factors that explain technical inefficiency was also estimated. Larson and Plessman (2002) found that diversification and technology choices affected efficiency outcomes among Bicol rice farmers, although these effects were not dominant. Other factors that determined efficiency were accumulated wealth, education, favourable market conditions and weather.

One factor that was considered in the early literature on efficiency analysis in rice farming in the Philippines was the proportion of irrigated land under rice production. In some cases, the availability of irrigation facilities was included in both the production function and the inefficiency model, such as the presence of tube wells and water pumps. In the same vein, some studies also examined the effect of institutional organisation or association. Recently, Gragasin, Maruyama and Kikuchi (2002) attempted to determine whether the existence of an association for irrigators increased the technical efficiency of rice farmers in the Philippines. The data used in their study were collected from Oriental Mindoro and Naic, Cavite. The estimation of stochastic frontier production functions for groups of rice farmers with and without membership of an association for irrigators revealed that the mean level of technical efficiency of farmers who were members of an association was higher than those who were not.

More recently, Umetsu, Lekprichakul and Chakravorty (2003) examined the regional differences in total factor productivity, efficiency and technological change in the Philippine rice sector in the post-Green Revolution era. Malmquist indices were constructed for 1971-1990 and were decomposed into efficiency and technological change. The factors affecting productivity, efficiency and technological change were analysed by second-stage regression analyses. The factors considered were irrigation infrastructure, population, technology variables (higher education, modern variety), an institutional variable (landlord share), factor price variables (land/fertiliser price, labour/machinery price), factor-intensity variables (fertiliser/land; hand tractor/land) and exogenous macro-variables (weather, disaster, oil shock, currency crisis) and geographical location (Luzon and Mindanao). It was found that regions such as Central Luzon, Western Visayas, Southern Tagalog and Northern Mindanao had higher rates of technological change than others because of higher investment in infrastructure and education, increased adoption of tractors and a better agroclimatic environment. This study was conducted on a regional basis, which provided a good macro-level analysis of the changes in efficiency, productivity and technological change. However, the input and output variables were aggregated, and information on farm-specific characteristics was not accounted for. Therefore, it is essential to look at what is happening at the farm level.

6.2.2 Other countries

Efficiency measurement in rice farming has also been the focus of much efficiency literature in other developing countries. A summary of selected studies in rice farming is presented in Table 6.2. Most of these studies examined the technical efficiency of rice farmers and identified factors affecting the level of technical inefficiency.

A majority of these studies involved the estimation of a single-equation production frontier using cross-section or panel data. Stochastic frontier models have been widely applied in the analysis of the efficiency of rice farming, and estimated using the method of maximum likelihood. Almost all of these studies assume that Cobb-Douglas or translog production frontiers were appropriate in the analysis of farm-level data on rice production.

Table 6.2: Selected efficiency studies in rice farming in other countries

Author (s)	Year of Publication	Location	Model
Kalirajan	1981	Tamil Nadu, India	Stochastic
Ekayanake	1987	Sri Lanka	Stochastic
Ali and Flinn	1989	Punjab, Pakistan	Stochastic
Kalirajan and Shand	1989	South India	Stochastic-panel
Erwidodo	1990	Java, Indonesia	Stochastic-panel
Squires and Tabor	1991	Java, Indonesia	Stochastic
Battese and Coelli	1992	India	Stochastic-panel
Battese and Coelli	1995	India	Stochastic-panel
Dev and Hossain	1995	Bangladesh	Stochastic
Trewin et al.	1995	Java, Indonesia	Stochastic-panel
Xu and Jeffrey	1998	Jiangsu, China	Stochastic
Ahmad, Rafiq and Ali	1999	Pakistan	Stochastic
Mythili and Shanmugam	2000	India	Stochastic-panel
Shanmugam	2000	India	Stochastic
Tian	2000	China	Stochastic-panel
Ajibefun, Battese and Kada	2002	Japan	Stochastic-panel
Coelli, Rahman and Thirtle	2002	Bangladesh	Non-parametric
Tian and Wan	2002	China	Stochastic-panel

Source: Adapted from Coelli (1995); Author's own literature search

The source of efficiency differentials that were observed among rice farmers was an issue of overriding concern. Most of these studies examined factors that explain why some farmers are more efficient than others. Studies on the sources of technical inefficiency in rice farming were concerned with characteristics of the farms and farmers. These variables were related to managerial and socio-economic characteristics.

By definition, managerial variables are concerned with the ability of the farmer to choose farm output mixes and patterns, for example, seed type and rates, the application of fertilisers and chemicals (rate, types and timing) and planting and harvesting techniques. From the literature, the most common socio-economic variables were farm size, the education, age and experience of the farmers, and their access to extension services and credit. Education was found to be one of the significant factors affecting the technical efficiency of farmers (Ali and Flinn 1989; Kalirajan and Shand 1989; Xu and Jeffrey 1998). This implies that human capital is an important factor in carrying out production and managerial activities.

6.3 The Empirical Stochastic Frontier Production Model

In line with the above review of empirical studies, this chapter revisits the stochastic frontier production methodology and seeks to estimate the farm-level technical efficiencies of rainfed rice farmers. Based on the above review of selected efficiency studies on rice, this chapter also seeks to identify the factors that determine the technical inefficiency of farmers. A distinct feature of this study is that it uses farm-level panel data collected from a purely rainfed environment. Previous studies on technical inefficiency in rainfed environments are based on regional or aggregate data. Hence, we obtain estimates of technical efficiency using a micro-level data set. This section specifies the model and defines the functional forms and variables. The empirical results and tests of hypotheses are presented in section 6.4.

6.3.1 The basic model

The stochastic frontier production function specified in Chapter 4 is used to model rainfed rice production in Tarlac, Central Luzon, Philippines. In accordance with the original models of Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977), the model of Battese and Coelli (1993, 1995) is used here. The model for the analysis of panel data has the general form:

$$Y_{it} = f(X_{it}, \alpha)\exp(\varepsilon_{it}) \tag{6.1}$$

where Y_{it} is the output of farm i ($i = 1, 2, \ldots, N$) in year t ($t = 1, 2, \ldots, T$); X_{it} is the corresponding matrix of inputs; α is the vector of parameters to be estimated; and ε_{it} is the error term that is composed of two independent elements, V_{it} and U_{it}, such that $\varepsilon_{it} \equiv V_{it} - U_{it}$. The V_{it}s are assumed to be symmetric identically and independently distributed errors that represent random variations in output due to factors outside the control of the farmers as well as the effects of measurement error in the output variable, left-out explanatory variables from the model and statistical noise. The V_{it}s are assumed to be normally distributed with mean zero and variance, σ_V^2.

Following Battese and Coelli (1995), the U_{it}s are non-negative random variables that represent the stochastic shortfall of outputs from the most efficient production. It is assumed that U_{it} is defined by truncation of the normal distribution with mean, $\mu_{it} = \delta_0 + \sum_{j=1}^{J} \delta_j Z_{jit}$, and variance, σ^2, where Z_{jit} is value of the j-th explanatory variable associated with the technical inefficiency effect of farm i in year t; and δ_0 and δ_j are unknown parameters to be estimated.

The parameters of both the stochastic frontier model and the inefficiency effects model can be consistently estimated by the maximum-likelihood method. The variance parameters of the likelihood function are estimated in terms of $\sigma_S^2 \equiv \sigma_V^2 + \sigma^2$ and $\gamma \equiv \sigma^2 / \sigma_S^2$.

6.3.2 Functional forms and variables

Most of the previous studies have specified the Cobb-Douglas and translog production functions to represent the production technology. The Cobb-Douglas functional form imposes severe *a priori* restrictions on the technology involved by restricting the production elasticities to be constant and the elasticities of input substitution to be unity.

Despite its limitations, the Cobb-Douglas function has been widely used in farm efficiency analyses in both developing and developed countries. This is supported by the reviews by Coelli (1995), Bravo-Ureta (1993) and Battese (1992). The translog function is the most frequently used flexible functional form for production studies.

Several studies have examined the effect of choice of functional form on efficiency measures derived from econometric stochastic frontier models.[1] These studies examined the sensitivity of the production structure (such as production elasticities, returns to scale, technological change and technical efficiency) to the different functional specifications. This chapter presents empirical results for three specifications – Cobb-Douglas, translog and quadratic functional forms – and examines the corresponding results.

The Cobb-Douglas form of the stochastic frontier production is given by:

$$\ln Y_{it} = \alpha_0 + \sum_{j=1}^{4} \alpha_j \ln X_{it} + \alpha_5 X_5 + \varphi_1 D_{1it} + V_{it} - U_{it} \tag{6.2}$$

where

Y represents the quantity of freshly threshed rice paddy (in tonnes)[2];

X_1 is the total area planted to rice (in hectares);

X_2 is the fertiliser (as nitrogen, phosphorus and potassium, or NPK) (in kilograms);

[1] Giannakas, Tran and Tzouvelekas (2003), Battese and Broca (1997), Zhu, Ellinger and Shumway (1995) and Gong and Sickles (1992) confirmed that estimates of the production structure are sensitive to the choice of functional form. However, Ahmad and Bravo-Ureta (1996) and Kopp and Smith (1980) suggest that the choice of functional form might not have a significant impact on measured efficiency levels.

[2] Traditionally, farmers measure their harvest in *cavans*. One cavan is approximately 46 kilograms.

X_3 is the herbicide applied (in grams of active ingredients)[3];

X_4 is the total labour input (person-days) by family, exchanged and hired labourers in the growing, harvesting and threshing of rice;[4]

X_5 denotes the year in which the observation on rice production is obtained; and

D_1 is the dummy variable for herbicide, with a value of 1 if $X_3 > 0$ and 0 if $X_3 = 0$.

the subscripts, j, i and t refer to the j-th input (j =1,2…5), i-th farmer (i=1,2,..,46) and t-th year (t =1,2,…,8), respectively; and

the αs and φ_1 are unknown parameters to be estimated.

The second specification is the translog model, which is given by:

$$\ln Y_{it} = \alpha_0 + \sum_{j=1}^{4} \alpha_j \ln X_{jit} + 0.5 \sum_{j\leq}^{4} \sum_{k}^{4} \alpha_{jk} \ln X_{jit} \ln X_{kit} + \alpha_5 X_{5it}$$
$$+ 0.5 \sum_{j\leq}^{4} \sum_{k}^{4} \alpha_{jk} \ln X_{jit} X_{5it} + \varphi_1 D_{1it} + V_{it} - U_{it} \quad (6.3)$$

where the variables are as previously defined.

The third specification of the stochastic frontier model is the quadratic form, which is defined as:

---

[3] This implies that the logarithm of the herbicide applied is taken only if it is positive, otherwise the "herbicide variable" is zero, as proposed by Battese (1997).

[4] Because the data are not disaggregated by gender, this is the total of labour used regardless of the gender of the farm labourers.

$$Y_{it} = \alpha_0 + \sum_{j=1}^{5} \alpha_j X_{jit} + 0.5 \sum_{j\leq}^{5} \sum_{k}^{5} \alpha_{jk} X_{jit} X_{kit} + V_{it} - U_{it}\,. \tag{6.4}$$

Given the functional specifications presented above, the technical inefficiency model that is estimated is the specification of Battese and Coelli (1995), which is defined as:

$$\mu_{it} = \delta_0 + \sum_{j=1}^{4} \delta_j Z_{jit} + \sum_{k=5}^{11} \delta_k D_{kit} \tag{6.5}$$

where the δ_js ($j = 0,1,\ldots 11$) are unknown parameters;

Z_1 is the age of the household head;

Z_2 is the years of education completed by the household head;

Z_3 represents the ratio of adults to the total household size;

Z_4 is the total income from non-farm activities (in thousands of US dollars); and

D_k $k = 5,..11$ denote the dummy variables for the last seven years of the data set.

The descriptive statistics of the variables included in the stochastic frontier production function are presented in Table 6.3. The statistics reported in this table are for the eight-year period. The average production of rice was approximately 6.5 tonnes per household, which translates to a mean yield of about 3.1 tonnes per hectare. Rice production is highly variable, ranging from 92 kilograms to a maximum of 31.1 tonnes per household. Average fertiliser use was 187 kilograms per household, which was equivalent to approximately 89 kilograms per hectare. The average labour use is approximately 51 person-days per hectare.

Table 6.3: Descriptive statistics of the variables included in the stochastic frontier production functions and inefficiency models

Variable Name	Mean	Standard Deviation	Minimum	Maximum
Rice harvested (t)	6.5	5.1	0.09	31.1
Area (ha)	2.1	1.5	0.20	7.00
Fertiliser (kg)	187.0	168.8	3.36	1030.9
Herbicide (grams)	0.39	0.62	0	4.41
Labour (person-days)	107.0	76.8	7.8	436.9
Age (years)	49.7	11.0	25	81
Education (years)	7.2	1.9	6	14
Adult ratio (%)	0.79	0.22	0.28	1
Non-farm income (US$ 1000)	0.28	0.61	0	4.34

The age of farmers varied from 25 to 81 years and almost 80 per cent of the household members were adults. While rice was still the dominant source of household income, income from non-farm activities accounted for almost 20 per cent, which was about 280 dollars per household.

The sign of δ_1 could be negative or positive. If older farmers were not willing to adopt better practices while younger farmers were more motivated to embrace better agricultural production practices that reduce technical inefficiency effects, then δ_1 would be positive. However, if older farmers have more experience and knowledge of the production activities and are more reliable in performing production tasks that need to be performed in a timely manner, then δ_1 would be negative.

The coefficient of *education* is expected to have a negative sign because a higher level of educational attainment would result in lower inefficiency. The educational attainment of the farm manager is a proxy for human capital.

The coefficient associated with *the ratio of adult members of the household* is expected to have a negative sign. More adult members in the household means more quality labour is available for carrying out farming activities, thus making the production process more efficient.

The *non-farm income* variable is expected to have a negative effect on efficiency and so its coefficient is expected to have a positive value. Non-farm activities can affect the timing of farming activities. Obtaining additional income for the household might result in neglect of the farm activities and, thereby, increase the inefficiency of the production system. However, extra non-farm income could assist in the timely purchase of inputs and increase efficiency.

The coefficients of year of observation in the stochastic frontier production functions allow the frontier to change over time to capture any technological changes. In the case of the translog and quadratic models, more than one parameter is associated with technical change (year) effects, hence the change is measured as the first-derivative of the frontier function with respect to variable year (X_5). Incorporating year-specific dummy variables in the inefficiency model captures changes in the inefficiency effects over time.[5]

The technical efficiency of production for the *i*-th farm in the *t*-th year is defined by

$$TE_{it} = \exp(-U_{it}) \tag{6.6}$$

The prediction of the technical efficiencies is based on its conditional expectation, given the observable value of (V_{it}-U_{it}) (Jondrow et al. 1982; Battese and Coelli 1988). The technical efficiency index is equal to one if the farm has an inefficiency effect equal to zero and it is less than one otherwise.

[5] A time trend was initially included in the model. The sign was positive and was found to be not significant. This assumes that the inefficiency effects change by a constant value each year. This may not necessarily be the case in the rainfed rice environment where farmers have to contend with erratic rainfall; therefore, efficiency levels might be different in different years.

The stochastic frontier production functions, defined by equations (6.2) to (6.4), and the technical inefficiency models, defined by equation (6.5), are jointly estimated by the maximum-likelihood method using FRONTIER 4.1 (Coelli 1996).[6]

Various tests of null hypotheses for the parameters in the frontier production functions and in the inefficiency model are performed using the generalised likelihood-ratio test statistic defined by:

$$\lambda = -2 \{\log [L(H_0) - \log [L(H_1)]\} \quad (6.7)$$

where $L(H_0)$ and $L(H_1)$ denote the values of the likelihood function under the null (H_0) and alternative (H_1) hypotheses, respectively. If the null hypothesis is true then the test statistic has approximately a chi-square or a mixed chi-square distribution with degrees of freedom equal to the difference between the parameters involved in the null and alternative hypotheses. If the inefficiency effects are absent from the model, as specified by the null hypothesis, H_0: $\gamma=\delta_0=\delta_1=\delta_2=\ldots\delta_{11}=0$, then λ is approximately distributed according to a mixed chi-square distribution with 13 degrees of freedom. In this case, critical values for the generalised likelihood-ratio test are obtained from Table 1 of Kodde and Palm (1986).

[6] This software uses a three-step estimation method to obtain the final maximum-likelihood estimates. First, estimates of the α-parameters are obtained by OLS. A two-phase grid search for γ is conducted in the second step with α-estimates set to the OLS values and other parameters set to zero. The third step involves an iterative procedure, using the Davidon-Fletcher-Powell Quasi-Newton method to obtain final maximum-likelihood estimates with the values selected in the grid search as starting values.

6.4 Empirical Results

6.4.1 Production frontier estimates

The maximum-likelihood estimates of the parameters of the Cobb-Douglas, translog and quadratic stochastic frontier production functions given by equations (6.2) to (6.5) are presented in Table 6.4.[7] The maximum-likelihood estimates of the parameters of the inefficiency model for the three cases are presented in Table 6.5. The values of the explanatory variables in the translog stochastic frontier model were mean-corrected by subtracting the means of the variables so that their averages were zero. This approach implies that the first-order parameters are estimates of output elasticities for the individual inputs at the mean values.

Except for herbicide, all the parameter estimates of the Cobb-Douglas specification are significant at the one per cent level. All estimated first-order coefficients in the translog model fall between zero and one, which satisfies the monotonicity condition at the mean of inputs – all marginal products are positive and diminishing. Except for herbicide, all estimated first-order coefficients are found to be significant at the five per cent level. In the case of the quadratic functional specification, only the coefficient of fertiliser and the interaction between area and other inputs are found to be significant.

[7] The standard errors of the coefficients are correct to two significant digits, and the respective coefficients are correct to corresponding digits behind the decimal place.

Table 6.4: Maximum-likelihood estimates for parameters of the stochastic frontier production models for rainfed lowland rice production in Tarlac

Variable	Parameter	Cobb-Douglas		Translog		Quadratic	
		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Constant	α_0	-1.12 [a]	0.27	1.713 [a]	0.067	0.34	0.67
Area	α_1	0.415 [a]	0.059	0.510 [a]	0.062	0.02	0.75
Fertiliser	α_2	0.182 [a]	0.033	0.240 [a]	0.035	0.0240 [a]	0.0049
Herbicide	α_3	-0.007	0.019	0.025	0.024	0.016	0.015
Labour	α_4	0.387 [a]	0.062	0.210 [a]	0.063	0.12	0.84
Year	α_5	0.029 [a]	0.010	0.106 [a]	0.047	0.22	0.27
(Area) ^{2}	α_{11}			-0.56 [a]	0.22	-0.67	0.55
(Area) (Fertiliser)	α_{12}			0.05	0.13	-0.0054 [a]	0.0025
(Area) (Herbicide)	α_{13}			-0.059	0.045	0.0309 [a]	0.0074
(Area) (Labour)	α_{14}			0.75 [a]	0.19	-1.32 [a]	0.42
(Area) (Year)	α_{15}			0.042	0.090	0.238 [a]	0.095
(Fertiliser) ^{2}	α_{22}			0.207 [a]	0.047	-0.000012	0.000011
(Fertiliser) (Herbicide)	α_{23}			0.036 [b]	0.032	0.000021	0.000046
(Fertiliser) (Labour)	α_{24}			-0.35	0.13	0.0086 [a]	0.0029
(Fertiliser) (Year)	α_{25}			-0.119 [b]	0.068	-0.00114	0.00072
(Herbicide)^2	α_{33}			-0.016	0.026	-0.00058 [a]	0.00015
(Herbicide) (Labour)	α_{34}			0.043	0.053	0.0073	0.0070
(Herbicide) (Year)	α_{35}			0.008	0.099	-0.0017	0.0017
(Labour) ^{2}	α_{44}			-0.51 [b]	0.29	0.20	0.87
(Labour) (Year)	α_{45}			0.044	0.022	0.10	0.13
(Year) ^{2}	α_{55}			0.35	0.11	-0.033	0.056
Dummy variable for herbicide	φ_1	0.006	0.049	0.025	0.052		
Variance parameters	σ^2	0.40 [c]	0.23	0.29 [a]	0.13	7.62 [a]	1.65
	γ	0.88 [a]	0.067	0.89 [a]	0.050	0.768 [a]	0.064
Log-likelihood function		-78.02		-44.08		-685.41	

[a] denotes significance at the one per cent level, [b] denotes significance at the five per cent level and [c] denotes significance at the ten per cent level.

Table 6.5: Maximum-likelihood estimates for parameters of the inefficiency effects model of the three production functions for rainfed lowland rice production in Tarlac

Variable	Parameter	Cobb-Douglas Coefficient	Cobb-Douglas Standard Error	Translog Coefficient	Translog Standard Error	Quadratic Coefficient	Quadratic Standard Error
Constant	δ_0	-0.8	1.1	-0.05	0.61	-14.1 [a]	6.3
Age	δ_1	0.015	0.010	0.0076	0.0057	-0.003	0.021
Education	δ_2	-0.054	0.054	-0.038	0.039	0.46 [a]	0.18
Adult Ratio	δ_3	-0.94	0.65	-0.49 [c]	0.30	1.1	1.2
Non-farm Income	δ_4	0.00049	0.00033	0.00044 [c]	0.00022	0.00008	0.00049
Year 2 (1991)	δ_5	0.22	0.33	-0.49 [c]	0.31	6.27 [a]	3.1
Year 3 (1992)	δ_6	-1.9	2.1	-2.5	2.5	-8.76 [a]	2.6
Year 4 (1993)	δ_7	-0.41	0.48	-0.98 [c]	0.55	7.46 [a]	3.4
Year 5 (1994)	δ_8	0.59	0.45	-0.13	0.24	10.48 [a]	3.8
Year 6 (1995)	δ_9	-0.16	0.41	-0.83	0.57	7.23 [a]	3.2
Year 7 (1996)	δ_{10}	1.13	0.70	0.45	0.32	11.9 [a]	4.1
Year 8 (1997)	δ_{11}	-0.24	0.53	-0.63 [c]	0.35	2.78	1.9

[a] denotes significance at the one per cent level, [b] denotes significance at the five per cent level and [c] denotes significance at the ten per cent level.

