Supply Response of Natural Rubber Production in Thailand

Kittikorn Soontaranurak

A thesis submitted for the degree of
Doctor of Philosophy

University of Newcastle upon Tyne
School of Agriculture, Food and Rural Development

February 2011

Declaration

This thesis has been composed by myself and has not been submitted as part of any previous application for a degree. The work of which this is a record has been done by myself unless otherwise stated. All sources of information have been specifically acknowledged by means of referencing.

Kittikorn Soontaranurak

Acknowledgements

I wish to use this chance to thank sincerely several individuals and organizations for their invaluable assistance toward the completions of this thesis. I would like to acknowledge and express my gratitude to my supervisors, Dr John Lingard and Dr. Phil Dawson from the School of Agriculture, Food and Rural Development, University of Newcastle upon Tyne. Their valuable suggestions, comments and reviews are extremely meaningful for this study. Particularly, thanks go to Dr Phil Dawson, whom I have mainly worked with, for being committed and patience throughout the study. I would like to thank Dr Lionel Hubbard and Dr Alastair Bailey for serving as my examiners.

My sincere appreciation is extended to Prof. David Harvey for his useful advice. Many thanks go to staff and friends in the School of Agriculture, Food and Rural Development for support and many helpful suggestions throughout my PhD study.

Special thanks go to the Office of Agricultural Economics (OAE), Thailand, the Office of Rubber Replanting Aid Fund (ORRAF), Thailand, the Office of Songkhla Central Rubber Market, Thailand, the Economic and Social Data Service (ESDS), UK, and the International Rubber Study Group (IRSG) for their services to me over the months of data collection. Thanks also go to Supawadee Innupat, my friend who helped me to collect some data.

I am grateful to acknowledge the Royal Thai Government for the financial support, the Nakhon Si Thammarat Rajabhat University for allowing me to take study leave, and my colleagues for their help and support.

I would like to express my deepest appreciation and gratitude to my parents, brothers and sister for their deep understanding, support, encouragement, and patience. I would like to dedicate this achievement to them.

Abstract

In the Thai economy, natural rubber is a major export crop and the natural rubber sector is an important source of employment. A key issue in the analysis of natural rubber production is its supply response to economic incentives. There are several empirical studies of the supply response of natural rubber in Thailand, but knowledge gaps exist. First, since most apply Nerlovian models, their models have an inadequate dynamic structure. Second, ordinary least squares is generally applied to potentially non-stationary data, so the results may be spurious. Third, the results may be biased because many studies omitted important variables. Finally, there is no consideration of risk. It is essential to seek alternative explanations of what and how both price and non-price factors cause changes in natural rubber production using modern econometric approaches and contemporary data.

Economic theory implies that the supply of a perennial crop depends on own price, the prices of competitive crops, input prices, and non-price variables, and risk and uncertainty. The time series data on these variables are examined for unit roots. Most variables are non-stationary and Johansen's cointegration approach is used to estimate both output and acreage-yield models. We find that unique long-run relationships exist in both models. However, weak exogeneity tests show that the rubber price in both the output and acreage equations is weakly exogenous. We therefore reformulate the output and acreage equations by setting rubber price to be weakly exogenous. Output in the output model is now weakly exogenous and there is no long-run output relationship. Thus, an output supply response model appears inappropriate to explain the supply response of rubber production of Thailand. In the acreage response model, we find a unique long-run relationship between the planted area and the rubber and fertiliser price. Results indicate that the estimated long-run own price elasticity of rubber planted acreage is 2.16, which is higher than those in previous studies, while the elasticity of rubber planted acreage in response to a change in the replanting subsidy is estimated to be 0.65. The estimated short-run price elasticity of rubber planted acreage is very low at 0.03. We also find that there is a unique long-run relationship between yield, the fertiliser price, and rainfall, but non-normal residuals might affect statistical inference. The long-run elasticity of yield with respect to the fertiliser price is estimated to be -5.50 while own price has no effect on yield. Rainfall has a negative effect on yield. Impulse response analysis shows that a shock in the replanting subsidy leads to a continual increase in acreage, and this might imply instability of the model. A one standard error shock in the fertiliser price causes a decrease of 7% in the yield; this effect is permanent and yield takes around seven years to restore to long-run equilibrium.