Several tests of hypotheses are performed on the estimated coefficients. A summary of the results of the tests of hypotheses is presented in Table 6.6. If the first null hypothesis, $H_0{:}\alpha_{ij}=0$, is true, given the specifications of the inefficiency effects model and a translog stochastic frontier model, equation (6.3) is identical to the Cobb-Douglas functional form. Given a quadratic functional form, the model becomes an ordinary linear model if this null hypothesis is true. At the five per cent level of significance, both hypotheses are rejected. While the Cobb-Douglas functional form is rejected, the following analysis includes results for this model for comparison purposes only.

The second null hypothesis is that there was no technical change in the eight-year period. Given the Cobb-Douglas and translog models, the null hypothesis $H_0{:}\alpha_5 = \alpha_{i5} = 0$, i=1,2,.., 5, was rejected indicating that the *Year* variable should not be excluded from the model. However, this variable was found not to be significant in the model with the quadratic functional form.

The γ-parameters associated with the variance of the technical inefficiency effects in the stochastic frontiers are estimated to be 0.88, 0.89 and 0.77 for the Cobb-Douglas, translog and quadratic models, respectively. These results indicate that the technical inefficiency effects are a significant component of the total variability of the rice outputs in the rainfed rice environments. This result is supported by the third test of hypotheses. The null hypothesis, $H_0:\gamma=\delta_0=\delta_1=\ldots=\delta_{11}=0$, indicates that the inefficiency effects in the frontier model are not present. If $\gamma=0$ and all the δ-coefficients are zero, this implies that the stochastic frontier production function is the same as the mean production function that does not account for the inefficiency effects. From Table 6.6, it can be seen that this null hypothesis is rejected at the five per cent level of significance for all models. This rejection suggests that the traditional production function is not an adequate representation of the data.

The coefficients of the explanatory variables in the inefficiency model are found to have the expected signs for the Cobb-Douglas and translog models. The variable *age* has a significant positive effect indicating that older farmers tend to be more inefficient. The coefficient of the e*ducation* variable has a negative sign, which implies that more educational training acquired by farm operators increased the technical efficiency of rice production. Conversely, the *income from non-farm activities* accruing to the household has a positive effect on inefficiency. However, this was only found to be significant in the case of the translog model. This result could suggest that the more household members engage in non-farm activities and earn more off-farm income, the more the farming operations become inefficient.

The proportion of adults in the household has a significant negative effect on technical inefficiency. This result implies that the higher the ratio of adults to children the less inefficient the rice production in the rainfed environment.

Table 6.6: Tests of null hypotheses for parameters in the stochastic frontier production functions and the inefficiency effects models

Hypothesis	Cobb-Douglas			Translog			Quadratic		
	λ	Critical Value	Decision	λ	Critical Value	Decision	λ	Critical Value	Decision
1. H_0: $\alpha_{ij} = 0$				72.5	25.7	Reject H_0	63.1	25.7	Reject H_0
2. H_0: $\alpha_5 = (\alpha_{i5}) = 0$	7.8	3.8	Reject H_0	25.4	11.9	Reject H_0	8.6	11.9	Accept H_0
3. H_0: $\gamma=\delta_0=\delta_1=\ldots=\delta_{11}=0$	51.9	21.7	Reject H_0	56.8	21.7	Reject H_0	57.8	21.7	Reject H_0
4. H_0: $\delta_1=\ldots=\delta_{11}=0$	41.6	19.0	Reject H_0	51.6	19.0	Reject H_0	43.8	19.0	Reject H_0
5. H_0: $\delta_1=\delta_2=\delta_3=\delta_4=0$	31.5	8.7	Reject H_0	16.2	8.8	Reject H_0	41.9	8.8	Reject H_0
6. H_0: $\delta_5=\delta_6=\ldots=\delta_{11}=0$	13.6	13.4	Reject H_0	40.8	13.4	Reject H_0	4.3	13.4	Accept H_0

The coefficients of the *Year* dummy variables show negative signs for 1992, 1993, 1995 and 1997. The negative signs for the effects of year on the inefficiency values imply that the level of technical efficiency of farmers tended to be greater than in the first year, 1990. The coefficient of the Year 7 dummy (1996) is positive. This can be attributed to the fact that late 1995 and 1996 were considered drought periods and, therefore, this phenomenon might have affected the effort of farmers in input allocation decisions.

The fourth null hypothesis, H_0: $\delta_0=\delta_1=\delta_2=....\delta_{11}=0$, specifies that all the parameters in the technical inefficiency model have value zero (technical inefficiency effects have half-normal distribution). This hypothesis is also rejected in all three cases at the five per cent level of significance. The null hypothesis, H_0: $\delta_1=\delta_2=....=\delta_{11}=0$, means that all the coefficients of the explanatory variables of the inefficiency model are zero (and therefore the technical inefficiency effects have a truncated normal distribution).

The test of the fifth null hypothesis, that the variables *age, education, adult* and *non-farm incomes* do not have any effects on inefficiency, was rejected. Finally, a test on the significance of the year-to-year dummy variables (that the inefficiency effects do not vary over time) was rejected in the case of the Cobb-Douglas and translog models, but was not rejected in the case of the quadratic model.

6.4.2 Elasticities and returns to scale

The estimates of the elasticities of output with respect to inputs of production are presented in Table 6.7. The estimated coefficients of the Cobb-Douglas functions are elasticity estimates. The variables of the translog model were mean-corrected to zero, so the first-order coefficients are the estimates of elasticities at the mean input level. The elasticities for the quadratic model are evaluated at the mean level using the following expression:

$$\frac{\partial f(\hat{\alpha}, X_i)}{\partial X_i} \times \frac{\overline{X}_i}{\overline{Y}}. \qquad (6.8)$$

Table 6.7: Output elasticity estimates for inputs in the stochastic frontier production functions*

Input	Cobb-Douglas	Translog	Quadratic
Area	0.415 (0.059)	0.510 (0.062)	0.477 (0.077)
Fertiliser	0.182 (0.033)	0.240 (0.035)	0.323 (0.002)
Herbicide	-0.007 (0.019)	0.0253 (0.024)	0.0147 (0.157)
Labour	0.387 (0.062)	0.210 (0.063)	0.284 (0.067)
Returns to Scale	0.977 (0.059)	0.985 (0.075)	1.10 (0.27)

* Figures in parentheses are standard errors.

From the estimates of the Cobb-Douglas and translog models, the parameters of the stochastic frontier model indicate that the elasticity of output with respect to area planted to rice is between 0.415 and 0.510, at the mean input values. The fertiliser output elasticity is estimated to range between 0.182 and 0.323, while the labour output elasticity is between 0.210 and 0.387. The elasticity of land under the translog model is the highest. The labour elasticity is highest in the Cobb-Douglas model, while the fertiliser elasticity is highest in the quadratic model. The herbicide output elasticity was found to be relatively small, although not significant.

The returns to scale at the mean input values, computed as the sum of estimated output elasticities of all inputs at the mean values, are 0.98, 0.99 and 1.10 for the Cobb-Douglas, translog and quadratic models, respectively. These estimates suggest that substantial scale diseconomies are unlikely to exist on the frontier.

6.4.3 Technical efficiency indexes

The technical efficiencies of the rainfed rice farmers were predicted under different specifications of the stochastic frontier models. The yearly average farm-level technical efficiency estimates are presented in Table 6.8. The average technical efficiency estimates for individual farmers are given in Appendices 6.1 to 6.3.

The salient feature of the estimates is the wide range of the technical efficiencies, ranging from 10.7 per cent to 98.8 per cent. The average predicted technical efficiencies under different frontier specifications are not significantly different (Table 6.8 and Figure 6.1). Overall, the mean technical efficiency is about 79 per cent. This means that over the eight-year period analysed, the average farm produced only 79 per cent of the maximum attainable output. The highest estimated technical efficiencies were in 1992 and the lowest were in 1996.

The upper bound of the average technical efficiency estimates reported here is similar to those of other studies in the nearby provinces in Central Luzon, such as the study by Dawson, Lingard and Woodford (1991). The years of interest in that study were only up to 1984. They reported that the best farm was over 95 per cent efficient. A majority of the farmers fell within the 81-90 per cent range with the average efficiency being 89 per cent. The lower bound estimate was recorded to be 84 per cent. Conversely, the eight-year data set used in this thesis shows that the minimum efficiency level was about 11 per cent. The high degree of variability in the technical efficiency estimates can be attributed to the instability of the farming conditions in the rainfed lowland environment. The study areas covered by Dawson, Lingard and Woodford (1991) were mostly of a favourable environment in which the farming conditions were relatively stable.

Table 6.8: Descriptive statistics of predicted technical efficiency indexes by production frontier model and year

Year	Cobb-Douglas			Translog			Quadratic		
	Mean	Minimum	Maximum	Mean	Minimum	Maximum	Mean	Minimum	Maximum
1990	0.803	0.395	0.938	0.719	0.379	0.927	0.884	0.631	0.984
1991	0.773	0.395	0.920	0.792	0.413	0.936	0.800	0.437	0.962
1992	0.902	0.714	0.950	0.917	0.821	0.964	0.939	0.825	0.988
1993	0.832	0.539	0.938	0.847	0.480	0.942	0.790	0.494	0.979
1994	0.739	0.376	0.917	0.759	0.378	0.934	0.671	0.332	0.976
1995	0.815	0.392	0.966	0.831	0.573	0.932	0.796	0.538	0.978
1996	0.650	0.345	0.864	0.644	0.308	0.897	0.582	0.107	0.874
1997	0.834	0.139	0.944	0.827	0.127	0.952	0.874	0.377	0.988
All Years	0.793	0.139	0.966	0.792	0.127	0.964	0.792	0.107	0.988

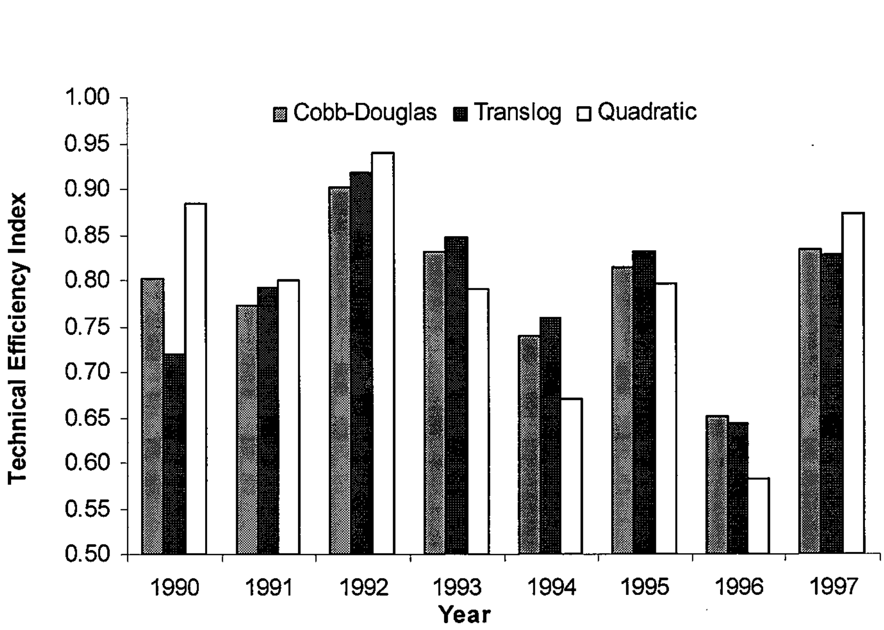


Figure 6.1: Average annual predicted technical efficiency estimates of rainfed rice farmers in Tarlac from different stochastic frontier specifications.

In Figure 6.2, about one in three farmers had a mean technical efficiency in the range of 0.81-0.90. There was also a high proportion in the range above 0.90. Approximately 17 per cent of the sample farmers had a mean technical efficiency in the range of 0.71-0.80, with about 25 per cent of farmers having technical efficiencies over 90 per cent. The farmers that fell within the 0.11 to 0.20 range were those who were badly affected with drought.

The technical efficiency estimates for the three models were used to obtain the average values by different farm-size categories. The average estimates of technical efficiencies by different farm-size categories are presented in Table 6.9. In general, larger farmers are more efficient than smaller farmers. However, there was no discernible pattern from year-to-year results.

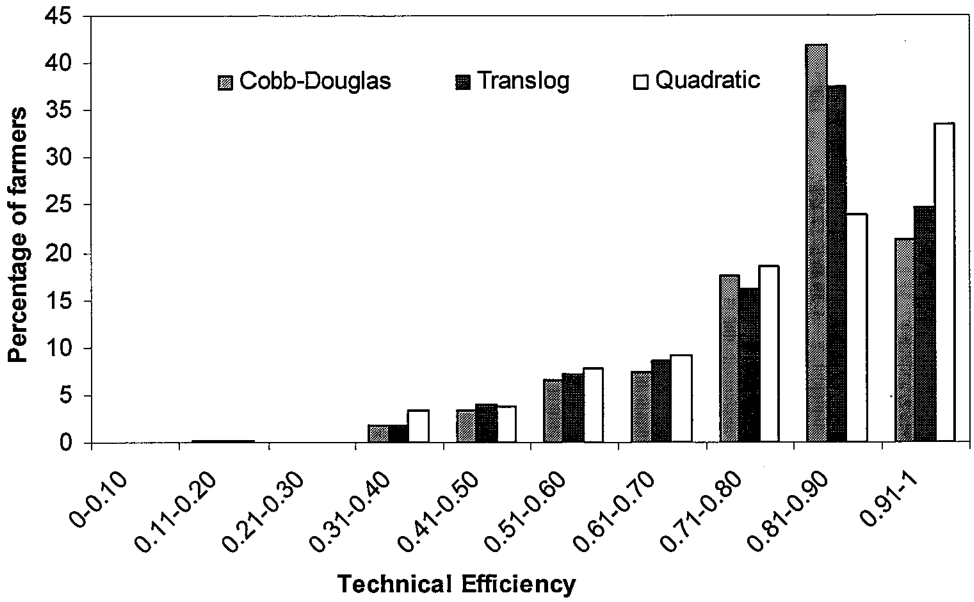


Figure 6.2: Percentage of sample rainfed rice farmers in Tarlac with technical efficiencies from different stochastic frontier specifications.

Table 6.9: Average technical efficiency estimates by farm-size categories

	Size of Farms			
Year	Small	Medium	Large	All Farms
1990	0.794	0.780	0.831	0.802
1991	0.775	0.761	0.827	0.788
1992	0.909	0.908	0.941	0.919
1993	0.804	0.840	0.836	0.823
1994	0.695	0.717	0.765	0.723
1995	0.792	0.781	0.871	0.814
1996	0.589	0.627	0.673	0.625
1997	0.801	0.876	0.879	0.845
All Years	0.770	0.786	0.828	0.792

6.5 Concluding Remarks

In this chapter, the technical efficiencies of rainfed rice farmers are analysed. A review of empirical efficiency studies in rice farming in the Philippines and other developing countries is also presented.

Rice production and input-use data in physical units, together with some farm-operation information, were used to estimate stochastic frontier models with three functional forms for production functions in which the inefficiency effects are modelled as a function of farm-specific variables and time. An eight-year panel of data, collected in Tarlac, Philippines, was used in this study. Our results indicate that the traditional production function model is inadequate for a farm-level analysis of rice production in the rainfed lowland environment. The estimated output elasticities of major inputs lie within the bounds reported in previous studies.

Several characteristics of farm operators, such as age and educational attainment, ratio of adults in the farm households and income from non-farm activities, were found to have significant effects on the technical inefficiency of rice production in the rainfed lowland environment. High variability of technical efficiency estimates was observed from farmer to farmer and from year to year. The positive and negative signs of the year dummy variables in the inefficiency model also support this finding.

After the analysis of technical efficiency using the standard stochastic frontier approach, the next step is to examine the technical efficiency of farmers using a joint estimation approach. This approach involves simultaneously estimating technical efficiency with production risk and risk preferences, and is the theme in the next chapter.

Chapter 7

Production Risk, Risk Preferences and Technical Efficiency: A Joint Estimation Approach

7.1 Introduction

As mentioned in the preceding chapters, the existence of risk in production environments affects decision making of farmers in terms of input allocation decisions and, therefore, output supply. The degree of riskiness of an outcome or event depends on the decision-maker's preferences and attitudes towards risk. It is therefore important to analyse how risk affects farmers' decisions on input allocations and, likewise, how it affects their efforts to achieve technical efficiency.

The technical sources of production inefficiency and variability in rice production are well studied and well known (Anderson and Hazell 1989). Most empirical studies have been devoted to understanding the causes of low productivity, and explaining technical inefficiency effects and the causes of variability of outputs. The pioneering work of Just and Pope (1978) paved the way for understanding production under risk. A shortcoming of their approach is that it examines the marginal effects of inputs on production risk independently of the effects of inputs on mean output and takes no account of the risk preferences of decision makers. Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) laid the foundation for examining technical efficiency in a stochastic frontier production framework. Research in this framework generally ignores the marginal effects on the risk component, despite the fact that the stochastic frontier model is consistent with the Just and Pope model (Jaenicke and Larson 2001).

The previous two chapters are devoted to analysing production risk and technical efficiency using the above frameworks. This chapter analyses production risk and technical inefficiency in rice production in the rainfed lowland environment in the Philippines by reconciling these two frameworks and extending them to accommodate the risk preferences of farmers. The risk preference function developed by Kumbhakar (2002) is used. Kumbhakar's model permits the simultaneous estimation of production risk, risk preferences and technical efficiency. This empirical analysis provides precise estimates of technical efficiency and production risk, which should prove useful for research managers and policy makers in the rice industry in the Philippines.

The chapter is organised as follows. A review of the methodological issues is presented in section 7.2. In section 7.3, a brief description of the data set is provided, and the empirical model and estimation procedures are outlined. The results are presented in section 7.4 and concluding remarks are made in section 7.5.

7.2 Review of Conceptual Issues

7.2.1 A stochastic frontier production function with flexible risk properties

The Just and Pope and stochastic frontier production frameworks are presented in preceding chapters. In this section, we concentrate on work leading up to the Kumbhakar (2002) model. Few empirical studies have attempted to analyse production risk and technical efficiency in a single framework.

Kumbhakar (1993) demonstrated a method to estimate production risk and technical efficiency using a flexible production function to represent the production technology. The model was estimated using panel data, and the risk function appears multiplicatively to accommodate negative and positive marginal risks with respect to output. The estimation of the individual technical efficiencies was also considered.

Battese, Rambaldi and Wan (1997) specified a stochastic frontier production function with an additive heteroscedastic error structure. Their model permits negative or positive marginal effects of inputs on production risk, consistent with the Just and Pope (1978) framework. Their model is now described.

Let the production process be characterised by

$$Y_i = f(X_i;\alpha) + \varepsilon_i \tag{7.1}$$

where:

Y_i is the scalar output for the i-th farmer;

X_i is a column vector of K inputs used by farmer i;

$f(X_i;\alpha)$ is the deterministic part of the production frontier;

α is a vector of technology parameters to be estimated; and

ε_i is the error term that can take different specifications depending on the nature of the analytical model.

Following the standard stochastic frontier framework developed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977), the error specification in equation (7.1) takes the form:

$$\varepsilon_i = g(X_i;\beta)[V_i - U_i] \tag{7.2}$$

where X_i are input vectors;

β is a vector of parameters to be estimated;

the $V_i s$ are error terms that are assumed to be independent and identically distributed standard normal random variables, representing production uncertainty; and

the $U_i s$ are non-negative random variables associated with the technical inefficiency of the farmers, and are assumed to be independent and identically distributed truncations of the half-normal distribution, $|N(0, \sigma_U^2)|$, independently distributed of the $V_i s$.