Our estimates suggest that farmers in Thailand respond to price incentives. Low estimated short-run and high estimated long-run price elasticities of acreage response imply that rubber farmers only adjust planted area in the short run in response to a price change by a small amount, whereas they make substantial adjustments in the long run. Therefore, any form of pricing policy requires a long lead time to take effect. Since small increases in the price of rubber lead to large increases in the planted rubber acreage, if the government aims to increase rubber acreage, the rubber price should not be allowed to fall. The government should develop domestic markets particularly central rubber markets, encourage the establishment of farmer groups, stimulate more domestic demand, and co-operate with other rubber producing

countries to intervene in the world market. Moreover, the government can stimulate the expansion of acreage planted in the long run by increasing the replanting subsidy. In our yield response model, the policy implication is that a sufficient amount of good quality fertiliser at reasonable prices should be provided. Also, the government should support research and development into rubber cultivation and harvesting, particularly those on integrated plantation, and then disseminate this knowledge to farmers.

Table of Contents

List of Tables

List of Figures

Chapter 1 Introduction

In the Thai economy, the structure of exports has changed from a heavy concentration in agricultural toward manufactured products. Nevertheless, exports of agricultural products are still important and in 2008 amounted to US$ 32,638m, or 19% of total exports (Centre for Agricultural Information Office of Agricultural Economices, 2009). Thailand is the world's largest exporter of natural rubber with exports in 2008 of 2,675,283 tonnes, or US$6,714m (Rubber Research Institute, n.d.). The rubber sector is not only an important source of foreign revenue, but also of employment where more than a million farm households work directly in natural rubber production with more being employed in related industries such as tyre and rubber glove industries. Thailand has a lower acreage than Indonesia, but is the world's largest producer due to higher productivity. In 2008, the total rubber planted acreage was 2,608,106 hectares while the harvested acreage was 1,827,890 hectares producing 3,283,572 tonnes (Centre for Agricultural Information Office of Agricultural Economics, n.d.).

To improve rubber production, the government has launched various policies and measures such as research in high-yielding varieties, good-practice harvesting systems and maintenance of trees, and teaching new technology to farmers. The most well-known project is the replanting scheme which helps farmers to replant old rubber holdings with high yielding varieties, and to introduce modern methods of cultivation. Even though the policies mainly focus on production, the government also provides various marketing measures such as establishing central and local markets, and supporting farmers to create co-operatives. Further, as a large producer and exporter Thailand influences the world price. The Thai government plays an important role via international organisations to stabilise world prices. Occasionally, the government has directly intervened in the domestic market when rubber prices were low or unstable. In 1999-2006, the government launched the One Million Rais Project which aimed to establish 160,000 hectares of new rubber areas. Further policies for 2010-2013 are currently being developed (National Natural Rubber Committee, 2010).

Agricultural supply response is crucial to resource allocation and is a key issue in agricultural economics in both developed and developing countries. An understanding of agricultural supply response to prices and other factors is essential because of the impact of agricultural policies. However, the success of policies on agricultural production is determined by estimates of supply elasticities, and policy-makers need to understand their characteristics and magnitudes (Hennebery and Tweeten, 1991, pp.49-50). This thesis examines the supply response of rubber farmers in Thailand. We aim to identify the factors that significantly determine rubber supply response and to measure their magnitudes.