By using the specification in equation (7.2) and rewriting equation (7.1), we obtain:

$$Y_i = f(X_i;\alpha) + g(X_i;\beta)[V_i - U_i]. \tag{7.3}$$

Equation (7.3) is the specification of the stochastic frontier production function with flexible risk properties that Battese, Rambaldi and Wan (1997 p. 270) used. Following their exposition, the mean and variance of output for the i-th farmer, given the values of the inputs and the technical inefficiency effect, U_i, are:

$$E(Y_i \mid X_i, U_i) = f(X_i;\alpha) - g(X_i;\beta)U_i. \tag{7.4}$$

The risk function is defined as:

$$Var(Y_i \mid X_i, U_i) = g^2(X_i;\beta). \tag{7.5}$$

The marginal production risk with respect to the j-th input is defined to be the partial derivative of the variance of production with respect to X_j. This can be either positive or negative:

$$\frac{\partial Var(Y_i | X_i, U_i)}{\partial X_{ij}} > 0 \text{ or } < 0. \tag{7.6}$$

Accordingly, the technical efficiency of the i-th farmer, denoted by TE_i, is defined by the ratio of the mean production for the i-th farmer, given the values of the inputs, X_i, and its technical inefficiency effect, U_i, to the corresponding mean production if there were no technical inefficiency of production (Battese and Coelli 1988, p. 389). It is specified as:

$$TE_i = \frac{E(Y_i \mid X_i, U_i)}{E(Y_i \mid X_i, U_i = 0)} = 1 - TI_i \tag{7.7}$$

where TI_i is technical inefficiency, defined as potential output loss and represented as:

$$TI_i = \frac{U_i \cdot g(X_i, \beta)}{E(Y_i \mid X_i, U_i = 0)} = \frac{U_i \cdot g(X_i; \beta)}{f(X_i; \alpha)}. \tag{7.8}$$

If the parameters of the stochastic frontier production function were known, then the best predictor of U_i would be the conditional expectation of TE_i, given the realised values of the random variable $E_i = V_i - U_i$ (Jondrow et al. 1982). It can be shown that $U_i|(V_i - U_i)$ is distributed as $N(\mu_i^*, \sigma_*^2)$, where μ^* and σ_*^2 are defined by:

$$\mu_i^* = \frac{-(V_i - U_i)\sigma_U^2}{(1 + \sigma_U^2)} \tag{7.9}$$

$$\sigma_*^2 = \frac{\sigma_U^2}{(1 + \sigma_U^2)}. \tag{7.10}$$

It can also be shown that $E[U_i|(V_i - U_i)]$, denoted by $\hat{U}_i$, is given as:

$$\hat{U}_i = \mu_i^* + \sigma_* \left[\frac{\phi(\mu_i^* / \sigma_*)}{\Phi(\mu_i^* / \sigma_*)} \right] \tag{7.11}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ represent the density and distribution functions of the standard normal random variable. Equation (7.11) can be estimated by using the corresponding predictors for the random variable E_i given by

$$\hat{E}_i = \frac{Y_i - f(X_i;\hat{\alpha})}{g(X_i;\hat{\beta})}. \tag{7.12}$$

After equation (7.11) is estimated, then equation (7.8) can be estimated as

$$TI_i = \frac{\hat{U}_i \cdot g(X_i;\hat{\beta})}{f(X_i;\hat{\alpha})}. \tag{7.13}$$

Consequently, the technical efficiency of the *i*-th farmers is predicted by $\hat{TE}_i = 1 - \hat{TI}_i$.

7.2.2 A model with risk preferences

Neither the stochastic frontier production function with flexible risk properties nor the Just and Pope model takes into account the risk preferences of individual farmers. While several attempts have been made to estimate production risk and technical efficiency in a single framework, a stumbling block has been how to incorporate the risk attitudes of producers in the model. The traditional approach to modelling behaviour under risk is based on the expected utility hypothesis. Most studies have sought to identify farmers' risk preferences without estimating the source of randomness, or to estimate the sources of randomness without simultaneously estimating the risk preference structure (Moschini and Hennessy 2001).

In an attempt to estimate production risk and producers' risk preferences simultaneously, Love and Buccola (1991, 1999), Chavas and Holt (1996), and Saha, Shumway and Talpaz (1994) considered the risk preferences of producers in a joint analysis of input allocations and output supply decisions. Love and Buccola (1991) proposed a primal model that allows the preferences of firms and their technology to be estimated jointly in the presence of risk. They used a Just and Pope specification with Cobb-Douglas mean and variance functions, a CARA risk preference structure, cross-equation restrictions and a nonlinear three-stage least-squares estimator. Their approach is restrictive in the sense that constant absolute risk aversion is imposed (Moschini and Hennessy 2001). Saha, Shumway and Talpaz (1994), on the other hand, developed a method using an expo-power utility function that imposes no restrictions on the risk preference structure. Their results showed that the combined estimation of production function parameters with the utility function parameters is more efficient than estimating them separately. Chavas and Holt (1996) developed a joint estimation method that is able to test for constant or decreasing absolute risk aversion.

One of the immediate problems of the empirical analysis of producers' attitudes towards risk is that an explicit form of the utility function has generally been assumed. Another drawback is that it is necessary to impose distributional assumptions on the errors that represent production risk. Even with these assumptions, the main problem to an applied researcher is that there are only a few utility functions and probability distributions that can be used to derive the risk preference function analytically. They are difficult to estimate and the model becomes quite complicated (Kumbhakar 2002).

Because the risk preferences of producers have an important bearing on input allocation decisions, it is fundamental to consider a model that permits the examination of the risk attitudes of producers as well as production risk and technical inefficiency. To meet this challenge, Kumbhakar (2002) proposed a method that allows the simultaneous estimation of production risk, risk preferences and technical inefficiency. In Kumbhakar (2002), a risk preference function is introduced in a model that follows Kumbhakar's method and is consistent with the Just and Pope and stochastic frontier production frameworks.

Assume that farmers maximise expected utility of profit:

$$Max\, E[U(\Pi)] \tag{7.14}$$

where $U(.)$ is assumed to be a continuous and differentiable utility function of expected profit, Π, normalised by the output price, p, and defined as:

$$\Pi = Y - W \times X - C$$

where W is the prices of variable inputs relative to the output price and C are fixed costs or income from other sources. Recall from equation (7.3) that uncertainty in profit comes from production uncertainty, given by V_i, as well as the technical inefficiency effect, U_i.

The first-order condition for the maximisation of $E[U(\Pi)]$ can be expressed as:

$$f_j(X_i;\alpha) = W_j - \theta \cdot g_j(X_i,\beta) + \lambda \cdot g_j(X_i;\beta) + \eta_j \tag{7.16}$$

where:

$f_j(X_i,\alpha) = \dfrac{\partial f(X_i,\alpha)}{\partial X_{ij}}$ is interpreted as the marginal product of input j, defined as the change in mean output for a unit change in the variable input, X_j;

$g_j(X_i;\beta) = \dfrac{\partial g(X_i,\beta)}{\partial X_{ij}}$ measures the effect of input, X_j, on output such that X_j is risk-increasing if $g_j(X_i;\beta) > 0$, risk-decreasing if $g_j(X_i;\beta) < 0$, and neither risk-increasing nor risk-decreasing if $g_j(X_i;\beta) = 0$;

$\theta = \dfrac{E[U'(\Pi)V]}{E[U'(\Pi)]}$ and $\lambda = \dfrac{E[U'(\Pi)U]}{E[U'(\Pi)]}$ capture the risk preferences of the producers, such that $\theta < 0$ and $\lambda > 0$ if producers are risk-averse (the effect of an increase of U_i on profit is the opposite of an increase in V_i) and risk-neutral if θ and λ are both zero; and

η_j represents allocative inefficiency associated with optimisation error.

Producers are said to be fully efficient if $U_i = 0$, in which case the risk preference function is given only by θ.

According to Kumbhakar (2002), the derivation of the risk preference function depends on neither the specific parametric form of the utility function nor any distributional assumption on the error term representing production risk. It is based on the second-order approximation of the marginal utility of profit, $U'(\Pi)$, rather than the utility of profit, $U(\Pi)$, and the specific probability distribution of production risk. The parameters of the risk preference functions are estimated by assuming a parametric form of the absolute risk aversion function, allowing the identification of increasing, constant and decreasing absolute risk aversion.

For the purpose of understanding the basic framework, the algebraic representation of the risk preference functions, θ and λ, are presented as follows.[1] Let

$$U(\Pi) = U(\mu_\pi + g(X_i;\beta)V_i - g(X_i;\beta)U_i) \tag{7.17}$$

where $\mu_\pi = f(X_i,\alpha) - W_i \cdot X_i - C$.

A second-order approximation of $U'(\Pi)$ at $V_i = U_i = 0$ yields the following forms of risk preference functions (Kumbhakar, 2002, p. 11):

$$\theta = \frac{-AR.g(X_i;\hat{\beta}) - DR.g^2(X_i;\hat{\beta}).a}{1 + AR.g(X_i;\hat{\beta})a + \frac{1}{2}DR.g^2(X_i;\hat{\beta}).(1 + b^2 + a^2)} \tag{7.18}$$

$$\lambda = \frac{a + AR.g(X_i;\hat{\beta})(b^2 + a^2) + \frac{1}{2}DR.g^2(X_i;\hat{\beta}).[a + c + 3ab^2 + a^3]}{1 + AR.g(X_i;\hat{\beta}).a + \frac{1}{2}DR.g^2(X_i;\hat{\beta}).(1 + b^2 + a^2)} \tag{7.19}$$

where:

[1] See Appendix 7.1 for the derivation of the risk preference functions, as per Kumbhakar (2002).

$g(X_i;\hat{\beta})$ and $g^2(X_i;\hat{\beta})$ are estimated values from the variance functions; and

a, b, c are the first, second and third central moments of U_i based on the assumptions of the standard frontier model with $U_i \sim i.i.d.\left|N(0,\sigma_u^2)\right|$.

The central moments are defined as:

$$E(U_i) = a = \sqrt{2/\pi}\sigma_u;$$

$$Var(U_i) = b^2 = \frac{\pi - 2}{\pi}\sigma_u^2; \text{ and}$$

$$E\{(U_i - a)^3\} = c = \sqrt{2/\pi}(4/\pi - 1)\sigma_u^3.$$

AR is the Arrow-Pratt measure of absolute risk aversion (Arrow 1971; Pratt 1964) defined by:

$$AR = \frac{-U''(\Pi)}{U'(\Pi)}. \tag{7.20}$$

A farmer is said to be risk-averse, risk-neutral or a risk taker if $AR > 0$, $AR = 0$ or $AR < 0$, respectively. Absolute risk aversion is useful for comparing the attitudes of farmers towards a given activity at different levels of wealth. Consequently, DR measures the downside risk aversion, which is defined by:

$$DR = \frac{-U'''(\Pi)}{U'(\Pi)}. \tag{7.21}$$

If DR is positive, farmers are averse to downside risk, and "generally avoid situations which offer the potential for substantial gains but which also leave them even slightly vulnerable to losses below critical level" (Menezes, Geiss and Tressler 1980, p. 921).

Equations (7.20) and (7.21) are related:

$$DR = \frac{-\partial AR}{\partial \Pi} + AR^2 \cdot \tag{7.22}$$

In this framework, a parametric form of AR has to be assumed, which subsequently allows testing for different forms of risk preferences.

By expanding (7.18) and substituting the values of θ and λ, we have:

$$f_j(X_i;\alpha) = W_j \text{-} \left[\frac{-AR.g(X_i;\beta) - DR.g^2(X_i;\beta).a}{1 + AR.g(X_i;\beta)a + \frac{1}{2}DR.g^2(X_i;\beta).(1+b^2+a^2)}\right].g_j(X;\beta)$$

$$+ \left[\frac{a + AR.g(X_i;\beta)(b^2+a^2) + \frac{1}{2}DR.g^2(X_i;\beta).[a+c+3ab^2+a^3]}{1 + AR.g(X_i;\beta).a + \frac{1}{2}DR.g^2(X_i;\beta).(1+b^2+a^2)}\right] g_j(X;\beta) + \eta_j. \tag{7.23}$$

From equation (7.23), it can be seen that input allocations are affected by the presence of technical inefficiency and production risk through the values of θ and λ. If technical inefficiency is neglected in the model, information on input allocation and predicted values of the risk preference function will be misleading. As a result, the measures of absolute, relative and downside risk aversion will be invalid (Kumbhakar 2002). Similarly, neglecting production risk can lead to inaccurate measures of technical efficiency.

The parameters of the mean function, risk function, inefficiency function and AR functions can be estimated using a multi-step procedure or maximum-likelihood estimation. Kumbhakar (2002) and Kumbhakar and Tveterås (2003) provided examples of a step-by-step procedure to estimate a model with production risk and risk preferences that is followed in this chapter.

7.3 Empirical Application

7.3.1 Empirical model

The model presented in the previous section is applied to the data discussed in Chapter 3. The data used consist of an eight-year panel of 46 farms. It has been stated that rainfed rice farmers, like farmers everywhere, have to carry out production activities in an inherently uncertain environment. Production is affected by droughts, floods, and pests and diseases, which occur in an unpredictable way.

It is assumed that decisions are made at a household level, and the variables included in the model are those for all farming activities. The output variable used in the model is the total production of the farm. The explanatory variables are area, labour, fertiliser and herbicide.

Following the Kumbhakar (2002) approach outlined in section 7.2, we specify the model for panel data:

$$Y_{it} = f(X_{it};\alpha) + g(X_{it};\beta)[V_{it} - U_{it}]$$

where:

Y_{it} represents the quantity of freshly threshed rice paddy (in tonnes) for the i-th farmer in the t-th year; and

$f(X_{it};\alpha)$ is the quadratic production function defined by

$$f(X_{it};\alpha)=\alpha_0+\sum_{j=1}^{5}\alpha_j X_{jit}+0.5\sum_{j\leq k}^{5}\sum^{5}\alpha_{jk}X_{jit}X_{kit}. \tag{7.24}$$

There are five explanatory variables are defined as follows:

X_1 is the total area planted to rice (in hectares);

X_2 is fertiliser (as nitrogen, phosphorus and potassium, or NPK) (in kilograms);

X_3 is total input of family, exchanged and hired labour involved in growing, harvesting and threshing rice (in person-days);

X_4 is the amount of herbicides applied (in grams of active ingredients); and

X_5 denotes the year in which the observation on rice production is obtained.

The output elasticity with respect to input X_j is given by

$$\eta_j=\frac{\partial E(Y)}{\partial X_{jit}}\frac{X_{jit}}{f(X_{it};\beta)}=\left[\left(\alpha_j+\sum_{k=1}^{5}\alpha_{jk}X_{kit}\right)\frac{X_{jit}}{f(X_{it};\beta)}\right]. \tag{7.25}$$

Descriptive statistics for the variables included in the model are presented in Chapter 5.

The variance function, $g(X_{it};\beta)$, is specified as:

$$g(X_{it};\beta)=\beta_0+\sum_{j=1}^{5}\beta_j X_{jit}+\sum_{j\leq k}^{5}\sum^{5}\beta_{jk}X_{jit}X_{kit}. \tag{7.26}$$

The marginal production risk at the frontier is given by

$$\frac{\partial Var(Y_{it} \mid U_{it}=0)}{\partial X_{jit}} = 2 \times g(X_{it};\beta)\left(\beta_j + \sum_{k=1}^{5} \beta_{jk} X_{kit}\right). \tag{7.27}$$

Equations (7.16), (7.24) and (7.26) are used to express the first-order conditions for input X_j:

$$\alpha_j + \sum_{k=1}^{5} \alpha_{jk} X_{kit} = W_j - \theta\left(\beta_j + \sum_{k=1}^{5} \beta_{jk} X_{kit}\right) + \lambda\left(\beta_j + \sum_{k=1}^{5} \beta_{jk} X_{kit}\right) + \eta_j \tag{7.28}$$

where θ and λ, as previously defined, contain the estimated values of $g(X_{it};\beta)$, values of the first, second and third central moments of U_i, and the *AR* and *DR* functions. We choose a linear form for the absolute risk aversion function:

$$AR = \gamma_0 + \gamma_1 \Pi^* \tag{7.29}$$

where Π^* is the initial wealth plus mean profit. The value of non-farm income and the estimated value of household assets are used as a proxy for initial wealth. An explicit form of the downside risk aversion function of the producers can also be estimated.

7.3.2 Estimation

The models presented in the preceding section are estimated using a multi-step procedure. In the first two steps the parameters of the mean function, $f(X_{it};\alpha)$, and the variance function, $g(X_{it};\beta)$, are estimated. These two steps are similar to those followed by Just and Pope (1978). The third step considers the estimation of the risk preference functions, θ and λ, which are, in turn, functions of the parameters of the *AR* and DR functions. Finally, the technical efficiencies of individual farmers are estimated using equation (7.13). Following Kumbhakar's procedure, the following steps are used.

Step 1: Estimation of the parameters in $f(X_{it};\alpha)$. Since the presence of $g(X_{it};\beta)$ in equation (7.3) makes the model heteroscedastic, we can obtain unbiased estimates of the parameters in $f(X_{it};\alpha)$ ignoring heteroscedasticity. The least-squares estimators of the parameters of this model are unbiased and consistent. After the estimation of the parameters of the mean function, the residuals are obtained. These residuals are used to estimate the parameters of the variance function, $g(X_{it};\beta)$.

Step 2: Estimation of the parameters in $g(X_{it};\beta)$. The estimated residuals are then regressed against the explanatory variables to obtain consistent estimates of the parameters of $g(X_{it};\beta)$. The estimated variance function is then used to correct for heteroscedasticity in Step 1 and obtain revised estimates of the parameters of the $f(X_{it};\alpha)$, which are more efficient.

Step 3: Estimation of the parameters in the risk preference functions, θ and λ. The parameters of the risk preference functions are estimated using the estimated parameters from Steps 1 and 2. Equation (7.28) is estimated using non-linear three-stage least-squares (NL3SLS) regression to obtain estimates of the risk preference functions. All of the estimated procedures are performed using SHAZAM Version 9.1 for Windows.

Step 4: Estimation of technical efficiencies. The corresponding estimates of technical efficiencies are obtained using equation (7.13). The estimates are presented in the following section.

7.4 Results

In this section, results are presented for the estimated models that are specified above. Table 7.1 contains results for the generalised flexible risk frontier model defined by equation (7.3). As expected, fertiliser was a significant input affecting mean output. The interaction of fertiliser between area, herbicide and the year variable were found to be significant at the five per cent level. In the risk function, the interaction of area with herbicide and fertiliser, labour with fertiliser and herbicide were all found to be significant at the five per cent level.

The estimated output elasticity estimates are presented in Table 7.2. It shows that the highest elasticity estimates are for area and labour, which are significant at the five per cent level. We found that some elasticity estimates were negative for a few farmers, implying some excessive use of inputs.

The marginal output risk estimates of the inputs are presented in Table 7.3. On average, it can be seen that area, fertiliser and labour are risk-increasing while herbicide is risk-decreasing. This implies that fertiliser and labour are estimated to increase the variance of the value of output.

Table 7.1: Estimates of the mean and risk functions for the flexible risk frontier model

	Mean function		Variance function	
Variable	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Constant	1.6	1.7	0.22	0.43
Area	0.18	0.74	0.15	0.42
Fertiliser	0.0156**	0.0076	0.0039	0.0028
Herbicide	1.8	1.3	-0.39	0.57
Labour	0.017	0.012	-0.00046	0.0082
Year	-0.23	0.21	0.04	0.14
$(\text{Area})^2$	-1.72**	0.97	0.43	0.30
(Area) (Fertiliser)	0.0030	0.0084	-0.0045**	0.0014
(Area) (Herbicide)	-2.2	1.1	0.57**	0.25
(Area) (Labour)	0.038**	0.011	-0.0030	0.0042
(Area) (Year)	0.179**	0.097	-0.019	0.052
$(\text{Fertiliser})^2$	0.000005	0.000016	-0.0000070	0.0000061
(Fertiliser) (Herbicide)	0.0105**	0.0044	-0.0007	0.0017
(Fertiliser) (Labour)	-0.00013	0.00018	0.000095**	0.000026
(Fertiliser) (Year)	-0.00179**	0.00070	-0.00020	0.00043
$(\text{Herbicide})^2$	1.4	1.3	0.28	0.51
(Herbicide) (Labour)	0.017	0.023	-0.0129**	0.0041
(Herbicide) (Year)	-0.32	0.31	0.136*	0.079
$(\text{Labour})^2$	-0.00057**	0.00021	-0.000056	0.000086
(Labour) (Year)	0.0005	0.0022	0.0011	0.0010
$(\text{Year})^2$	0.056	0.054	-0.019	0.028
Log-likelihood function	-629.46		-535.63	

* and ** denote significance at five and one per cent levels, respectively.

Table 7.2: Output elasticity estimates at the mean input values

Input	Elasticity	Standard Error
Area	0.383*	0.073
Fertiliser	0.14	0.11
Labour	0.34*	0.15
Herbicide	0.010	0.022

* denotes significance at the five per cent level.

Table 7.3: Marginal production risk estimates at the mean input values

Input	Coefficient	Standard Error
Area	0.03	1.9
Fertiliser	0.0038	0.0055
Labour	0.012	0.020
Herbicide	-0.02	0.75

We examined the risk preferences of each farmer based on the predicted values of the risk preference functions, θ and λ, in equation (7.16). The risk preference estimates of all farmers are presented in Table 7.4. Results show that all farmers are risk-averse, indicated by the negative values of θ and positive values of λ. The mean value of θ estimated over the eight-year period is -0.45, correct to the two digit behind the decimal place, with a standard error of 0.22, correct to two significant digits. The magnitude of the estimates varies across farms, with a range of 0.609. The estimated mean value of the λ-parameter is 0.556, with all estimates being positive. The magnitudes of the risk preference functions are found to vary from year to year.

It can also be seen from Table 7.4 that the values of θ are larger than the values of λ. This implies that the risk component has greater influence on input-use decisions than the inefficiency component, although the difference is not great.

The estimated AR function is given as

$$\underset{}{AR} = \underset{(0.069)}{-0.059} - \underset{(0.0016)}{0.0027}\, \Pi^{*} \tag{30}$$

where the figures in parentheses are the corresponding standard errors correct to two significant digits. The estimated coefficient, γ_1, is negative and is significant at the five per cent level. This implies that the rice farmers exhibit decreasing absolute risk aversion.