There are a number of approaches to explain the dynamics of agricultural supply response and they can be categorised into two groups: econometric and programming approaches. Econometric approaches range from single-equation models to more theoretically accurate models like error correction models. Each method has its own strengths and weaknesses. Two of the most important models which have been used extensively in the literature are Nerlove's (1958) adaptive expectations and partial adjustment models but they have several limitations. One of the most important is the *ad hoc* theoretical assumption in the partial adjustment model, that is, the concept of a fixed target supply or fixed long-run equilibrium is unrealistic in the context of optimising behaviour under dynamic conditions (Hallam and Zanoli, 1993, p.154). Further, in traditional econometric time series analysis, ordinary least squares (OLS) is based on the assumption that the underlying data generating processes are stationary, but most economic variables are non-stationary and applying OLS to non-stationary data may produce spurious results (Granger and Newbold, 1974). This leads to misleading conclusions and inappropriate policy recommendations.

There are a number of empirical previous studies of the supply response of rubber in Thailand using various econometric models, different explanatory variables, and different data and sample periods. Most apply Nerlovian models and OLS, so their models may have an inadequate dynamic structure and results may be unreliable. Another shortcoming is that the results may be biased because many studies omitted important variables such as alternative crop prices, the prices of inputs, the role of the government, and no consideration on the influence of risk. These criticisms imply knowledge gaps and this thesis attempts to address these shortcomings.

In general, two alternative models, i.e., an output and acreage-yield response models, have been considered in the supply response literature. The latter model, in which acreage and yield components are estimated separately, is perhaps preferable because farmers respond to various stimuli not only by adjusting area, but also by adjusting other inputs. Further, this approach is sometimes applied because output is influenced by exogenous factors including weather, diseases, and insects which are uncontrollable, while acreage is more directly connected with factors that the farmer can control. In this study, we develop both models theoretically. We then employ modern econometric techniques of cointegration to examine the empirical response of rubber farmers to economic incentives in both models. The first step in cointegration analysis is to examine the underlying properties of the time series to distinguish between stationary and non-stationary variables. Then, cointegration tests are applied to examine whether a long-run equilibrium relationship exists among the time series. This provides a framework for the estimation within an error correction model in which short-run disequilibrium adjusts towards long-run equilibrium in a theoretically consistent way. As a result, we avoid spurious results and employ a more theoretically accurate model. The results of this study provide useful information about the responsiveness of natural rubber production in Thailand to guide policy-makers.

The aim of this thesis is to examine the responsiveness of natural rubber farmers in Thailand to various factors using cointegration analysis. The objectives are:

i) to specify an economic model of the supply response of rubber farmers in Thailand;

ii) to estimate the dynamic responsiveness of natural rubber supply with respect to changes in price, non-price factors, and risk, and to analyse the system's response to shocks; and

iii) to consider the economic implications of the empirical results for maintaining sustained and balance growth of rubber production in Thailand.

The thesis is organised into eight chapters. Chapter 2 provides an overview of natural rubber production in Thailand. We begin with an historical background of natural rubber production and then discuss rubber production and marketing in Thailand. This includes a discussion on cultivation, harvesting, wood sawing, labour and the costs of production, and the market flow and distribution of rubber products. The role of the government is discussed. Key trends in the sector are illustrated.

Chapter 3 presents a literature review of agricultural supply response. We discuss the two main empirical approaches, namely, econometric and programming approaches. The econometric approach can be further separated into three: direct estimation of the supply function, the indirect or two-stage approach, and the cointegration approach. Empirical supply response studies for perennial crops using econometric approaches are examined, and we focus particularly on natural rubber supply response studies in Thailand where both output and acreage-yield models are examined.

Chapter 4 provides a theoretical framework of supply response. We introduce some fundamental production concepts, the economic aspects of production from an output perspective, and the conditions for profit maximisation. We also examine some comparative static propositions. We then discuss the influence of price and non-price variables and the implications of risk and uncertainty in agricultural supply response analysis. Finally, we consider modelling natural rubber supply response in an error correction framework. Two models, output and acreage-yield models, are considered in this study. Output is expect to be influenced by the rubber price, alternative crop prices, input prices, technology, government subsidies, the weather, and risk. Rubber acreage, both in terms of acreage being tapped and planted rubber acreage, is a function of the rubber price, alternative crop prices, wages, technology, government subsidies, and risk. The yield response model has a similar specification to the acreage model except that the fertiliser price and rainfall are included while subsidies are excluded.

Chapter 5 explains our empirical method. We describe some important concepts of modern time series analysis such as stationary, non-stationary, cointegration, and the error correction model. We consider unit root tests to examine whether a time series is stationary. Cointegration tests, especially those in a multivariate system, are discussed. Finally, we discuss modelling of short-run dynamics and impulse response analysis.

Chapter 6 examines the properties of our data. We start with a graphical analysis of each data series and then apply and present results of unit root tests.

Chapter 7 presents the results of cointegration tests for both output and acreage-yield response models. The results suggest that an output supply response model appears inappropriate to explain supply response of rubber production of Thailand and the preferred model comprises acreage and yield responses. The short- and long-run acreage and yield elasticities are estimated and comparisons are made with estimates from previous studies. We then use impulse response analysis to examine how acreage and yield respond to shocks.

Chapter 8 summarises the thesis, drawing some conclusions and providing policy implications. The contribution and limitations of the study are indicated and some potential issues for further research are suggested.

Chapter 2 Overview of Natural Rubber Production in Thailand

2.1 Introduction

Imported from the Dutch East Indies (now Indonesia), rubber was first planted in the South of Thailand in 1901. Subsequently, rubber cultivation has been promoted and acreage has continually increased in the Southern and Eastern regions (Office of the Rubber Replanting Aid Fund, n.d.-a). Before 1960s rubber cultivation was generally produced on traditional farms, also known as rubber forestry, where rubber trees were cultivated with other trees, for example, fruit trees. Labour mainly came from households. Rubber areas were dominated by low-yielding rubber varieties and the quality of rubber was normally poor. However, since the Office of the Rubber Replanting Aid Fund (ORRAF) was established as a legal institution to promote high-yielding rubber planting in 1961, rubber production in Thailand has adopted green revolution technology where improved varieties, fertiliser use and the use of other chemicals, and more efficient tapping method are applied. The rubber cultivated areas have also expanded to the North East and the North. By 1990, Thailand had developed into the world's largest producer of natural rubber with production of 1,418,000 tonnes, and it has held this position since (FAO, n.d.).

This chapter presents an overview of natural rubber production in Thailand so that the development of an economic framework for estimating natural rubber supply response can be developed. Section 2.2 provides a brief history and general description of natural rubber. Section 2.3 describes the production and marketing of rubber in

Thailand. Section 2.4 presents the role of government. Section 2.5 describes changes in acreage, yield, production, and price, and the prices of paddy and palm oil which are alternative crops, and fertiliser prices. Time series are presented in Appendices.

2.2 Background

2.2.1 A Brief History of Natural Rubber

Generated from several latex yielding trees, natural rubber was first known and used by the indigenous peoples of the Amazon in early times where latex was processed into functional things such as balls, shoes, and clothes. In 1735, the scientific description of natural rubber was first undertaken by Charles de la Condamine, a member of a French geographic expedition to South America. In England, the chemist Joseph Priestley discovered in 1770 that it was able to rub out pencil marks and it became known as "rubber". Afterwards, it was steadily used in other applications such as waterproof footwear and clothes. In the 18th century, the world rubber industry began to develop along with advances in rubber production processes, particularly vulcanised rubber. Leading to the rubber boom in the Amazon region, the demand for rubber grew rapidly due to the growth of both the automobile and electrical industries (UNCTAD, n.d.).