The predicted values of absolute and downside risk aversion for each farmer are presented in Table 7.5. The average degree of absolute risk aversion is 0.394, correct to the third digit behind the decimal place, with a standard deviation of 0.028, correct to two significant digits. A larger value of *AR* implies a stronger aversion to risk. The predicted values of downside risk aversion, presented in Table 7.5, are all positive, indicating aversion to downside risk. Again, a larger value of *DR* shows greater downside risk aversion. The average value of *DR* is 0.156, correct to the third digit behind the decimal place, with a standard deviation of 0.021, correct to two significant digits.

Estimates of the risk preference functions are summarised on the basis of farm sizes. From Table 7.6, it appears that smaller farmers are more risk-averse than the larger farmers.

Table 7.4: Average risk preference estimates for all sample farmers

	θ		λ	
Farmer	**Mean**	**Std**	**Mean**	**Std**
1	-0.656	0.055	0.524	0.014
2	-0.74	0.16	0.498	0.047
3	-0.75	0.22	0.494	0.061
4	-0.379	0.080	0.583	0.013
5	-0.624	0.030	0.5287	0.0070
6	-0.194	0.037	0.6010	0.00097
7	-0.43	0.12	0.544	0.024
8	-0.536	0.079	0.552	0.017
9	-0.573	0.062	0.542	0.013
10	-0.73	0.13	0.506	0.039
11	-0.301	0.044	0.5935	0.0036
12	-0.151	0.024	0.60057	0.00038
13	-0.377	0.072	0.583	0.011
14	-0.455	0.079	0.570	0.015
15	-0.154	0.039	0.59815	0.00037
16	-0.194	0.060	0.5976	0.0027
17	-0.70	0.18	0.497	0.045
18	-0.73	0.28	0.486	0.067
19	-0.76	0.15	0.490	0.043
20	-0.75	0.13	0.494	0.035
21	-0.64	0.10	0.525	0.025
23	-0.446	0.080	0.572	0.015
24	-0.73	0.26	0.490	0.067
26	-0.59	0.12	0.532	0.028
27	-0.51	0.12	0.528	0.019
28	-0.340	0.043	0.5877	0.0054
29	-0.418	0.075	0.568	0.012
30	-0.41	0.12	0.573	0.017
31	-0.45	0.15	0.563	0.031
32	-0.20	0.13	0.577	0.011
33	-0.214	0.058	0.5993	0.0028
34	-0.242	0.026	0.5871	0.0015
35	-0.29	0.10	0.5825	0.0084
36	-0.227	0.045	0.5989	0.0020
37	-0.60	0.18	0.534	0.039
38	-0.432	0.071	0.575	0.011
39	-0.307	0.056	0.5868	0.0059
40	-0.327	0.093	0.574	0.010
41	-0.58	0.27	0.530	0.054
42	-0.174	0.036	0.59349	0.00073
43	-0.466	0.023	0.5656	0.0044
44	-0.308	0.024	0.5931	0.0024
45	-0.499	0.073	0.554	0.014
46	-0.346	0.075	0.5746	0.0080
All	**-0.45**	**0.22**	**0.556**	**0.045**

Table 7.5: Predicted values of the absolute and downside risk aversion

	Absolute (AR)		Downside (DR)	
Farmer	Mean	Std	Mean	Std
1	0.4073	0.0034	0.1658	0.0028
2	0.4076	0.0063	0.1661	0.0052
3	0.4130	0.0044	0.1706	0.0037
4	0.4150	0.0029	0.1722	0.0025
5	0.3924	0.0071	0.1540	0.0056
6	0.4123	0.0013	0.1699	0.0011
7	0.3009	0.0072	0.0906	0.0044
8	0.4060	0.0050	0.1648	0.0041
9	0.4008	0.0030	0.1606	0.0024
10	0.4240	0.0061	0.1797	0.0052
11	0.4136	0.0024	0.1711	0.0020
12	0.40758	0.00078	0.16612	0.00063
13	0.4128	0.0025	0.1704	0.0021
14	0.4123	0.0010	0.16997	0.00087
15	0.40171	0.00046	0.16137	0.00034
16	0.40471	0.00053	0.16379	0.00043
17	0.3614	0.0053	0.1306	0.0038
18	0.376	0.011	0.1413	0.0084
19	0.3968	0.0082	0.1574	0.0065
20	0.3946	0.0069	0.1558	0.0055
21	0.4013	0.0057	0.1611	0.0046
23	0.4140	0.0044	0.1714	0.0036
24	0.382	0.016	0.146	0.012
26	0.3892	0.0067	0.1515	0.0053
27	0.2797	0.0070	0.0782	0.0039
28	0.4091	0.0021	0.1673	0.0017
29	0.3831	0.0039	0.1467	0.0030
30	0.4045	0.0018	0.1636	0.0015
31	0.3975	0.0052	0.1581	0.0041
32	0.35282	0.00099	0.12448	0.00070
33	0.41178	0.00072	0.16956	0.00059
34	0.3763	0.0019	0.1416	0.0014
35	0.3818	0.0010	0.1457	0.0010
36	0.4116	0.0025	0.1693	0.0020
37	0.4140	0.0055	0.1714	0.0045
38	0.4180	0.0041	0.1748	0.0034
39	0.3952	0.0018	0.1562	0.0014
40	0.36237	0.00152	0.1313	0.0011
41	0.4101	0.0075	0.1682	0.0062
42	0.38858	0.00068	0.15099	0.00053
43	0.4004	0.0043	0.1603	0.0034
44	0.4133	0.0014	0.1708	0.0012
45	0.3867	0.0052	0.1495	0.0041
46	0.3713	0.0031	0.1379	0.0023
All	**0.394**	**0.028**	**0.156**	**0.021**

Table 7.6: Average values of the absolute and downside risk aversion coefficients and risk preference functions by farm size

	Size of farms			
Item	**Small**	**Medium**	**Large**	**All farms**
Absolute	0.398	0.403	0.380	0.394
Downside	0.159	0.163	0.146	0.156
θ	-0.281	-0.484	-0.661	-0.453
λ	0.587	0.558	0.511	0.556

The predicted values of the technical inefficiency effects, U_{it}, are used to estimate the technical efficiencies of individual farmers. The annual averages and ranges of estimated technical efficiencies are presented in Table 7.7. The average technical efficiency estimates of individual farmers using this joint estimation approach are presented in Appendix 7.2. The mean technical efficiency is 0.88 with a range of 0.40. Sample households were most likely less efficient in 1996 (a drought year) than in other years, but the mean and maximum efficiency estimates are similar across all years. The minimum efficiencies vary considerably, however, from 0.58 in 1995 (another drought year) to 0.79 in 1993.

The frequency distribution table of the technical efficiencies for individual years is given in Table 7.8. On average, most of the farmers have technical efficiency levels of more than 0.80 for all years. From the table, it can be seen that the distribution of the levels of technical efficiency of farmers were more dispersed in 1996. About 20 per cent of the farmers had technical efficiencies between 0.71 and 0.80.

Table 7.7: Annual estimates of technical efficiency

Year	Mean	Minimum	Maximum
1990	0.89	0.62	0.97
1991	0.88	0.77	0.98
1992	0.90	0.74	0.96
1993	0.89	0.79	0.97
1994	0.88	0.76	0.97
1995	0.88	0.58	0.97
1996	0.85	0.59	0.95
1997	0.88	0.71	0.96
All years	0.88	0.58	0.98

Table 7.8: Relative frequency distribution of farmers in different technical efficiency intervals

	Percentage of farmers (%)				
Year	**0.51-0.60**	**0.61-0.70**	**0.71-0.80**	**0.81-0.90**	**0.91-1.00**
1990		2.27	15.91	22.73	59.09
1991			11.36	38.64	50.00
1992			9.09	31.82	59.09
1993			2.27	54.55	43.18
1994			4.55	56.82	38.64
1995	2.27		2.27	56.82	38.64
1996	2.27		20.45	56.82	20.45
1997			11.36	40.91	47.73

7.5 Concluding Comments

The primary objective of this chapter is to provide an empirical application of the estimation of production risk, risk preferences and technical efficiency using a joint estimation approach. The models used in this chapter are consistent with the specifications of Just and Pope (1978), Aigner, Lovell and Schmidt (1977), Battese, Rambaldi and Wan (1997) and Kumbhakar (2002).

The empirical application is based on an eight-year panel data set of 46 farmers in a rainfed lowland rice environment in the Philippines. Rice production in the rainfed rice environment is inherently risky, because of the highly variable rainfall and heterogeneous production environment. The study area is representative of the rainfed environment in the Philippines.

A stochastic frontier production function is estimated with flexible risk properties. The estimated effects of inputs on the output variance show that labour and fertiliser are risk-increasing while herbicide is risk-decreasing.

The technique proposed by Kumbhakar (2002) is used to estimate the risk preference functions of farmers. All estimates of the risk preference functions and risk aversion coefficients confirm that farmers were risk-averse. The results show further that the degree of risk aversion varied across farms and over time. The estimates of the risk preference functions imply that the risk component had a slightly greater influence on the input use decisions than the inefficiency component. Finally, the technical efficiencies of individual farmers were estimated and were shown to vary over time and across farmers.

Chapter 8

Summary, Implications and Conclusions

8.1 Introduction

This chapter summarises the major results, discusses their implications and draws some conclusions. The chapter is organised as follows. Section 8.2 presents a general overview of the thesis. The main findings are summarised and discussed in section 8.3. Section 8.4 discusses research implications. The chapter is concluded in section 8.5 where we summarise the study's main contributions to risk and efficiency analysis.

8.2 Overview of the Study

The study was initially motivated by the fact that rice is the staple food and principal crop of almost half of the world's population, especially in the humid and sub-humid regions of Asia. Rainfed lowland rice production offers substantial potential for increasing total rice production. However, low and unstable productivity, a high incidence of poverty and low resource use efficiency characterise most of the 48 million hectares of rainfed lowland rice environments, 90 per cent of which are in South and Southeast Asia. Because of the uncertainty and variability of rainfall, production environments are risky and farmers are discouraged from investing in input-intensive technologies because of persistent drought, excess water and weed problems. Modern rice technologies have so far had little impact on the rainfed agro-ecosystem because of the incapacity of farmers to cope with the adverse effects of drought and submergence.

The themes of risk and technical efficiency have not been adequately studied in rainfed rice environments, with most research being focused on irrigated rice environments. While the conceptual and theoretical advances of the past couple of decades are applicable in both environments, there are few empirical applications in rainfed rice environments. Thus, a more comprehensive and up-to-date study on the nature of risk and technical inefficiency in rainfed rice production is warranted. A careful delineation of rice production based on the risk profile and technical efficiencies of farmers is needed to target technology developments and policy interventions.

The central theme of this study is to investigate the nature of production risk and technical inefficiency in rainfed rice environments. Specifically, this study examines the nature of production risk using a heteroscedastic production function, evaluates the technical efficiency levels of rainfed rice farmers using a stochastic frontier production model, and jointly estimates the risk preferences, production risk and technical efficiency of farmers using a generalised stochastic frontier production model.

In order to attain the objectives stated above, some preliminary investigations were undertaken to highlight the research problems, examine the nature of the data set and identify adequate analytical methods for the study. The investigation is covered in Chapters 2, 3 and 4 of this study.

A review of the importance of, and issues surrounding, the rainfed rice environment is presented in Chapter 2. The role of rainfed rice, in terms of area and yield, is examined and the importance of rainfed rice in the Philippine economy is discussed. Issues and empirical evidence is presented on the constraints to production using the yield-gap approach. A critique of the yield-gap approach is also presented and used to justify conducting this study.

This study uses an eight-year panel data set collected by IRRI as part of research activities undertaken by the Rainfed Lowland Rice Research Consortium. A farm survey was conducted to gather information on the resource base of farmers, rice crop management, including the amount of inputs and output, and general characteristics of farm households residing in four *barangays* within the Municipality of Victoria, Province of Tarlac, Philippines. In Chapter 3, the survey area is described and a descriptive analysis is presented of its socio-economic and environmental characteristics. The major agricultural production activities and the sources of household income are also discussed.

Theoretical and conceptual considerations in the estimation of risk and efficiency are presented in Chapter 4. The first section introduces the basic concepts of production technology and the properties of the production function. This is followed by a discussion of the concepts, modelling issues and approaches in risk analysis and efficiency measurement. The analytical approaches discussed are parametric and non-parametric methods, with the discussion of parametric methods given emphasis. Salient features of the stochastic frontier production model are considered including a discussion of the estimation using panel data models, explaining inefficiency and estimating stochastic frontier models with flexible properties.

As a result of the preliminary investigation and discussions of the theoretical aspects pertaining to the analysis of risk and efficiency, three different approaches were selected for the current study. An econometric approach involving the use of a heteroscedastic production function was selected for examining production risk. A stochastic production frontier approach was chosen for analysing technical inefficiency. A generalised stochastic production frontier model was selected to estimate the risk preferences, production risk and technical efficiency of rainfed rice farmers.

In Chapter 5 we analyse production risk using the heteroscedastic production function approach developed by Just and Pope (1978, 1979). This specification of the model allows the examination of the differential impacts of inputs on the mean output and the variance of output. In this framework, the residuals of the regression model were recovered and used to investigate the marginal effects of inputs on production risk. Quadratic mean and variance functions are specified. Farm-level data on total area, fertiliser, herbicide, labour and a time trend are used in the estimation of the model. The main focus of this specification was to allow inputs to be either risk-increasing or risk-decreasing, independently of the mean output. The elasticities of mean output and variance of output are estimated. Alternative specifications of the mean function, namely, the Cobb-Douglas and translog models, facilitate a comparison of the elasticities obtained from the quadratic production function.

The analysis of technical inefficiency in a stochastic frontier production framework is considered in Chapter 6. The first part of the chapter reviews some efficiency studies on rice farming. Then, the stochastic frontier production function incorporating a model for technical inefficiency effects is estimated. A quadratic functional form is used for the specification of the stochastic frontier production function. Four inputs—area, fertiliser, herbicide and labour—are considered in the production function. A time trend variable is also included to account for technical change. In addition, a dummy variable is employed to indicate the incidence of the use of herbicide. The technical inefficiency model used in this study assumes that the technical inefficiency effects are a function of several characteristics of the farm operators, such as age and educational attainment, ratio of adults in the farm households and income from non-farm activities. Year dummy variables are also included in the inefficiency model. The technical efficiencies of individual farmers over eight years are estimated.

In Chapter 7, the methodology of Kumbhakar (2002) is used to re-examine production risk and technical efficiency and the results are presented. The approach accounts for production risk, risk preferences and technical inefficiency simultaneously. An algebraic expression of the risk preference function is derived, without having to assume an explicit form of the utility function and a specific distribution on the error term representing production risk. In this section, the effects of inputs on the variance of output are re-examined by taking into account the attitudes of individual farmers. Likewise, estimates of technical efficiency are also considered. Accordingly, individual estimates of the risk preferences of farmers are calculated.

The main findings of the above empirical analyses are discussed below.

8.3 Summary of Results

Analysis of production risk using the heteroscedastic production function revealed the following main findings.

Tests for the presence of homoscedasticity provide substantial evidence that the variance of the error term in the output function varies with changes in input levels, and, accordingly, indicate that output risk is significant in the production of rainfed rice. Therefore, the quadratic production model is estimated using generalised least-squares regression to account for the presence of heteroscedasticity in the values of output.

Area, fertiliser and labour inputs have significant positive effects on the mean output of rice. As expected, area has the largest effect on the mean output, followed by labour and fertiliser. Although its coefficient has the expected positive sign, herbicide is found not to affect mean output significantly.

The estimate of returns to scale using the quadratic function indicates that there are slightly increasing returns to scale, but constant returns to scale at mean input levels could not be rejected at usual levels of significance.

The estimated elasticities from the quadratic models are comparable to the estimates obtained using the Cobb-Douglas and translog model specifications.

Results of tests of hypotheses on the risk structure of the production technology indicate that there are significant marginal effects of inputs on output risk. Some inputs increased the level of risk while others reduced it. As expected, fertiliser and labour significantly and positively affected the variance of output, indicating that they were risk-increasing inputs. Although the empirical results indicate that herbicide was a risk-reducing input, its coefficient was not statistically significant. These results imply that a risk-averse rice farmer would use fewer risk-increasing inputs and more risk-reducing inputs than risk-neutral farmers.

The estimated variance model predicts that an expansion in the scale of operation leads to a substantial increase in total output risk. Therefore, diversification may be a possible risk-management strategy for risk-averse rainfed rice farmers.

The estimated average annual technical change for the mean and the variance functions are 5.6 per cent and 12 per cent, respectively. These estimates imply that the mean output and variance of output increased over the eight-year period. However, the effect of time in the variance function was not significant, as supported by the test of hypotheses on the effect of time on total output risk.

The findings in this analysis support the arguments put forward in earlier literature that major inputs of production significantly affect both the mean and the variance of output. By using farm-level data for a panel of farmers, we have confirmed that risk is an important element that needs careful attention in rainfed rice environments.

The findings from the application of a stochastic frontier production function model reveal a number of features of the performance of farmers in the rainfed rice environments. The tests of the specification of the stochastic production models indicate that the rice production system in the rainfed rice environment cannot be represented adequately by first-order flexible functional forms.

A test of hypotheses on the parameters associated with the variance of the technical inefficiency effects in the stochastic frontiers reveals that technical inefficiency effects are a significant component of the total variability of rice outputs in rainfed rice environments. These results indicate that the traditional production functions that do not account for technical inefficiencies are inadequate for modelling the rainfed rice production system.

The estimates of elasticities of output with respect to area, fertiliser and labour lie within the bounds reported in previous studies. The elasticity of output with respect to area planted to rice was between 0.415 and 0.510, at the mean input values. The fertiliser output elasticity was estimated to range between 0.182 and 0.323, while labour output elasticity was between 0.210 and 0.387. These results imply that area planted to rice, labour and fertiliser are important factors of production in the rainfed rice environment. The herbicide output elasticity was found to be relatively small and not significant.

A mean technical efficiency of 79 per cent was achieved by rainfed rice farmers in the study area, showing the scope for increasing rice production by 21 per cent with the present technology. A significant variation was observed in the mean level of technical efficiency across farmers over the eight-year period, with a minimum value of 11 per cent and a maximum value of more than 95 per cent. Likewise, the mean level of technical efficiency also varied among small, medium and large farms.

Several characteristics of farm operators, such as age and educational attainment, ratio of adults in the farm households and income from non-farm activities, were found to have significant effects on the technical inefficiency of rice production in the rainfed lowland environment.

The results of this modelling exercise indicate there is still scope for improving rice production in the rainfed rice environment. They also reveal an important implication in terms of the methods for estimating technical efficiency. The measurement of technical efficiency should consider the effects of random shocks in the production system. For example, it was revealed that production was least efficient in 1996 and most efficient in 1992. The year 1996 was recorded to be a drought year while 1992 was a good year. Therefore, attention should be given to the effects of random shocks in the estimation of technical efficiencies.

Accounting for technology risk in the estimation of technical efficiency is addressed in the generalised stochastic frontier production model. The simultaneous estimation of production risk, risk preferences and technical efficiency revealed the following findings.

First, output elasticity estimates of inputs are consistent with those estimates obtained from the heteroscedastic production function approach and the stochastic frontier production function approach. All inputs have positive effects on the mean output. After taking into account the attitudes of farmers, area, fertiliser and labour were found to be risk-increasing inputs, while herbicide was a risk-reducing input.

Second, all estimates of the risk preference functions and risk aversion coefficients confirmed that rainfed rice farmers are risk-averse. The degree of risk aversion varied across farms and over time. Estimates of the risk preference functions imply that the risk component had a slightly greater influence on input-use decisions than the inefficiency component. Furthermore, the results also reveal that farmers were downside risk-averse, which implies that farmers generally avoided situations that offered potentially substantial gains but which also left them vulnerable to losses below some critical level.

Third, higher estimates of mean technical efficiency estimates were obtained using the joint estimation approach. The average technical efficiency was 88 per cent over the eight-year period compared with 79 per cent using the stochastic frontier modelling approach. These estimates take into account the effects of the technology risk and the risk preferences of farmers.

The results of the last modelling exercise emphasise the importance of examining risk and efficiency in a joint analytical framework rather than using individual analytical frameworks. The results indicate conclusively that risk and inefficiency are significant in rainfed rice environments and, therefore, need careful attention by research managers and policy makers. The results obtained in this study should help agricultural policy makers formulate better strategies and programs for the improvement of the rainfed rice industry.

There is still scope for improving the productivity of rice in these environments. Increases in yields can come from technologies that shift the production frontier or that improve the efficient use of the current technology. Although efforts have been made to address the issue of shifting the production frontier in rainfed rice environments, it appears from the results of this study that rainfed rice farmers could also increase rice output through more efficient use of the current technology.

8.4 Research Implications

Understanding risk and technical inefficiency in rainfed rice environments is a complex process. The conclusions drawn from this study should be viewed with caution because the approach and data used are subject to some limitations. Some of the limitations and research implications are discussed in this section.

The first limitation relates to the data used. The data used in this study were collected from a typical rainfed lowland rice environment where rainfall and water availability are both seasonal and highly variable, and soil conditions are highly heterogeneous. The data on rainfall and other weather variables were limited. Because of the aggregation of data to the farm level, information about the heterogeneity in soil types and land types was not captured. Consideration of these factors in future studies may lead to better understanding of the true nature of risk and inefficiency in these environments. In addition, data from other locations or sites should be included in future analyses. Also, information on other crops was limited; therefore, an examination of a multi-output farming system to analyse diversification strategies was not possible.

Another limitation is the use of the heteroscedastic production function approach in analysing the risky production processes. The specification of the model was based on the additive heteroscedastic error structure that restricts the estimation of other functional forms, such as Cobb-Douglas and translog models. A re-evaluation of this model using non-linear estimation is suggested; however, convergence might be a potential problem.

In addition, a model that would incorporate pest and disease management should be given consideration. In our empirical analysis, no variable to account for pesticide infestation was included in the model because of the limitations of the data and inconsistent results.

The inclusion of a pesticide input variable resulted in a negative coefficient, which is misleading. More pesticide is used when the incidence of pests is high, so it is the negative effect of pest incidence on rice output that this coefficient is most likely reflecting and not the negative effect of pesticide on rice output. A more appropriate specification would be an index of infestation by pests and diseases and a quantity of pesticides variable. Nevertheless, the effectiveness of the application of pesticide is also dependent on some variables such as the timing and rate of application that would ultimately determine the effects on total production. Therefore, variables such as timing and rate of application and the degree of pest infestation should be included in the model specification.

Moreover, very limited information about irrigation precludes us from capturing the effects of irrigation water management. Although, the study area is under a rainfed environment, it is mentioned in Chapter 3 that 29 per cent of farmers owned an irrigation pump. These pumps were used for supplementary irrigation when rainfall was not adequate. However, incomplete data prevented us from taking into account the supplementary water management practices as a risk-management coping strategy.

A comprehensive assessment of risk and inefficiency is important in order to have a full understanding of the nature of production risk and inefficiency in rainfed rice environments. Risk, by definition, is a phenomenon that is out of the control of farmers while inefficiency is something that is controlled by farmers. For example, weather is a form of risk and affects farmers equally, and the way farmers cope and adjust to different weather conditions affects inefficiency. Because risk is an important element in the production process in rainfed rice environments, farmers adopt risk-management strategies that lessen the impact of risk. Although it was not investigated in this thesis, a good example of a risk-management strategy is diversification. Evidence exists that varietal diversification is used to reduce risk in rainfed areas (Pandey, Singh and Villano 1999, 2000; Singh, Pandey and Villano 2000). Likewise, agronomic manipulation can reduce the yield risk associated with stress conditions such as drought, floods and pests. For example, improved nutrient management may help reduce risk by making plants more tolerant of stress caused by drought, as well as by helping them to recover faster when the stress level is relieved (Wade et al. 1999). In addition, options may exist for reducing risk by manipulating the timing, placement and quantities of inputs. In effect, farmers who have similar exposure to risk can make different adjustments and decisions that ultimately affect their levels of efficiency. A careful delineation of risk and inefficiency in a more rigorous manner would help us better target technology and policy interventions.

While it is established in this thesis and other studies that most inputs are risk-increasing, an in-depth analysis of the effects of uncertainty on input use in a dynamic context is another important area for further research. Instead of committing all inputs at the beginning of the cropping season, inputs are used sequentially, with farmers revising the level of input used depending on crop conditions and their expectations regarding stochastic variables such as prices and weather. Analysis of the dynamic adjustment of input use would provide a better picture of the risk management strategies of farmers.

Decomposition of input adjustments for stochastic technologies under the state-contingent approach proposed by Chambers and Quiggin (2000, 2001) would provide a different view of analysing production under uncertainty. In this scenario, the use of inputs and levels of production of producers are analysed for different "states of nature". The crucial characteristic of production under uncertainty is that a specific input may yield different responses in different states of nature. According to Chambers and Quiggin (2000), some inputs may influence production in some or all states of nature (inputs are completely non-state specific). Some inputs may influence production in only one state of nature (state-specific input) and some inputs may be allocated between different states of nature (state-allocable inputs). An example of a non-state specific input is the use of fertiliser in rice production. If the uncertain event is the weather during the growing season, the two possible outcomes are production in state 1 and production in state 2.[1] The concept of non-joint inputs means that even if one is willing to sacrifice some of the output in one state of nature it is not possible to influence the yield in the other state of nature. Yield in state 1 is completely independent of yield in state 2 and only depends on the amount of fertiliser applied (Rasmussen 2003). A state-specific input is defined as an input that influences production in only one state of nature. An example of these inputs is a chemical (herbicide or pesticide) that is only effective under certain weather conditions. An input can also be state-allocable in that it can affect output in two or more states of

[1] Examples of different states are too much rainfall (state 1) and too little rainfall (state 2).

nature. For example, labour can be used to build a dam that prevents flooding if there is too much rainfall, or to improve the irrigation system that prevents drought if rainfall is too little.[2] Analysis of production using the state-contingent approach would provide a better understanding of how farmers allocate inputs in different states of nature. This method was not employed in this thesis because of the limitations of the data set.

Parallel to analysing technical inefficiency in a risky environment, an analysis of productivity growth when output is risky should also be given due consideration. A possible methodology is the generalisation and extension of the methodology proposed by Buccola (2002).

No empirical estimation of allocative efficiency is conducted in this study. The main intention is to evaluate the relationship between inputs and output. Although, it was mentioned in Chapter 7 that an error term is appended to the first-order condition associated with the maximisation of the expected utility of profit, which, in effect, captures the allocative inefficiency. However, no thorough examination of allocative efficiency of farmers was conducted. Further studies in this area would give a better picture of the real performance of the rice sector in the rainfed environments.

8.5 Concluding Comments and Contributions of the Study

We conclude this thesis by summarising its contributions in the literature. Despite the shortcomings and limitations of the data set, the main contributions of this study are summarised into the following areas:

First, this study provides a farm-level analysis of a production system in a rainfed rice environment. The results obtained from a micro-economic analysis of a rice production system in the rainfed rice environment using farm-level panel data enhance our knowledge of the complexity and heterogeneity of these environments. The results confirm that production risk and technical inefficiency are important factors that should be given consideration in terms of technology and policy development and dissemination.

[2] This example is based on Chambers and Quiggin (2000, p. 38).

Second, this study makes a contribution to the study of technical efficiency in agriculture. It uses standard and generalised stochastic frontier production models in the estimation of the technical efficiency of rice farmers. Most efficiency studies of rice farming are based on the use of a standard stochastic frontier production approach only, but this study also uses a stochastic frontier production function with flexible risk properties. In addition, technical efficiency is computed by taking into account production risk and the risk preferences of farmers.

Third, this study makes a contribution to the study of production risk in agriculture. The application of a Just-Pope heteroscedastic production function to farm-level panel data confirms the riskiness of the production technology in rainfed rice environments. The results reinforce those obtained in previous studies of rice farming.

Fourth, this study makes a contribution to the study of risk attitudes of rice farmers. Risk preferences of farmers are estimated using a generalised method that is not dependent on the specific form of utility functions. The results confirm that rainfed rice farmers are risk-averse.

Finally, the results obtained in this study should help research managers, policy makers and extension agents in developing strategies to improve the living conditions of poor farmers in rainfed rice environments.

Appendices

Appendix 5.1: Ordinary least squares estimates of the parameters of the mean function using the quadratic model

Variable	Parameter	Coefficient	Standard Error
Constant	α_0	1.31**	0.56
Area	α_1	-0.10	0.75
Fertiliser	α_2	0.0285 **	0.0054
Herbicide	α_3	0.006	0.015
Labour	α_4	0.8	1.3
Year	α_5	-0.55 **	0.23
$(\text{Area})^2$	α_{11}	-0.92	0.72
(Area) (Fertiliser)	α_{12}	-0.0039	0.0036
(Area) (Herbicide)	α_{13}	0.0342 **	0.0092
(Area) (Labour)	α_{14}	-1.57**	0.70
(Area) (Year)	α_{15}	0.24**	0.11
$(\text{Fertiliser})^2$	α_{22}	-0.000010	0.000012
(Fertiliser) (Herbicide)	α_{23}	-0.000040	0.000067
(Fertiliser) (Labour)	α_{24}	0.0110**	0.0042
(Fertiliser) (Year)	α_{25}	-0.00184*	0.00091
$(\text{Herbicide})^2$	α_{33}	-0.00053**	0.00019
(Herbicide) (Labour)	α_{34}	0.014	0.010
(Herbicide) (Year)	α_{35}	-0.0010	0.0020
$(\text{Labour})^2$	α_{44}	-0.8	1.2
(Labour) (Year)	α_{45}	-0.03	0.17
$(\text{Year})^2$	α_{55}	0.112**	0.047

** and * denote significance at one and five per cent levels, respectively.

Appendix 5.2: Ordinary least squares estimates of the parameters of the mean function using the traditional Cobb-Douglas model

Variable	Parameter	Coefficient	Standard Error
Constant	α_0	-1.57*	0.27
Area	α_1	0.359**	0.064
Fertiliser	α_2	0.191**	0.039
Herbicide	α_3	0.014	0.021
Labour	α_4	0.442	0.070
Year	α_5	0.0121	0.0089
Herbicide Dummy	φ_1	0.050	0.057

** and * denote significance at one and five per cent levels, respectively.

Appendix 5.3: Ordinary least squares estimates of the parameters of the mean function using the traditional translog model

Variable	Parameter	Coefficient	Standard Error
Constant	α_0	1.494**	0.063
Area	α_1	0.479**	0.072
Fertiliser	α_2	0.204**	0.044
Herbicide	α_3	0.275**	0.072
Labour	α_4	0.042	0.030
Year	α_5	0.0096	0.0088
$(\text{Area})^2$	α_{11}	-0.47	0.27
(Area) (Fertiliser)	α_{12}	0.06	0.16
(Area) (Herbicide)	α_{13}	0.73**	0.23
(Area) (Labour)	α_{14}	-0.034	0.050
(Area) (Year)	α_{15}	0.012	0.029
$(\text{Fertiliser})^2$	α_{22}	0.198**	0.066
(Fertiliser) (Herbicide)	α_{23}	-0.38**	0.15
(Fertiliser) (Labour)	α_{24}	0.016	0.039
(Fertiliser) (Year)	α_{25}	-0.039	0.021
$(\text{Herbicide})^2$	α_{33}	-0.59	0.33
(Herbicide) (Labour)	α_{34}	0.021	0.059
(Herbicide) (Year)	α_{35}	0.016	0.033
$(\text{Labour})^2$	α_{44}	-0.002	0.029
(Labour) (Year)	α_{45}	0.0157**	0.0077
$(\text{Year})^2$	α_{55}	0.0094	0.0083
Herbicide Dummy	φ_1	0.086	0.067

** denotes significance at one per cent level.

Appendix 6.1: Predicted technical efficiencies of rainfed rice farmers in Tarlac using the Cobb-Douglas stochastic frontier production model

Farm	1990	1991	1992	1993	1994	1995	1996	1997	All
1	0.85	0.78	0.91	0.80	0.75	0.60	0.47	0.85	0.75
2	0.84	0.86	0.92	0.91	0.89	0.89	0.76	0.91	0.87
3	0.84	0.79	0.88	0.78	0.58	0.85	0.44	0.87	0.76
4	0.90	0.76	0.95	0.90	0.84	0.81	0.73	0.81	0.84
5	0.88	0.84	0.91	0.89	0.75	0.82	0.74	0.85	0.83
6	0.91	0.81	0.92	0.80	0.80	0.84	0.61	0.79	0.81
7	0.91	0.92	0.93	0.92	0.85	0.85	0.74	0.90	0.88
8	0.89	0.88	0.85	0.85	0.82	0.75	0.53	0.85	0.80
9	0.85	0.88	0.92	0.84	0.81	0.76	0.78	0.88	0.84
10	0.81	0.77	0.91	0.89	0.57	0.87	0.66	0.85	0.79
11	0.51	0.51	0.82	0.82	0.57	0.82	0.43	0.80	0.66
12	0.91	0.85	0.90	0.94	0.74	0.91	0.85	0.91	0.88
13	0.86	0.72	0.90	0.75	0.62	0.77	0.73	0.85	0.77
14	0.78	0.71	0.90	0.87	0.83	0.82	0.85	0.86	0.83
15	0.85	0.82	0.84	0.86	0.80	0.84	0.34	0.67	0.75
16	0.67	0.89	0.92	0.89	0.89	0.89	0.86	0.89	0.86
17	0.81	0.46	0.92	0.92	0.92	0.91	0.58	0.88	0.80
18	0.90	0.87	0.93	0.89	0.84	0.86	0.76	0.90	0.87
19	0.91	0.92	0.93	0.59	0.85	0.90	0.40	0.93	0.80
20	0.88	0.89	0.93	0.88	0.85	0.83	0.73	0.87	0.86
21	0.76	0.56	0.93	0.66	0.78	0.90	0.83	0.79	0.78
23	0.90	0.82	0.93	0.90	0.61	0.66	0.58	0.81	0.78
24	0.64	0.73	0.91	0.54	0.78	0.83	0.46	0.81	0.71
26	0.84	0.79	0.92	0.85	0.45	0.81	0.50	0.50	0.71
27	0.87	0.90	0.93	0.91	0.60	0.77	0.73	0.91	0.83
28	0.84	0.72	0.91	0.77	0.86	0.87	0.74	0.88	0.82
29	0.68	0.87	0.92	0.84	0.71	0.88	0.61	0.88	0.80
30	0.91	0.92	0.94	0.89	0.87	0.84	0.83	0.89	0.89
31	0.83	0.70	0.88	0.91	0.59	0.39	0.65	0.86	0.73
32	0.79	0.82	0.85	0.84	0.78	0.80	0.62	0.14	0.70
33	0.94	0.76	0.93	0.81	0.87	0.90	0.47	0.94	0.83
34	0.54	0.81	0.92	0.85	0.74	0.60	0.69	0.94	0.76
35	0.87	0.82	0.90	0.87	0.89	0.88	0.61	0.90	0.84
36	0.39	0.40	0.71	0.72	0.38	0.64	0.48	0.59	0.54
37	0.90	0.90	0.92	0.88	0.69	0.81	0.81	0.90	0.85
38	0.53	0.76	0.87	0.75	0.68	0.77	0.56	0.88	0.72
39	0.87	0.72	0.91	0.72	0.39	0.97	0.64	0.89	0.76
40	0.92	0.91	0.95	0.92	0.82	0.87	0.71	0.85	0.87
41	0.91	0.85	0.92	0.91	0.69	0.90	0.81	0.94	0.86
42	0.66	0.51	0.86	0.85	0.89	0.86	0.59	0.74	0.74
43	0.71	0.61	0.85	0.77	0.68	0.73	0.48	0.84	0.71
44	0.87	0.91	0.93	0.89	0.71	0.91	0.73	0.92	0.86
45	0.92	0.89	0.92	0.83	0.70	0.79	0.69	0.87	0.83
46	0.45	0.40	0.86	0.76	0.82	0.91	0.78	0.91	0.74
All Farmers	0.80	0.77	0.90	0.83	0.74	0.81	0.65	0.83	0.79

Appendix 6.2: Predicted technical efficiencies of rainfed rice farmers in Tarlac using the translog stochastic frontier production model

Farm	1990	1991	1992	1993	1994	1995	1996	1997	All
1	0.76	0.81	0.91	0.78	0.77	0.57	0.44	0.82	0.73
2	0.68	0.86	0.93	0.94	0.89	0.91	0.70	0.91	0.85
3	0.69	0.71	0.88	0.79	0.55	0.84	0.40	0.84	0.71
4	0.88	0.77	0.96	0.92	0.88	0.83	0.80	0.76	0.85
5	0.76	0.86	0.93	0.91	0.75	0.81	0.75	0.85	0.83
6	0.91	0.89	0.93	0.80	0.80	0.84	0.64	0.77	0.82
7	0.84	0.92	0.94	0.93	0.85	0.86	0.72	0.92	0.87
8	0.85	0.90	0.87	0.90	0.87	0.75	0.61	0.87	0.83
9	0.79	0.90	0.93	0.88	0.83	0.78	0.76	0.88	0.84
10	0.67	0.76	0.93	0.92	0.61	0.90	0.74	0.91	0.80
11	0.45	0.53	0.82	0.86	0.62	0.83	0.41	0.78	0.66
12	0.90	0.90	0.92	0.94	0.83	0.91	0.84	0.92	0.89
13	0.84	0.77	0.93	0.82	0.64	0.80	0.75	0.84	0.80
14	0.65	0.70	0.92	0.91	0.86	0.86	0.85	0.84	0.82
15	0.65	0.79	0.83	0.87	0.79	0.80	0.31	0.59	0.70
16	0.58	0.91	0.87	0.91	0.90	0.89	0.90	0.87	0.85
17	0.69	0.53	0.93	0.94	0.93	0.93	0.54	0.84	0.79
18	0.82	0.87	0.94	0.90	0.88	0.88	0.73	0.90	0.86
19	0.84	0.93	0.94	0.58	0.87	0.91	0.43	0.93	0.80
20	0.81	0.91	0.93	0.88	0.87	0.86	0.72	0.89	0.86
21	0.56	0.51	0.94	0.67	0.76	0.92	0.83	0.75	0.74
23	0.88	0.86	0.95	0.94	0.63	0.76	0.63	0.82	0.81
24	0.43	0.63	0.90	0.48	0.76	0.84	0.45	0.84	0.67
26	0.69	0.77	0.94	0.85	0.46	0.85	0.48	0.53	0.70
27	0.65	0.88	0.93	0.92	0.57	0.79	0.70	0.91	0.79
28	0.72	0.75	0.93	0.79	0.86	0.87	0.73	0.85	0.81
29	0.47	0.89	0.93	0.82	0.71	0.86	0.55	0.88	0.76
30	0.86	0.92	0.95	0.91	0.88	0.88	0.83	0.88	0.89
31	0.79	0.74	0.94	0.93	0.59	0.66	0.63	0.86	0.77
32	0.87	0.86	0.85	0.85	0.79	0.79	0.56	0.13	0.71
33	0.93	0.80	0.95	0.87	0.90	0.91	0.45	0.94	0.84
34	0.39	0.81	0.94	0.90	0.79	0.60	0.58	0.95	0.74
35	0.82	0.85	0.92	0.91	0.89	0.84	0.67	0.91	0.85
36	0.38	0.66	0.85	0.57	0.57	0.63	0.57	0.61	0.60
37	0.85	0.92	0.94	0.90	0.72	0.84	0.81	0.90	0.86
38	0.49	0.82	0.90	0.77	0.71	0.78	0.59	0.86	0.74
39	0.80	0.67	0.93	0.74	0.38	0.93	0.58	0.86	0.74
40	0.87	0.94	0.94	0.91	0.84	0.87	0.68	0.82	0.86
41	0.86	0.84	0.93	0.92	0.72	0.91	0.78	0.93	0.86
42	0.62	0.60	0.92	0.89	0.90	0.89	0.52	0.75	0.76
43	0.58	0.63	0.86	0.82	0.74	0.80	0.46	0.81	0.71
44	0.84	0.93	0.95	0.90	0.71	0.89	0.71	0.92	0.86
45	0.90	0.91	0.94	0.87	0.71	0.84	0.67	0.84	0.83
46	0.38	0.41	0.89	0.80	0.83	0.93	0.84	0.91	0.75
All Farmers	0.72	0.79	0.92	0.85	0.76	0.83	0.64	0.83	0.79

Appendix 6.3: Predicted technical efficiencies of rainfed rice farmers in Tarlac using the quadratic stochastic frontier production model

Farm	1990	1991	1992	1993	1994	1995	1996	1997	All
1	0.94	0.84	0.96	0.78	0.72	0.64	0.47	0.90	0.78
2	0.95	0.95	0.98	0.98	0.97	0.96	0.87	0.97	0.95
3	0.95	0.91	0.97	0.72	0.60	0.90	0.50	0.93	0.81
4	0.91	0.80	0.94	0.86	0.78	0.82	0.69	0.84	0.83
5	0.95	0.90	0.97	0.92	0.76	0.84	0.77	0.95	0.88
6	0.72	0.44	0.87	0.49	0.39	0.54	0.31	0.78	0.57
7	0.94	0.91	0.96	0.90	0.76	0.89	0.78	0.93	0.88
8	0.94	0.88	0.94	0.87	0.81	0.76	0.61	0.92	0.84
9	0.95	0.92	0.97	0.88	0.81	0.80	0.76	0.93	0.88
10	0.94	0.88	0.98	0.94	0.66	0.94	0.79	0.97	0.89
11	0.75	0.65	0.88	0.77	0.56	0.81	0.45	0.86	0.72
12	0.63	0.50	0.84	0.56	0.33	0.56	0.38	0.74	0.57
13	0.88	0.75	0.93	0.76	0.57	0.75	0.60	0.87	0.76
14	0.93	0.84	0.95	0.85	0.76	0.81	0.73	0.87	0.84
15	0.69	0.53	0.84	0.50	0.36	0.54	0.11	0.66	0.53
16	0.77	0.71	0.92	0.65	0.59	0.70	0.46	0.78	0.70
17	0.94	0.63	0.98	0.98	0.98	0.98	0.82	0.96	0.91
18	0.98	0.96	0.99	0.96	0.93	0.93	0.81	0.99	0.94
19	0.97	0.96	0.98	0.59	0.88	0.95	0.50	0.99	0.85
20	0.97	0.96	0.98	0.92	0.90	0.86	0.75	0.97	0.91
21	0.91	0.76	0.97	0.65	0.73	0.96	0.87	0.90	0.84
23	0.92	0.84	0.95	0.90	0.63	0.77	0.65	0.88	0.82
24	0.93	0.94	0.98	0.80	0.91	0.95	0.67	0.96	0.89
26	0.94	0.87	0.97	0.88	0.55	0.86	0.59	0.77	0.80
27	0.95	0.96	0.98	0.95	0.60	0.83	0.70	0.96	0.87
28	0.88	0.77	0.94	0.75	0.76	0.82	0.64	0.88	0.80
29	0.88	0.89	0.97	0.78	0.63	0.84	0.58	0.94	0.82
30	0.92	0.90	0.96	0.86	0.81	0.85	0.58	0.82	0.84
31	0.90	0.78	0.91	0.90	0.61	0.74	0.61	0.91	0.79
32	0.82	0.79	0.83	0.55	0.38	0.54	0.32	0.38	0.57
33	0.87	0.70	0.90	0.74	0.63	0.78	0.36	0.86	0.73
34	0.75	0.70	0.90	0.77	0.56	0.59	0.41	0.91	0.70
35	0.92	0.86	0.94	0.70	0.81	0.73	0.39	0.82	0.77
36	0.72	0.55	0.87	0.66	0.37	0.70	0.50	0.79	0.65
37	0.97	0.92	0.96	0.88	0.67	0.86	0.83	0.95	0.88
38	0.84	0.79	0.92	0.79	0.71	0.80	0.57	0.93	0.79
39	0.89	0.73	0.92	0.70	0.45	0.89	0.53	0.88	0.75
40	0.91	0.86	0.95	0.84	0.64	0.77	0.44	0.82	0.78
41	0.98	0.90	0.98	0.93	0.70	0.73	0.49	0.85	0.82
42	0.78	0.59	0.87	0.66	0.48	0.62	0.33	0.77	0.63
43	0.89	0.75	0.94	0.79	0.74	0.82	0.49	0.90	0.79
44	0.90	0.87	0.94	0.80	0.60	0.85	0.58	0.90	0.81
45	0.95	0.91	0.96	0.83	0.64	0.84	0.63	0.92	0.83
46	0.83	0.66	0.92	0.75	0.81	0.92	0.67	0.94	0.81
All Farmers	0.88	0.80	0.94	0.79	0.67	0.80	0.58	0.87	0.79

Appendix 7.1: Derivation of the risk preference functions

Following Kumbhakar (2002, p.21), the derivation of the risk preference functions using the additive model is outlined below. The subscripts are dropped for notational convenience.