Rubber cultivation was brought to Europe in 1876, when rubber seeds (*Hevea Brasiliensis*) were smuggled from Brazil to the botanical Kew Gardens, in the UK. Seedlings were later shipped to the British colonies in Asia including Ceylon (now Sri Lanka) and Singapore. H.N. Ridley, director of the Singapore Botanic Gardens, suggested new cultivating and tapping methods and rubber cultivation spread to nearby regions, especially the Malay area, Java, and Sumatra, which were the first rubber plantations in Asia. Research in the Dutch East Indies advanced breeding procedures, such as selecting high-yielding trees to obtain seedlings and bud grafting, which increased productivity. Although rubber was originally grown as a plantation crop, rubber cultivation by smallholders emerged in the early 1900s.

Natural rubber was the only source of industrial elastomer[1] until World War II. Then, when Western Europe and the USA were separated from their major suppliers in Asia, the manufacture of synthetic rubbers[2] on a large scale was developed. By the early 1960s, synthetic rubber production exceeded that of natural rubber (IRRDB, n.d.; UNCTAD, n.d.). While the percentage of natural rubber consumption has decreased substantially, natural rubber cannot be replaced by synthetic rubber in all products especially in tyres (Clay, 2003, p.335).

Nowadays, rubber trees are mainly cultivated in South East Asia and the largest areas are in Indonesia, Thailand and Malaysia, respectively.[3] Figure 2.1 shows rubber harvested acreages in major producing countries between 1961-2008. In Indonesia, acreages increased from 1,350,000 hectares in 1961 to 2,897,670 hectares in 2008. In the same period Thailand expanded from 400,160 hectares to 1,827,890 hectares. In Malaysia, acreage decreased from a peak of 1,890,000 hectares in 1978 to 1,247,000 hectares in 2008. For other countries, the acreages generally increased but decreased

---

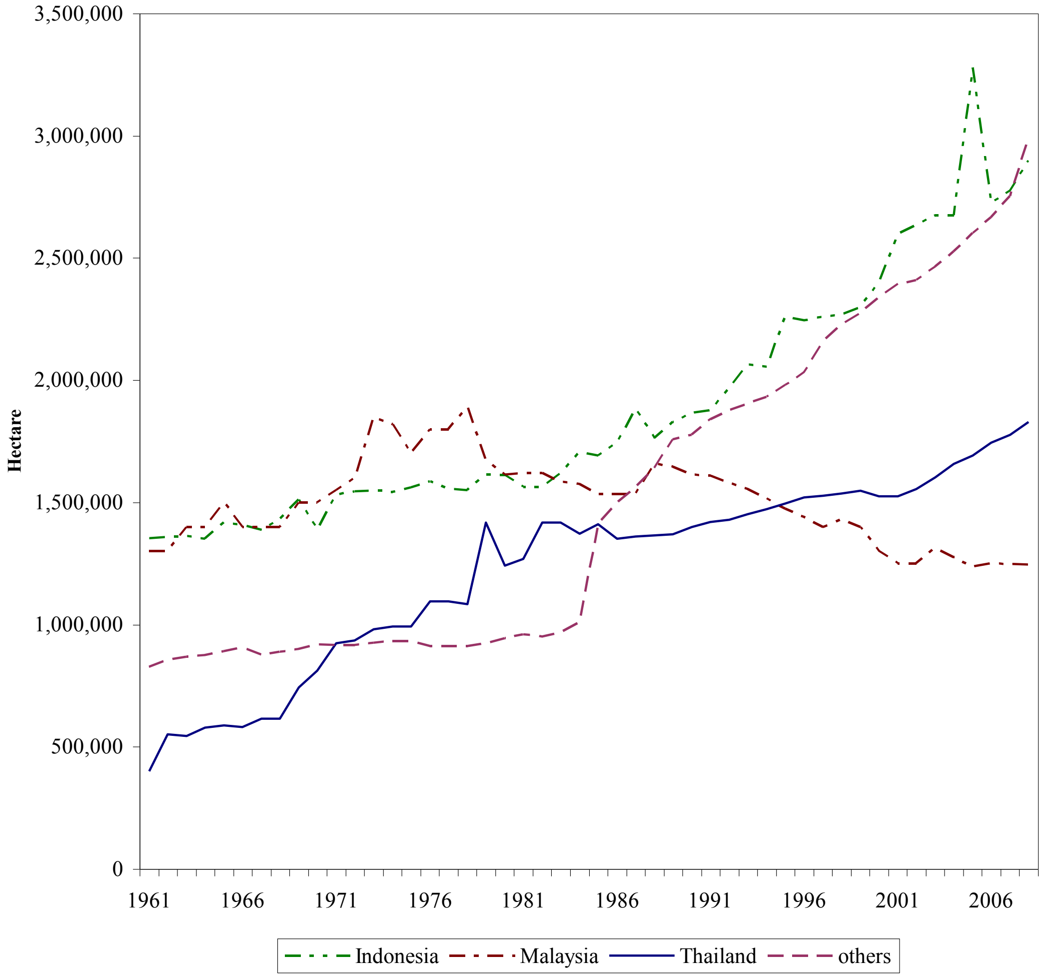
[1] Elastomer means both natural rubber and synthetic rubber.