Let $U(\Pi)$ be continuous and differentiable. Write $U(\Pi)$ as

$$U(\mu_\pi + g(X,\beta)V - g(X,\beta)U) \tag{A1}$$

where:

$$\mu_\pi = f(X,\alpha) - W_i \cdot X_i - C \tag{A2}$$

Taking a Taylor series expansion of $U'(\Pi)$ at $V = U = 0$, gives:

$$\begin{aligned} U'(\Pi) = {} & U'(\mu_\pi) + U''(\mu_\pi)\cdot g(X,\beta)\times[V-U] + \tfrac{1}{2}U'''(\mu_\pi).g^2(X,\beta) \\ & \times[V^2 - 2VU + U^2] + \textit{higher order terms} \end{aligned} \tag{A3}$$

The $E[U'(\Pi)V]$ can be expressed as:

$$\begin{aligned} E[U'(\Pi)V] = {} & U''(\mu_\pi)\cdot g(X,\beta) + \tfrac{1}{2}U'''(\mu_\pi).g^2(X,\beta)(-2\cdot a) \\ & + \textit{higher order terms} \end{aligned} \tag{A4}$$

$$\begin{aligned} E[U'(\Pi)U] = {} & U'(\mu_\pi)\cdot a - U''(\mu_\pi)\times g(X,\beta)\cdot E(U^2) \\ & + \tfrac{1}{2}U'''(\mu_\pi).g^2(X,\beta)\times[a + E(U^3)] + \textit{higher order terms} \end{aligned} \tag{A5}$$

and

$$\begin{aligned} E[U'(\Pi)] = {} & U'(\mu_\pi) + U''(\mu_\pi)\cdot g(X,\beta)\cdot a + \tfrac{1}{2}U'''(\mu_\pi).g^2(X,\beta) \\ & \cdot[1 + E(U^2)] + \textit{higher order terms} \end{aligned} \tag{A6}$$

Using the above results and assuming $U \sim i.i.d.N(0,\sigma_U^2), U \geq 0$ and $V \sim i.i.d.N(0,1)$ and symmetric, we get:

$$\theta = \frac{E[U'(\Pi)V]}{E[U'(\Pi)]} \tag{A7}$$

$$= (U''(\mu_\pi)\cdot g(X,\beta) - U'''(\mu_\pi)\cdot g^2(X,\beta)\cdot a)/(U'(\mu_\pi) - U''(\mu_\pi)\times g(X,\beta)\cdot a$$
$$+0.5U'''(\mu_\pi)\cdot g^2(X,\beta)\cdot[1+b^2+a^2])$$

$$= \frac{-AR.g(X_i;\beta) - DR.g^2(X_i;\beta).a}{1 + AR.g(X_i;\beta)a + \frac{1}{2}DR.g^2(X_i;\beta).(1+b^2+a^2)}$$

$$\lambda = \frac{E[U'(\Pi)U]}{E[U'(\Pi)]} \tag{A8}$$

$$= \frac{a + AR.g(X_i;\hat{\beta})(b^2+a^2) + \frac{1}{2}DR.g^2(X_i;\hat{\beta}).[a + c + 3ab^2 + a^3]}{1 + AR.g(X_i;\hat{\beta}).a + \frac{1}{2}DR.g^2(X_i;\hat{\beta}).(1+b^2+a^2)}$$

where

$$E(U_i) = a = \sqrt{2/\pi\sigma_u}\,; \tag{A9}$$

$$Var(U_i) = b^2 = \frac{\pi - 2}{\pi}\sigma_u^2;\text{ and} \tag{A10}$$

$$E\{(U_i - a)^3\} = c = \sqrt{2/\pi}(4/\pi - 1)\sigma_u^3. \tag{A11}$$

$$AR = \frac{-U''(\Pi)}{U'(\Pi)}\text{ and } DR = \frac{-U'''(\Pi)}{U'(\Pi)}. \tag{A12}$$

Appendix 7.2: Predicted technical efficiencies of rainfed rice farmers in Tarlac using the quadratic stochastic frontier production model with flexible risk properties

Farmer	1990	1991	1992	1993	1994	1995	1996	1997	All Years
1	0.86	0.82	0.84	0.79	0.81	0.69	0.65	0.85	0.79
2	0.86	0.91	0.93	0.97	0.96	0.95	0.91	0.96	0.93
3	0.88	0.89	0.87	0.78	0.72	0.90	0.68	0.90	0.83
4	0.81	0.72	0.85	0.81	0.79	0.78	0.77	0.75	0.78
5	0.88	0.86	0.88	0.90	0.82	0.83	0.85	0.90	0.87
6	0.59	0.47	0.58	0.50	0.54	0.54	0.50	0.61	0.54
7	0.86	0.88	0.87	0.88	0.83	0.90	0.88	0.90	0.87
8	0.86	0.83	0.74	0.84	0.83	0.75	0.73	0.85	0.80
9	0.88	0.90	0.90	0.87	0.86	0.81	0.86	0.89	0.87
10	0.85	0.84	0.92	0.92	0.74	0.92	0.85	0.94	0.87
11	0.49	0.53	0.55	0.71	0.62	0.76	0.60	0.74	0.63
12	0.46	0.43	0.45	0.46	0.37	0.42	0.49	0.56	0.46
13	0.76	0.69	0.77	0.74	0.70	0.74	0.74	0.79	0.74
14	0.85	0.81	0.84	0.84	0.82	0.81	0.81	0.79	0.82
15	0.49	0.47	0.45	0.42	0.44	0.44	0.36	0.43	0.44
16	0.53	0.63	0.65	0.58	0.62	0.62	0.58	0.61	0.60
17	0.84	0.66	0.92	0.97	0.97	0.97	0.90	0.94	0.90
18	0.96	0.94	0.96	0.94	0.93	0.93	0.90	0.98	0.94
19	0.92	0.95	0.93	0.67	0.91	0.95	0.65	0.98	0.87
20	0.92	0.93	0.94	0.90	0.92	0.86	0.84	0.94	0.91
21	0.76	0.73	0.92	0.69	0.80	0.95	0.91	0.82	0.82
23	0.83	0.78	0.85	0.87	0.70	0.73	0.75	0.78	0.79
24	0.81	0.90	0.95	0.80	0.92	0.94	0.80	0.94	0.88
26	0.84	0.81	0.91	0.85		0.85	0.70	0.68	0.81
27	0.90	0.95	0.95	0.95	0.73	0.89	0.83	0.95	0.89
28	0.72	0.67	0.79	0.71	0.77	0.77	0.72	0.78	0.74
29	0.72	0.84	0.89	0.74	0.69	0.81	0.71	0.90	0.79
30	0.83	0.86	0.87	0.83	0.83	0.82	0.66	0.69	0.80
31	0.76	0.69	0.71	0.87	0.69	0.68	0.72	0.83	0.74
32	0.68	0.72	0.42	0.47	0.45	0.45	0.50	0.31	0.50
33	0.76	0.60	0.68	0.67	0.64	0.72	0.52	0.75	0.67
34	0.54	0.65	0.69	0.74	0.66	0.57	0.61	0.86	0.67
35	0.81	0.81	0.79	0.64	0.82	0.67	0.55	0.69	0.72
36	0.47	0.44	0.52	0.58	0.42	0.63	0.62	0.61	0.54
37	0.94	0.88	0.87	0.85	0.74	0.84	0.88	0.92	0.87
38	0.61	0.71	0.70	0.76	0.76	0.77	0.70	0.88	0.74
39	0.74	0.65	0.73	0.65	0.57	0.86	0.66	0.78	0.71
40	0.81	0.82	0.83	0.83	0.72	0.77	0.65	0.72	0.77
41	0.95	0.89	0.95	0.93	0.81	0.70	0.66	0.75	0.83
42	0.56	0.50	0.53	0.58	0.51	0.53	0.50	0.58	0.54
43	0.71	0.68	0.74	0.76	0.77	0.79	0.64	0.81	0.74
44	0.77	0.82	0.82	0.75	0.65	0.80	0.69	0.83	0.77
45	0.91	0.89	0.88	0.82	0.74	0.84	0.78	0.87	0.84
46	0.59	0.58	0.69	0.72	0.83	0.89	0.75	0.88	0.74
All Farms	0.76	0.75	0.78	0.76	0.73	0.77	0.70	0.79	0.76

References

Abedullah (1998), *Risk, Information, and Fertiliser Use in Rainfed Lowland Rice Areas of Tarlac, Philippines*, Unpublished PhD Thesis, University of the Philippines at Los Baños, Laguna.

Abedullah and Pandey, S. (2004), 'Risk and Fertilizer Use in the Rainfed Rice Ecosystem of Tarlac, Philippines', *Journal of Agricultural and Applied Economics* 36, 241-250.

Afriat, S.N. (1972), 'Efficiency Estimation of Production Functions', *International Economic Review* 38, 203-220.

Ahmad, M. and Bravo-Ureta, B.E. (1996), 'Technical Efficiency Measures for Dairy Farms Using Panel Data: A Comparison of Alternative Model Specifications', *Journal of Productivity Analysis* 7, 399-415.

Ahmad, M., Rafiq, M. and Ali, A. (1999), 'An Analysis of Technical Efficiency of Rice Farmers in Pakistani Punjab', *Bangladesh Journal of Agricultural Economics* 22, 79-86.

Aigner, D.J. and Chu, S.F. (1968), 'On Estimating the Industry Production Function', *American Economic Review* 58, 826-839.

Aigner, D., Lovell, C.A.K. and Schmidt, P. (1977), 'Formulation and Estimation of Stochastic Frontier Production Function Models', *Journal of Econometrics* 6, 21-37.

Ajibefun, I.A., Battese, G.E. and Daramola, A.G. (2002), 'Determinants of Technical Efficiency in Smallholder Food Crop Farming: Application of Stochastic Frontier Production Function', *Quarterly Journal of International Agriculture* 41, 225-240.

Ali, A.I. and Seiford, L.M. (1993), 'The Mathematical Programming Approach to Efficiency Analysis', in Fried, H.O., Lovell, C.A.K. and Schmidt, S.S. (eds), *The*

Measurement of Productive Efficiency: Techniques and Applications, Oxford University Press, New York, 120-159.

Ali, M. and Flinn, J.C. (1989), 'Profit Efficiency among Basmati Rice Producers in Pakistan Punjab', *American Journal of Agricultural Economics* 71, 303-310.

Anderson, J.R. (1974), 'Risk Efficiency in the Interpretation of Agricultural Production Research', *Review of Marketing and Agricultural Economics* 42, 131-184.

Anderson, J.R. (1995), 'Confronting Uncertainty in Rainfed Rice Farming: Research Challenges', in *Fragile Lives in Fragile Ecosystems*, Proceedings of the International Rice Research Conference, International Rice Research Institute, Los Baños, Laguna, 101-108.

Anderson, J.R. and Dillon, J.L. (1992), *Risk in Dryland Farming Systems*, Food and Agriculture Organization of the United Nations, Rome.

Anderson, J.R. and Griffiths, W.E. (1981), 'Production Risk and Input Use: Pastoral Zone of Eastern Australia', *Australian Journal of Agricultural Economics* 25, 149-159.

Anderson, J.R. and Griffiths, W.E. (1982), 'Production Risk and Efficient Allocation of Resources', *Australian Journal of Agricultural Economics* 26, 226-232.

Anderson, J.R. and Hamal, K.B. (1983), 'Risk and Rice Technology in Nepal', *Indian Journal of Agricultural Economics* 38, 217-222.

Anderson, J.R. and Hazell, P.B.R. (1989), *Variability in Grain Yields: Implications for Agricultural Research and Policy in Developing Countries*, International Food Policy Research Institute, Johns Hopkins University Press, Baltimore.

Anderson, J.R. and Hazell, P.B.R. (1994), 'Risk Considerations in the Design and Transfer of Agricultural Technology', in Anderson, J.R. (ed.), *Agricultural Technology: Policy Issues for the International Community*, CAB International, Wallingford, 321-342.

Anderson, J.R, Dillon, J.L. and Hardaker, J.B. (1977), *Agricultural Decision Analysis,* Iowa State University Press, Ames, Iowa.

Anderson, J.R., Dillon, J.L. and Hardaker, J.B. (1986), 'Farmers and Risk', in *Proceedings of the Nineteenth International Conference of Agricultural Economists*, Malaga, September 1985, Gower, Aldershot, 638-648.

Antle, J.M. (1983), 'Testing the Stochastic Structure of Production: A Flexible Moment-Based Approach', *Journal of Business and Economic Statistics* 1, 192-201.

Antle, J.M. (1988), *Pesticide Policy, Production Risk and Producer Welfare: An Econometric Approach to Applied Welfare Economics*, Resources for the Future, Washington, D.C.

Antle, J.M. and Crissman, C.C. (1990), 'Risk, Efficiency, and the Adoption of Modern Crop Varieties: Evidence from the Philippines', *Economic Development and Cultural Change* 38, 517-537.

Antle, J.M. and Goodger, W.J. (1984), 'Measuring Stochastic Technology: The Case of Tulare Milk Production', *American Journal of Agricultural Economics* 66, 342-350.

Arrow, K.J. (1953), *Le Rôle Des Valeurs Boursiers Pour La Repartition La Meillure Des Risques* 53, CNRS, Paris, Cahiers Du Seminair d'Economie.

Arrow, K.J. (1965), *Aspects of the Theory of Risk Bearing*, Yrjio Jahnssonian Saatio, Helsinki.

Arrow, K.J. (1971), *Essays in the Theory of Risk-Bearing*, North Holland, Amsterdam.

Asche, F. and Tveterås, R. (1999), 'Modeling Production Risk with a Two-Step Procedure', *Journal of Agricultural and Resource Economics* 24, 424-439.

Balisacan, A.M (1990), *Fertilizers and Fertilizer Policies in the Philippine Agricultural Development*, UPLB-APRP Monograph, 90-12, Los Baños, Laguna.

Banker, R.D., Charnes, A. and Cooper, W.W. (1984), 'Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis', *Management Science* 30, 1078-1092.

Baquet, A., Hambleton, R. and Jose, D. (1997), *Understanding Agricultural Risks: Production, Marketing, Financial, Legal and Human Resources*, U.S Department of Agriculture, Risk Management Agency, Washington, D.C.

Battese, G.E. (1992), 'Frontier Production Functions and Technical Efficiency: A Survey of Empirical Applications in Agricultural Economics', *Agricultural Economics* 7, 185-208.

Battese, G.E. (1997), 'A Note on the Estimation of Cobb-Douglas Production Functions when some Explanatory Variables Have Zero Values', *Journal of Agricultural Economics* 48, 250-252.

Battese, G.E. and Broca, S.S. (1997), 'Functional Forms of Stochastic Frontier Production Functions and Models for Technical Efficiency Effects: A Comparative Study for Wheat Farmers in Pakistan', *Journal of Productivity Analysis* 8, 269-280.

Battese, G.E. and Coelli, T.J. (1988), 'Prediction of Firm-Level Technical Efficiencies with a Generalised Frontier Production Function and Panel Data', *Journal of Econometrics* 38, 387-399.

Battese, G.E. and Coelli, T.J. (1992), 'Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India;' *Journal of Productivity Analysis* 3, 153-169.

Battese, G.E. and Coelli, T.J. (1993), 'A Stochastic Frontier Production Function Incorporating a Model for Technical Inefficiency Effects', *Working Papers in Econometrics and Applied Statistics* No. 69, Department of Econometrics, University of New England, Armidale.

Battese, G.E. and Coelli, T.J. (1995), 'A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data', *Empirical Economics* 20, 325-332.

Battese, G.E. and Corra, G.S. (1977), 'Estimation of a Production Frontier Model: With Application to the Pastoral Zone of Eastern Australia', *Australian Journal of Agricultural Economics* 21, 169-179.

Battese, G.E., Coelli, T.J. and Colby, T.C. (1989), 'Estimation of Frontier Production Functions and the Efficiencies of Indian Farms Using Panel Data from ICRISAT's Village Level Studies', *Journal of Quantitative Economics* 5, 327-348.

Battese, G.E., Rambaldi, A.N. and Wan, G.H. (1997), 'A Stochastic Frontier Production Functions with Flexible Risk Properties', *Journal of Productivity Analysis* 8, 269-280.

Bauer, P.W. (1990), 'Recent Developments in the Econometric Estimation of Frontiers', *Journal of Econometrics* 46, 39-56.

Bera, A.K. and Sharma, S.C. (1999), 'Estimating Production Uncertainty in Stochastic Frontier Production Function Models', *Journal of Productivity Analysis* 12, 187-210.

Bernoulli, D. (1738), 'Specimen Theoriae Novae de Mensura Sortis', *Commentarri Academiae Scietiarum Imprialis Petropolitanae, Tomus V*, pp. 175-92. Translated by Sommer, L. 1954, as 'Expositions of a New Theory on the Measurement of Risk', *Econometrica* 22, 23-26.

Binswanger, H.P. (1978), 'Risk Attitudes of Rural Households in Semi-Arid Tropical India', *American Journal of Agricultural Economics* 62, 396-407.

Binswanger, H.P. (1980), 'Attitude Towards Risk: Experimental Measurement in Rural India', *American Journal of Agricultural Economics* 62, 395-407.

Binswanger, H.P. (1981), 'Attitude Towards Risk: Theoretical Implications of an Experiment in Rural India', *Economic Journal* 91, 867-890.

Binswanger, H.P., Jodha, N.S. and Barah, B.C. (1980), *The Nature and Significance of Risk in the Semi-Arid Tropics*, Proceedings of the International Workshop on

Socioeconomic Constraints to Development of Semi-Arid Tropical Agriculture, ICRISAT, Hyderabad.

Blondaz, P., Gavoret, L. and Jourdain, D. (1991), *Regional Agro-Pesticide Index – Asia, Volume 1*, Third Edition, International Cooperation Centre in Agronomic Research for Development, Bangkok.

Buccola, S. (2002), 'Productivity Measurement when Output is Risky', Paper presented at the North American Productivity Workshop, Union College, Schenectady, N.Y.

Boussard, J.M. and Petit, M. (1967), Representation of Farmer's Behavior Under Uncertainty with Focus-Loss Constraint', *Journal of Farm Economics* 49, 869-880.

Bravo-Ureta, B.E. and Pinheiro, A.E. (1993), 'Efficiency Analysis of Developing Country Agriculture: A Review of the Frontier Function Literature', *Agricultural and Resource Economics Review* 22, 88-101.

Breusch, T. and Pagan, A. (1979), 'A Simple Test for Heteroscedasticity and Random Coefficient Variation', *Econometrica* 47, 1287-1294.

Byrnes, P., Färe, R., Grosskopf, S. and Kraft, S. (1987), 'Technical Efficiency and Size: The Case of Illinois Grain Farms', *European Review of Agricultural Economics* 14, 367-381.

Cancian, F. (1972), *Change and Uncertainty in a Peasant Economy*, Stanford University Press, Stanford.

Caudill, S.B. and Ford, J.M. (1993), 'Biases in Frontier Estimation Due to Heteroscedasticity', *Economics Letters* 41, 17-20.

Caudill, S.B., Ford, J.M. and Gropper, D.M. (1995), 'Frontier Estimation and Firm-Specific Inefficiency Measures in the Presence of Heteroscedasticity', *Journal of Business and Economic Statistics* 13, 105-111.

Chambers, R.G. (1988), *Applied Production Analysis: A Dual Approach.* Cambridge University Press, New York.

Chambers, R.G. and Quiggin, J. (1998), 'Cost Functions and Duality for Stochastic Technologies', *American Journal of Agricultural Economics* 80, 288-295.

Chambers, R.G. and Quiggin, J. (2000), *Uncertainty, Production, Choice and Agency: The State-Contingent Approach*, Cambridge University Press, Cambridge.

Chambers, R.G. and Quiggin, J. (2001), 'Decomposing Input Adjustments under Price and Production Uncertainty', *American Journal of Agricultural Economics* 83, 20-34.

Charnes, A., Cooper, W.W. and Rhodes, E. (1978), 'Measuring the Efficiency of Decision Making Units', *European Journal of Operational Research* 2, 429-444.

Chaudhury, R.C. (2000), 'Strategies for Bridging the Yield Gap in Rice: A Regional Perspective in Asia', *International Rice Commission Newsletter* 46, Food and Agriculture Organization of the United Nations, Rome.

Chavas, J.P. and Holt, T. (1996), 'Economic Behaviour under Uncertainty: A Joint-Analysis of Risk Preferences and Technology', *Review of Economics and Statistics* 73, 802-805.

Coelli, T.J. (1995), 'Recent Developments in Frontier Estimation and Efficiency Measurement', *Australian Journal of Agricultural Economics* 39, 219-245.

Coelli, T.J. (1996), 'A Guide to FRONTIER Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation', *CEPA Working Papers* No. 7/96, Department of Econometrics, University of New England, Armidale.

Coelli, T.J., Rahman, S. and Thirtle, C. (2002), 'Technical, Allocative, Cost and Scale Efficiencies in Bangladesh Rice Cultivation: A Non-Parametric Approach', *Journal of Agricultural Economics* 53, 607-626.

Coelli, T.J., Rao, D.S.P. and Battese, G.E. (1998), *An Introduction to Efficiency and Productivity Analysis*, Kluwer-Nijhoff, Boston.

Cruz, R.T. and Fabiosa, J.F. (1997), 'Drought Problems in Rainfed Lowland Rice in the Philippines', in Fukai, S., Cooper, M. and Salisbury, J. (eds), *Breeding Strategies for Rainfed Lowland Rice in Drought-Prone Environment,* ACIAR Proceedings 77, Australian Centre for International Agricultural Research, Canberra, 58-64.

David, C. and Balisacan, A. (1995), *Philippine Rice Supply and Demand: Prospects and Policy Implications*, Philippine Institute of Development Studies, Makati City.

Dawson, P.J. and Lingard, J. (1989), 'Measuring Farm Efficiency over Time on Philippine Rice Farms', *Journal of Agricultural Economics* 40, 168-177.

Dawson, P.J., Lingard, J. and Woodford, C.H. (1991), 'A Generalised Measure of Farm-Specific Technical Efficiency', *American Journal of Agricultural Economics* 73, 1098-1104.

Debreu, G. (1951), 'The Coefficient of Resource Utilisation', *Econometrica* 19, 273-92.

Debreu, G. (1959), *The Theory of Value*, Yale University Press, New Haven

Department of Agriculture (2002), *Ginintuang Masaganang Ani (GMA) Program – Rice*, (accessed: December 12, 2003), http://www.da.gov.ph/programs/.

Deprins, D. and Simar, L. (1989), 'Estimating Technical Inefficiencies with Corrections for Environmental Conditions with an Application to Railway Companies', *Annals of Public and Cooperative Economics* 60, 81-102.

Dev, U.K. and Hossain, M. (1995), 'Farmer's Education, Modern Technology and Technical Efficiency of Rice Growers', *Bangladesh Journal of Agricultural Economics* 18, 1-13.

Diamond, P.A. and Stiglitz, J.E. (1974), 'Increase in Risk and in Risk Aversion', *Journal of Economic Theory* 8, 337-360.

Dillon, J.L. and Anderson, J.R. (1971), 'Allocative Efficiency, Traditional Agriculture and Risk', *American Journal of Agricultural Economics* 53, 26-32.

Dillon, J.L. and Scandizzo, P.L. (1978), 'Risk Attitudes of Subsistence Farmers in Northeast Brazil: A Sampling Approach', *American Journal of Agricultural Economics* 60, 425-435.

Doll, J.P. and Orazem, F. (1984), *Production Economics: Theory with Applications*, Second Edition, Wiley, Singapore.

Duwayri, M., Tran, D.V. and Nguyen, V.N. (1998), *Reflections on Yield Gaps in Rice Production: How to Narrow the Gaps*, International Rice Commission, 98/7-12, Cairo.

Duwayri, M., Tran, D.V. and Nguyen, V.N. (2000), 'Reflections on Yield Gaps in Rice Production: How to Narrow the Gaps', in Papademetriou, M.K., Dent, F.J. and Herath, E.M. (eds), *Bridging the Rice Yield Gap in the Asia Pacific Region,* Food and Agriculture Organization of the United Nations – Regional Office for Asia and the Pacific, Bangkok, 26-46.

Eeckhoudt, L. and Gollier, C. (1995), *Risk Evaluation, Management and Sharing*, Harvester Wheatsheaf, Brighton.

Ekanayake, S.A.B. (1987), 'Location Specificity, Settler Type and Productive Efficiency: A Study of the Mahaweli Project in Sri Lanka', *Journal of Development Studies* 23, 509-521.

Erwidodo (1990), *Panel Data Analysis on Farm-Level Efficiency, Input Demand and Output Supply of Rice Farming in West Java, Indonesia,* Unpublished Ph.D. dissertation, Michigan State University, East Lansing.

Evenson, R.E., Herdt, R.W. and Hossain, M. (1996), *Rice Research in Asia: Progress and Priorities*, International Rice Research Institute and CAB International, Wallingford.

FAO (2000), 'The FAO Regional Expert Consultation on Bridging the Rice Yield Gap in the Asia and the Pacific Region', *International Rice Research Newsletter*, http://www.fao.org/docrep/X7174T/x7164t09.htm.

FAO (2001), Statistical Databases, (accessed 24 October 2002), http://apps.fao.org/.

Färe, R. and Grosskopf, S. (1994), *Cost and Revenue Constrained Production*, Bilkent University Lecture Series, Springer-Verlag, Berlin.

Färe, R., and Hunsaker, W. (1986), 'Notions of Efficiency and their Reference Sets', *Management Science* 32, 237-43.

Färe, R., Grabowski, R. and Grosskopf, S. (1985), 'Technical Efficiency of Philippine Agriculture', *Applied Economics* 17, 205-214.

Färe, R., Grosskopf, S. and Lovell, C.A.K. (1985), *The Measurement of Efficiency of Production*, Kluwer-Nijhoff, Boston.

Farrell, M.J. (1957), 'The Measurement of Productive Efficiency', *Journal of Royal Statistical Society, Series A* 120, 253-290.

Feder, G. (1980), 'Farm Size, Risk Aversion, and the Adoption of New Technology Under Uncertainty', *Oxford Economic Papers* 32, 263-283.

Feder, G., Just, R.E. and Zilberman, D. (1985), 'Adoption of Agricultural Innovations in Developing Countries: A Survey', *Economic Development and Cultural Change* 32, 225-298.

Flinn, J.C. and Hazell, P.B.R. (1988), 'Production Instability and Modern Rice Technology: A Philippine Case Study', *The Developing Economies* 26, 34-50.

Førsund, F.R., Lovell, C.A.K. and Schmidt, P. (1980), 'A Survey of Frontier Production Functions and of their Relationship to Efficiency Measurement', *Journal of Econometrics* 13, 5-25.

Francisco, E.M. and Anderson, J.R. (1972), 'Choice and Chance West of the Darling', *Australian Journal of Agricultural Economics* 16, 82-93.

Freund, R. (1956), 'The Introduction of Risk into a Programming Model', *Econometrica* 21, 253-263.

Friedman, M. and Savage, L.J. (1948), 'The Utility Analysis of Choice Involving Risk', *Journal of Political Economy* 56, 279-304.

Giannakas, K., Tran, K. and Tzouvelekas, V. (2003), 'On the Choice of Functional Form in Stochastic Frontier Modeling', *Empirical Economics* 28, 75-100.

Gomez, K.A. (1977), 'On-Farm Assessment of Yield Constraints: Methodological Problems', in *Constraints to High Yields in Asian Rice Farms: An Interim Report*, International Rice Research Institute, Los Baños, Laguna.

Gomez, K.A., Herdt, R.W., Barker, R. and De Datta, S.K. (1979), 'A Methodology of Identifying Constraints to High Rice Yields on Farmers' Fields', in *Farm-Level Constraints to High Yields in Asia: 1974-77*, International Rice Research Institute, Los Baños, Laguna, 27-48.

Gong, B. and Sickles, R. (1992), 'Finite Sample Evidence on the Performance of Stochastic Frontiers and Data Envelopment Analysis Using Panel Data', *Journal of Econometrics* 51, 259-284.

Gonzales, L. (1999), *The Global Rice Industry*, Philippine Technical Bulletin, Vol. 4, PhilRice, Munoz.

Gragasin, M., Maruyama, A. and Kikuchi, M. (2002), 'Irrigation, Farm Productivity and Irrigators' Association: A Comparative Study of Two Philippine Irrigation Systems', *Journal of Rural Economics Special Issue*, 345-349.

Greene, W.H. (1980), 'Maximum Likelihood Estimation of Econometric Frontier Functions', *Journal of Econometrics* 13, 27-56.

Greene, W.H. (1993) 'The Econometric Approach to Efficiency Analysis', in Fried, H.O., Lovell, C.A.K. and Schmidt, S.S. (eds), *The Measurement of Productive Efficiency: Techniques and Applications*, Oxford University Press, New York.

Greene, W.H. (1995), *LIMDEP (Version 7): User's Manual and Reference Guide*, Econometric Software Inc., New York.

Greenland, D.J. (1997), *The Sustainability of Rice Farming*, International Rice Research Institute and CAB International, Wallingford.

Griffiths, W.E. and Anderson, J.R. (1982), 'Using Time-Series and Cross-Section Data to Estimate a Production Function with Positive and Negative Marginal Risks', *Journal of the American Statistical Association* 77, 529-536.

Griffiths, W., Hill, R.C. and Judge, G.G. (1993), *Learning and Practicing Econometrics*, Wiley, New York.

Hadar, J. and Russell, W.R. (1969), 'Rules for Ordering Uncertain Prospects', *American Economic Review* 59, 25-34.

Hadri, K. (1999), 'Estimation of a Doubly Heteroscedastic Stochastic Frontier Cost Function', *Journal of Business and Economic Statistics* 17, 359-363.

Hadri, K., Guermat, C. and Whittaker, J. (2003), 'Estimation of Technical Inefficiency Effects Using Panel Data and Doubly Heteroscedastic Stochastic Production Frontiers', *Empirical Economics* 28, 203-222.

Hamal, K.B. and Anderson, J.R. (1982), 'A Note on Decreasing Absolute Risk Aversion Among Farmers in Nepal', *Australian Journal of Agricultural Economics* 26, 220-225.

Hanoch, G. and Levy, H. (1969), 'The Efficiency Analysis of Choices Involving Risk', *Review of Economic Studies* 36, 335-346.

Hardaker, J.B., Huirne, R.B.M. and Anderson, J.R. (1997), *Coping with Risk in Agriculture*, CAB International, Wallingford.

Harvey, A.C. (1976), 'Estimating Regression Models with Multiplicative Heteroscedasticity', *Econometrica* 44, 461-465.

Hazell, P.B.R. (1984), 'Sources of Increased Instability in Indian and U.S. Cereal Production', *American Journal of Agricultural Economics* 66, 302-311.

Hazell, P.B.R. and Norton, R.P. (1986), *Mathematical Programming for Economic Analysis in Agriculture*, Macmillan, New York.

Herdt, R.W. (1996), 'Summary, Conclusions and Implications – Chapter 23', in Evenson, R.E., Herdt, R.W. and Hossain, M. (eds), *Rice Research in Asia: Progress and Priorities*, International Rice Research Institute and CAB International, Wallingford, 393-406.

Herrero, I. and Pascoe, S. (2002), 'Estimation of Technical Efficiency: A Review of Some of the Stochastic Frontier and DEA Software', *Computers in Higher Education Review* Virtual Edition 15, http://www.economics.ltsn.ac.uk/cheer/ch15_1/dea.htm.

Heshmati, A. and Kumbhakar, S.C. (1994), 'Farm Heterogeneity and Technical Efficiency: Some Results from the Swedish Dairy Farms', *Journal of Productivity Analysis* 5, 45-61.

Heshmati, A., Kumbhakar, S.C. and Hjalmarsson, L. (1995), 'Efficiency of the Swedish Pork Industry: A Farm Level Study Using Rotating Panel Data, 1976-1988', *European Journal of Operational Research* 80, 519-533.

Hirshleifer, J. (1965), 'Investment Decisions Under Uncertainty: Choice-Theoretic Approaches', *Quarterly Journal of Economics* 79, 509-36.

Hirshleifer, J. (1966), 'Investment Decisions Under Uncertainty: Applications of the State-Theoretic Approach', *Quarterly Journal of Economics* 80, 52-77.

Hirshleifer, J. and Riley, J. (1992), *The Analytics of Uncertainty and Information*, Cambridge University Press, Cambridge.

Hossain, M. (1995), 'Sustaining Food Security for Fragile Environments in Asia: Achievements, Challenges, and Implications for Rice Research', in *Fragile Lives in Fragile Ecosystems, Proceedings of the International Rice Research Conference*, 13-17 February, International Rice Research Institute, Los Baños, Laguna, 3-24.

Hossain, M. (1997), 'Rice Supply and Demand in Asia: A Socio-Economic and Biophysical Analysis', in Teng, P.S., Kropff, M.J., Ten Berg, H.F.M., Dent, J.B., Lansigan, F.P. and Van Laar, H.H. (eds), *Applications of Systems Approaches at the Farm and Regional Levels*, Kluwer, Dordrecht, 263-280.

Hossain, M., Gascon, F.B. and Revilla, I.A. (1996), 'Constraints to Growth in Rice Production in the Philippines', in Evenson, R.E., Herdt, R.W. and Hossain, M. (eds), *Rice Research in Asia: Progress and Priorities*, International Rice Research Institute and CAB International, Wallingford, 239-250.

Huang, C.J. and Liu, J-T. (1994), 'Estimation of a Non-Neutral Stochastic Frontier Production Function', *Journal of Productivity Analysis* 4, 171-180.

Huke, R. and Huke, E. (1996), *Rice Area by Type of Culture: South, South East and East Asia. Revised and Updated Database*, International Rice Research Institute, Los Baños, Laguna.

Ingram, K.T. (1995), *Rainfed Lowland Rice: Agricultural Research for High-Risk Environments*, International Rice Research Institute, Los Baños, Laguna.

IRRI (1993), *1993-1995 IRRI Rice Almanac*, International Rice Research Institute, Los Baños, Laguna.

IRRI (1998), Medium-Term Plan, 1999-2001, International Rice Research Institute, Los Baños, Laguna.

IRRI (2000), *Sustaining Food Security beyond the Year 2000: A Global Partnership for Rice Research*, International Rice Research Institute, Los Baños, Laguna.

IRRI (2001) (updated 8 November 2001), *RiceWeb: A Compendium of Facts and Figures from the World of Rice*, http://www.riceweb.org/environment.htm.

IRRI (2003) (date accessed: June 2003), *World Rice Statistics*, http://www.irri.org/txtonly/science/ricestat/index.html

Jaenicke, E.C. and Larson, J.A. (2001), 'Production Risk Revisited in a Stochastic Frontier Framework: Evaluating Noise and Inefficiency in Cover Crop Systems', Selected paper at the American Agricultural Economics Association, Annual Meeting, Chicago, 5-8 August.

Janaiah, A. and Hossain, M. (2001), 'Environmental Consequences of Agricultural Intensification and their Impact on Sustainability: Insights from a Farm-Level Evaluation of Irrigated Rice Systems in Asia', Paper presented at the 2nd Asian Agricultural Congress, 24-27 April, Manila.

Jondrow, J., Lovell, C.A.K., Materov, I.S. and Schmidt, P. (1982), 'On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model', *Journal of Econometrics* 19, 233-238.

Just, R.E. and Pope, R.D. (2002), 'Past Progress and Future Opportunities for Agricultural Risk Research', in Just, R.E. and Pope R.D. (eds), *A Comprehensive Assessment of the Role of Risk in US Agriculture*, Kluwer Academic Publishers, Boston.

Just, R.E. (2003), 'Risk Research in Agricultural Economics: Opportunities and Challenges for the Next Twenty-Five Years', *Agricultural Systems* 75, 123-159.

Just, R.E. and Pope, R.D. (1978), 'Stochastic Specification of Production Functions and Economic Implications', *Journal of Econometrics* 7, 67-86.

Just, R.E. and Pope, R.D. (1979), 'Production Function Estimation and Related Risk Considerations', *American Journal of Agricultural Economics* 61, 249-257.

Kalirajan, K.P. (1981), 'An Econometric Analysis of Yield Variability in Paddy Production', *Canadian Journal of Agricultural Economics* 29, 283-294.

Kalirajan, K.P. (1984), 'Farm-Specific Technical Efficiencies and Development Policies', *Journal of Economic Studies* 11, 3-13.

Kalirajan, K.P. (1990), *Rice Production: An Econometric Analysis*, Aspect Publishing, London.

Kalirajan, K.P. (1991), 'The Importance of Efficient Use in the Adoption of Technology: A Macro Panel Data Analysis', *Journal of Productivity Analysis* 2, 113-126.

Kalirajan, K.P. and Flinn, J.C. (1983), 'The Measurement of Farm-Specific Technical Efficiency', *Pakistan Journal of Applied Economics* 2, 167-180.

Kalirajan, K. and Huysman, A. (1984), 'An Econometric Analysis of Production Risk Using Farm Level Panel Data in the Philippines', *Indian Journal of Agricultural Economics* 39, 614-629.

Kalirajan, K.P. and Shand, R.T. (1989), 'A Generalized Measure of Technical Efficiency', *Applied Economics* 21, 25-34.

Kalirajan, K.P. and Shand, R.T. (1994), *Economics in Disequilibrium*, Macmillan India, New Delhi.

Kennedy, J.O.S. (1986), *Dynamic Programming: Applications to Agriculture and Natural Resources*, Elsevier, Amsterdam.

Khush, G.S. (1995), 'Modern Varieties – Their Real Contribution to Food Supply and Equity', *Geojournal* 35, 275-284.

Kim, J.B. (1998), 'Testing for Heterogeneous Technology: A Rao's Score Test', *Journal of Quantitative Economics* 14, 59-79.

Knight, F.H. (1972), *Risk, Uncertainty and Profit,* Houghton Mifflin, Boston.

Kodde, D.A. and Palm, F.C. (1986), 'Wald Criteria for Jointly Testing Equality and Inequality Restrictions', *Econometrica* 54, 1243-1246.

Koopmans, T.C. (1951), 'An Analysis of Production as an Efficient Combination of Activities', in Koopmans, T.C. (ed.), *Activity Analysis of Production and Allocation*, Cowles Commission for Research in Economics, Monograph No. 3, Wiley, New York.

Kopp, R.J. and Smith, V.K. (1980), 'Frontier Production Function Estimates for Steam Electric Generation: A Comparative Analysis', *Southern Economic Journal* 46, 163–173.

Kumbhakar, S.C. (1990), 'Production Frontiers, Panel Data and Time-Varying Technical Inefficiency', *Journal of Econometrics* 46, 201-211.

Kumbhakar, S.C. (1993), 'Production Risk, Technical Efficiency, and Panel Data', *Economics Letters* 41, 11-16.

Kumbhakar, S.C. (2002), 'Specification and Estimation of Production Risk, Risk Preferences and Technical Efficiency', *American Journal of Agricultural Economics* 84, 8-22.

Kumbhakar, S.C. and Lovell, C.A. (2000), *Stochastic Frontier Analysis*, Cambridge University Press, New York.

Kumbhakar, S.C. and Tveterås, R. (2003), 'Risk Preferences, Production Risk and Firm Heterogeneity', *Scandinavian Journal of Economics* 105, 275-293.

Kumbhakar, S.C., Ghosh, S. and McGuckin, J.T. (1991), 'A Generalized Production Frontier Approach for Estimating Determinants of Inefficiency in U.S. Dairy Farms', *Journal of Business and Economic Statistics* 9, 279-286.

Larson, D.F. and Plessmann, F. (2002), 'Do Farmers Choose to be Inefficient? Evidence from Bicol, Philippines', *Working Paper in Agriculture, Land, Commodity Prices and Markets*, No. 2787, World Bank, Washington D.C.

Lee, Y.H. and Schmidt, P. (1993), 'A Production Frontier Model with Flexible Temporal Variation in Technical Inefficiency', in Fried, H.O., Lovell, C.A.K. and Schmidt, S.S. (eds), *The Measurement of Productive Efficiency: Techniques and Applications*, Oxford University Press, New York, 237-255.

Lin, W., Dean, G.W. and Moore, C.V. (1974), 'An Empirical Test of Utility vs. Profit Maximisation in Agricultural Production', *American Journal of Agricultural Economics* 56, 497-508.

Lingard, J., Castillo, L. and Jayasuriya, S. (1983), 'Comparative Efficiency of Rice Farms in Central Luzon, the Philippines', *Journal of Agricultural Economics* 34, 37–76.

Love, H.A. and Buccola, S.T. (1991), 'Joint Risk Preference-Technology Estimation with a Primal System', *American Journal of Agricultural Economics* 73, 765-774.

Love, H.A. and Buccola, S.T. (1999), 'Joint Risk Preference-Technology Estimation with a Primal System: Reply', *American Journal of Agricultural Economics* 81, 245-247.

Lovell, C.A.K. (1993), 'Production Frontiers and Productive Efficiency', in Fried, H.O., Lovell, C.A.K. and Schmidt, S.S. (eds), *The Measurement of Productive Efficiency: Techniques and Applications*, Oxford University Press, New York, 3-67.

Lovell, C.A.K. (1995), 'Econometric Efficiency Analysis: A Policy-Oriented Review', *European Journal of Operational Research* 80, 452-461.

Machina, M. (1987), 'Choice Under Uncertainty: Problems Solved and Unsolved', *Journal of Economic Perspectives* 1, 121-154.

Mackill, D.J., Coffman, W.R. and Garrity, D.P. (1996), *Rainfed Lowland Rice Improvement*, International Rice Research Institute, Los Baños, Laguna.

Maclean, J.L., Dawe, D.C., Hardy, B. and Hettel, G.P. (2002), *Rice Almanac: Source Book for the Most Important Economic Activity on Earth,* Third Edition, International Rice Research Institute, Los Baños, Laguna.

Markowitz, H. (1952), 'Portfolio Selection', *Journal of Finance* 7, 77-91.

Markowitz, H. (1959), *Portfolio Selection*, Wiley, New York.

McFadden, D. (1978), 'Cost, Revenue and Profit Functions', in Fuss M. and McFadden, D. (eds), *Production Economics: A Dual Approach to Theory and Applications*, Volume 1, North Holland, 19-35.

Meeusen, W. and van den Broeck, J. (1977), 'Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error', *International Economic Review* 18, 435-444.

Menezes, C., Geiss, C. and Tressler, J. (1980), 'Increasing Downside Risk', *American Economic Review* 70, 921-932.

Meyer, J. (2002), 'Expected Utility as a Paradigm for Decision Making in Agriculture?', in Just, R.E. and Pope, R.D. (eds), *A Comprehensive Assessment of the Role of Risk in US Agriculture*, Kluwer Academic Publishers, Boston, 3-20.

Moscardi, E.R. (1979), 'Methodology to Study Attitudes towards Risk: the Pueblo Project', in Valdés, A., Scobie, G. and Dillon, J. (eds), *Economics and the Design of Small-Farmer Technology*, Iowa State University Press, Ames.

Moscardi, E.R. and de Janvry, A. (1977), 'Attitudes Towards Risk among Peasants: An Econometric Approach', *American Journal of Agricultural Economics* 59, 710-716.

Moschini, G. and Hennessy, D. (2001), 'Uncertainty, Risk Aversion, and Risk Management for Agricultural Producers', in Gardner, B. and Rausser, G. (eds), *Handbook of Agricultural Economics, Volume 1*, Elsevier, Amsterdam, 88-153.

Musser, W.N. and Patrick, G.F. (2002), 'How Much Does Risk Really Matter in Agriculture?', in Just, R.E. and Pope, R.D. (eds), *A Comprehensive Assessment of the Role of Risk in US Agriculture*, Kluwer, Boston, 537-556.

Mythili, G. and Shanmugan, K.R. (2000), 'Technical Efficiency of Rice Growers in Tamil Nadu: A Study Based on Panel Data', *Indian Journal of Agricultural Economics* 55, 15.

Nelson, C.H. and Preckel, P.V. (1989), 'The Conditional Beta Distribution as a Stochastic Production Function', *American Journal of Agricultural Economics* 71, 370-378.

NSO (2002), *The Philippines Census 2000*, (accessed 9 October 2003), http://www.census.gov.ph/.

Ortiz, S. (1979), 'The Effect of Risk Aversion Strategies on Subsistence and Cash Crop Decisions', in Roumasset, J., Boussard, J. and Singh, I. (eds), *Risk, Uncertainty* *and Agricultural Development*, Agricultural Development Council, New York, 231-246.

Pal, S., Pandey, S. and Abedullah (2000), 'Growth and Variability in Agriculture Revisited: District-Level Evidence of Rice Production in Eastern India', in Pandey, S., Barah, B.C., Villano, R.A. and Pal, S. (eds) *Risk Analysis and Management in Rainfed Rice Systems*, Limited Proceedings of the NCAP/IRRI Workshop on Risk Analysis and Management in Rainfed Rice Systems, 21-23 September 1998, National Centre for Agricultural Economics and Policy Research, New Delhi, and International Rice Research Institute, Los Baños.

Pandey, S. (1997), 'Rainfed Lowland Rice Research: Challenges and Priorities for the 21st Century', in Fukai, S., Cooper, M. and Salisbury, J. (eds), *Breeding Strategies for Rainfed Lowland Rice in Drought-Prone Environments*, ACIAR Proceedings No. 77, Australian Centre for International Agricultural Research, Canberra, 1-12.

Pandey, S.P., Barah, B.C., Villano, R.A. and Pal, S. (eds) (2000), *Risk Analysis and Management in Rainfed Rice Systems*, Limited Proceedings of the NCAP/IRRI Workshop on Risk Analysis and Management in Rainfed Rice Systems, 21-23 September 1998, National Centre for Agricultural Economics and Policy Research, New Delhi, and International Rice Research Institute, Los Baños.

Pandey, S.P., Masicat, P., Velasco, L. and Villano, R.A. (1999), 'Risk Analysis of Rainfed Rice Production Systems in Tarlac, Central Luzon', *Experimental Agriculture* 35, 225-237.

Pandey, S., Singh, H.N. and Villano, R.A. (1999), 'Rainfed Rice and Risk-Coping Strategies: Some Micro-Economic Evidence from Eastern India', Paper presented at the Annual Meeting of the American Agricultural Economics Association, 8-11 August, Nashville.

Pandey, S., Singh, H.N. and Villano, R.A. (2000), 'Rainfed Rice and Risk-Coping Strategies: Some Microeconomic Evidence from Eastern Uttar Pradesh', in Pandey, S., Barah, B.C., Villano, R.A. and Pal, S. (eds), *Risk Analysis and*

Management in Rainfed Rice Systems, Limited Proceedings of the NCAP/IRRI Workshop on Risk Analysis and Management in Rainfed Rice Systems, 21-23 September 1998, National Centre for Agricultural and Policy Research, New Delhi, and International Rice Research Institute, Los Baños, 115-134.

Parikh, A. and Shah, K. (1994), 'Measurement of Technical Efficiency in the North West Frontier Province of Pakistan', *Journal of Agricultural Economics* 45, 132-138.

PhilRice-BAS (1995), *Provincial Rice Statistics*, PhilRice Communication Office, Philippine Rice Research Institute-Bureau of Agricultural Statistics, Muñoz.

Philrice-BAS (1998), *Rice Statistics Handbook, 1970-1997, A Collaborative Project of the Philippine Rice Research Institute and Bureau of Agricultural Statistics*, Department of Agriculture, Manila.

Pingali, P., Hossain, M. and Gerpacio, R.V. (1997), *Asian Rice Bowls: The Returning Crisis*, International Rice Research Institute and CAB International, Wallingford.

Pitt, M.M. and Lee, L.F. (1981), 'Measurement and Sources of Technical Efficiency in the Indonesian Weaving Industry', *Journal of Development Economics* 9, 43-64.

Pratt, J. (1964), 'Risk Aversion in the Small and in the Large', *Econometrica* 32, 122-136.

Quiggin, J. (1993), *Generalised Expected Utility Theory – The Rank Dependent Model*, Kluwer Academic Publishers, Boston.

Radner, R. (1968), 'Competitive Equilibrium under Uncertainty', *Econometrica* 36, 31-54.

Ramaswami, B. (1992), 'Production Risk and Optimal Input Decisions', *American Journal of Agricultural Economics* 74, 860-869.

Rasmussen, S. (2003), 'Criteria for Optimal Production Under Uncertainty. The State-Contingent Approach', *Australian Journal of Agricultural and Resource Economics* 47, 447-476.

Richmond, J. (1974), 'Estimating the Efficiency of Production', *International Economic Review* 15, 515-521.

Robison, L.J. and Barry, P.J. (1987), *The Competitive Firm's Response to Risk*, Macmillan Publishing Company, New York.

Rola, A. and Quintana-Alejandrino, J.T. (1993), 'Technical Efficiency of Philippine Rice Farmers in Irrigated, Rainfed Lowland and Upland Environments: A Frontier Production Function Analysis', *Philippine Journal of Crop Science* 18, 56-69.

Rosegrant, M.W. and Svendsen, M. (1993), 'Irrigation Investments and Management Policy for Asian Food Production Growth in the 1990s', *Food Policy* 18, 13-32.

Rosegrant, M., Agcaoili, M.C. and Perez, N. (1995), *Global Food Projections to 2020: Implications for Investment, Food, Agriculture and the Environment*, Discussion Paper No. 5, International Food Policy Research Institute, Washington, D.C.

Rosegrant, M.W. and Herdt, R.W. (1981), 'Simulating the Impacts of Credit Policy and Fertiliser Subsidy on Central Luzon Rice Farms, Philippines', *American Journal of Agricultural Economics* 63, 655-65.

Rosegrant, M.W. and Roumasset, J.A. (1985), 'The Effect of Fertilizer on Risk: A Heteroscedastic Production Function With Measurable Stochastic Inputs', *Australian Journal of Agricultural Economics* 29, 107-121.

Rothschild, M. and Stiglitz, J.E. (1970), 'Increasing Risk I: Definition', *Journal of Economic Theory* 2, 225-243.

Roumasset, J.A. (1976), *Rice and Risk: Decision-Making among Low-Income Farmers*, North-Holland, Amsterdam.

Roumasset, J.A. (1979), 'Unimportance of Risk for Technology Design and Agricultural Development Policy', in Valdés, A., Scobie, G.M. and Dillon, J.L. (eds), *Economics and the Design of Small Farmer Technology*. Iowa State University Press, Ames, 48-65.

Saha, A. (1993), 'Expo-Power Utility: A "Flexible" Form for Absolute and Relative Risk Aversion', *American Journal of Agricultural Economics* 75, 905-913.

Saha, A., Havenner, A. and Talpaz, H. (1997), 'Stochastic Production Function Estimation: Small Sample Properties of ML and FGLS', *Applied Economics* 29, 459-469.

Saha, A., Shumway, C.R. and Talpaz, H. (1994), 'Joint Estimation of Risk Preference Structure and Technology Using Expo-Power Utility', *American Journal of Agricultural Economics* 76, 173-184.

Sandmo, A. (1971), 'On the Theory of the Competitive Firm Under Price Uncertainty', *American Economic Review* 61, 65-73.

Sasmal, J. (1993), 'Considerations of Risk in the Production of High-Yielding Variety Paddy: A Generalized Stochastic Formulation for Production Function Estimation', *Indian Journal of Agricultural Economics* 48, 694-701.

Sattar, S.A. (2000), 'Bridging the Rice Yield Gap in Bangladesh', in Papademetriou, M.K., Dent, F.J. and Herath, E.M. (eds), *Bridging the Rice Yield Gap in the Asia-Pacific Region,* Food and Agriculture Organization of the United Nations Regional Office for Asia and the Pacific, Bangkok, 58-68.

Schmidt, P. (1976), 'On the Statistical Estimation of Parametric Frontier Production Functions', *Review of Economics and Statistics* 58, 238-239.

Schmidt, P. (1986), 'Frontier Production Functions', *Econometric Reviews* 4, 289-328.

Schmidt, P. and Sickles, R.C. (1984), 'Production Frontier and Panel Data', *Journal of Business and Economic Statistics* 2, 367-374.

Schmidt, P. and Wang, H.J. (2002), 'One-Step and Two-Step Estimation of the Effects of Exogenous Variables on Technical Efficiency Levels', *Journal of Productivity Analysis* 18, 129-144.

Schultz, T.W. (1975), 'The Value and Ability to Deal with Disequilibria', *Journal of Economic Literature* 13, 827-846.

Sebastian, L., Alviola, P.A. and Francisco, S.R. (2000), 'Bridging the Rice Yield Gap in the Philippines', in Papademetriou, M.K., Dent, F.J. and Herath, E.M. (eds), *Bridging the Rice Yield Gap in the Asia-Pacific Region*, Food and Agriculture Organization of the United Nations Regional Office for Asia and the Pacific, Bangkok, 122-134.

Seiford, L.M. and Thrall, R.M. (1990), 'Recent Developments in DEA: The Mathematical Approach to Frontier Analysis', *Journal of Econometrics* 46, 7-38.

Sena, V. (1999), 'Stochastic Frontier Estimation: A Review of the Software Options', *Journal of Applied Econometrics* 14, 579-586.

Seyoum, E.T., Battese, G.E. and Fleming, E.M. (1998), 'Technical Efficiency and Productivity of Maize Producers in Eastern Ethiopia: A Case Study of Farmers Within and Outside the Sasakawa-Global 2000 Project', *Agricultural Economics* 19, 341-348.

Shanmugam, K.R. (2000), 'Technical Efficiency of Rice Growers in Bihar', *Indian Journal of Applied Economics* 8, 377-389.

Siddiq, E.A. (2000), 'Bridging the Rice Yield Gap in India', in Papademetriou. M.K., Dent, F.J. and Herath, E.M. (eds), *Bridging the Rice Yield Gap in the Asia-Pacific Region*, Food and Agriculture Organization of the United Nations Regional Office for Asia and Pacific, Bangkok, 84-111.

Sillers, D.A. (1980), *Measuring Risk Preferences of Rice Farmers in Nueva Ecija, Philippines: An Experimental Approach*, PhD Dissertation, Yale University, New Haven.

Singh, H.N., Pandey, S. and Villano, R.A. (2000), 'Rainfed Rice, Risk and Technology Adoption: Microeconomic Evidence from Eastern India', in Toung, T.P, Kam. S.P., Wade, L., Pandey, S., Bouman, B.A.M. and Hardy, B. (eds), *Characterizing and Understanding Rainfed Environments*, International Rice Research Institute, Los Baños, Laguna, 323-338.

Singh, V.P., Toung, T.P. and Kam, S.P. (2000), 'Characterizing Rainfed Rice Environments: An Overview of the Biophysical Aspects", in Tuong, T.P., Kam, S.P., Wade, L., Pandey, S., Bouman, B.A.M. and Hardy, B. (eds), *Characterizing and Understanding Rainfed Environments*, International Rice Research Institute, Los Baños, Laguna, 3-32.

Smale, M., Hartell, J., Heisey, P.W. and Senauer, B. (1998), 'The Contribution of Genetic Resources and Diversity to Wheat Production in the Punjab of Pakistan', *American Journal of Agricultural Economics* 80, 482-493.

Smith, J. and Umali, G. (1985), 'Production Risk and Optimal Fertilizer Rates: An Application of the Random Coefficient Model', *International Rice Research Institute Research Paper Series*, 115-127.

Smith, J., Umali, G., Rosegrant, M.W. and Mandac, A.M. (1983), 'Risk and Fertilizer Use on Rainfed Rice in Bicol, Philippines', *Department of Agricultural Economics Paper* No. 83-25. International Rice Research Institute, Los Baños, Laguna.

Squires, D. and Tabor, S. (1991), 'Technical Efficiency and Future Production Gains in Indonesian Agriculture', *Developing Economies* 29, 258-270.

Stevenson, R.E. (1980), 'Likelihood Functions for Generalised Stochastic Frontier Estimation', *Journal of Econometrics* 13, 57-66.

Swamy, P.A.V.B. (1970), 'Efficient Inference in a Random Coefficient Regression Model', *Econometrica* 38, 311-323.

Talawar, S. (1996), *Local Soil Classification and Management Practices: Bibliographic Review*, Research Paper 2, Laboratory of Agricultural and Natural Resources Anthropology, University of Georgia, Athens, Georgia.

Taylor C.R. and Zacharias, T.P. (2002), 'Programming Methods for Risk-Efficient Choice', in Just, R.E. and Pope, R.D. (eds), *A Comprehensive Assessment on the Role of Risk in U.S. Agriculture*, Kluwer, Boston, 193-212.

Tian, W.M. (2000), 'Technical Efficiency of China's Grain Production', in Yang, Y.Z. and Tian, W.M. (eds), *China's Agriculture at the Crossroads*, Macmillan, Basingstoke, 148-165.

Tian, W.M. and Wan, G.H. (2000), 'Technical Efficiency and its Determinants in China's Grain Production', *Journal of Productivity Analysis* 13, 159-174.

Timmer, C.P. (1971), 'Using a Probabilistic Frontier Function to Measure Technical Efficiency', *Journal of Political Economy* 79, 401-405.

Tobin, J. (1958), 'Liquidity Preference as Behaviour Toward Risk', *Review of Economic Studies* 26, 65-86.

Traxler, G., Falck-Zepeda, J., Ortiz-Monasterio, R.J.I. and Sayre, K. (1995), 'Production Risk and the Evolution of Varietal Technology', *American Journal of Agricultural Economics* 77, 50-64.

Trewin, R., Weiguo, L., Erwidodo and Bahri, S. (1995), 'Analysis of Technical Efficiency Over Time of West Javanese Rice Farms', *Australian Journal of Agricultural Economics* 39, 143-163.

Tveretås, R. (1999), 'Production Risk and Productivity Growth: Some Findings for Norwegian Salmon Aquaculture', *Journal of Productivity Analysis* 12, 161-179.

Tveterås, R. (2000), 'Flexible Panel Data Models for Risky Production Technologies with an Application to Salmon Aquaculture', *Econometrics Reviews* 19, 367-389.

Umetsu, C., Lekprichakul, T. and Chakravorty (2003), 'Efficiency and Technical Change in the Philippines Rice Sector: A Malmquist Total Factor Productivity Analysis', *American Journal of Agricultural Economics* 85, 943-963.

Von Neuman, J. and Morgenstern, O. (1944), *Theory of Games and Economic Behavior*, Princeton University Press, Princeton.

Wade, L.J., McLaren, C.G., Quintana, L., Harnpichitivitaya, D., Rajatasereekul, S., Sarawgi, A.K., Kumar, A., Ahmed, H.U., Sarwoto, Singh, A.K., Rodriguez, R., Siopongco, J. and Sarkarung, S. (1999), 'Genotype by Environment Interaction across Diverse Rainfed Lowland Rice Environments', *Field Crops Research* 64, 35-50.

Walker, T.S. and Ryan, J.G. (1990), *Village and Household Economies in India's Semi-Arid Tropics,* Johns Hopkins University Press, Baltimore.

Wallace, T.D. and Hussain, A. (1969), 'The Use of Error Components Models in Combining Cross Section With Time Series Data', *Econometrica* 37, 55-68.

Wan, G.H. and Anderson, J.R. (1990), 'Estimating Risk Effects in Chinese Foodgrain Production', *Journal of Agricultural Economics* 41, 85-93.

Wan, G.H. and Battese, G.E. (1992), 'A Stochastic Frontier Production Function Incorporating Flexible Risk Properties', *Working Papers in Econometrics and Applied Statistics* No. 66, Department of Econometrics, University of New England, Armidale.

Widawsky, D.A. and O'Toole, J.C. (1996), 'Prioritising the Rice Research in India', in Evenson, R.E., Herdt, R.W. and Hossain, M. (eds), *Rice Research in Asia: Progress and Priorities*, International Rice Research Institute and CAB International, Wallingford.

Wik, M. and Holden, S.T. (1996), 'Risk in Peasant Adaptation: Do Peasants Behave According to Sandmo Model?', *Discussion Paper D-24/1996*, Department of Economics and Social Sciences, Agricultural University of Norway, http://www2.nlh.no/ios/publikasjoner/Fulltekst/D9624.pdf (accessed March 3, 2003).

Winsten, C.B. (1957), 'Discussion on Mr. Farrell's Paper', *Journal of the Royal Statistical Society Series A, General* 120, 282-284.

Xu, X. and Jeffrey, S.R. (1998), 'Efficiency and Technical Progress in Traditional and Modern Agriculture: Evidence from Rice Production in China', *Agricultural Economics* 18, 157-165.

Zeigler, R.S. (1999), 'The Rainfed Lowland Rice Research Consortium: A Multi-Institutional Approach for Sustainable Productivity Increases in Asian Rice-Based Systems', *Experimental Agriculture* 35, 115-125.

Zellner, A. and Revankar, N.S. (1969), 'Generalised Production Functions', *Review of Economic Studies* 36, 241-250.

Zhu, S., Ellinger, P.N. and Shumway, C.R. (1995), 'The Choice of Functional Form and Estimation of Banking Inefficiency', *Applied Economics Letters* 2, 185-191.

Zilberman, D. (2002), 'Economic Analysis of Behaviour Under Risk', http://are.berkeley.edu/~zilber/ Last updated: 18 Feb. 2003.