[2] Synthetic rubbers are synthetically derived from petrochemical products. Their origin occurred in the 19th century when the isolation of isoprene, the chemical compound present in natural rubber, was discovered. During World War I, a crude synthetic rubber was produced by Germany, and during the 1920s and 1930s advances in polymerising processes arose in Germany, the Soviet Union, the UK, and the USA (UNCTAD, n.d.).

[3] However, in terms of production, the largest producing countries are Thailand, Indonesia, and Malaysia, respectively.

in countries such as Sri Lanka and Democratic Republic of Congo. In aggregate, the world's natural rubber harvested acreage is increasing.

Figure 2.1 Natural Rubber Harvested Acreages in Major Producing Countries, 1961-2008



Source: adapted from FAO (n.d.) and Centre for Agricultural Information Office of Agricultural Economics (n.d.)

The decline in natural rubber harvested acreages in some countries is caused by more profitable, substitute crops being grown, especially palm oil which is less labour-intensive, and by controlling acreage to manage production and prices. The decline of rubber acreages in Africa is mainly caused by political instability.

2.2.2 General Description of Natural Rubber

The rubber tree, *Hevea Brasiliensis*, is a tall, tropical, softwood tree with upward-extending branches and a straight trunk. Although its height can exceed 40 meters, a mature rubber tree normally grows to 20-30 meters in plantations. As a perennial, the rubber tree can be older than 100 years but it is generally replanted after 25-35 years when latex yields reach unprofitable levels. The rubber tree grows well at temperatures of 20-28°C and yearly rainfall of 1,800-2,000 mm. Although it can grow on higher land, the rubber tree grows properly up to 600 metres above sea level. It can grow on a variety of soil types provided there is sufficient drainage, but highly productive soils can give higher yields. The prime growing areas for rubber trees are within the 10° latitudes north and south of the equator although cultivation occurs further North, e.g., Guatemala, Mexico and China, and further South, e.g. Sao Paulo region of Brazil (IRRDB, n.d.).

Freshly tapped latex may be sold in its original form or as an initial processed product such as in raw or unsmoked rubber sheets. Both are transported from farm to factory for manufacture into other types of natural rubber which are separated into either latex concentrate or dry rubbers. Conventional rubber is sheet rubber which is principally Ribbed Smoked Sheet (RSS) and crepe rubber. Blocked rubber is a newer rubber known as technically specified rubber (TSR) which has gained increasing importance. Latex concentrate is directly produced from freshly tapped latex, and dry rubbers are manufactured from coagulated field latex, i.e., sheet rubbers and pale crepes, or remilled rubber sheets. Most natural rubber, especially TSR and RSS, is used in car tyre manufacture while concentrated latex and higher quality dry rubbers are used to produce medical products.

2.3 Natural Rubber Production and Marketing in Thailand

Most rubber cultivation in Thailand is on smallholdings of less than eight hectares; the rest is on medium holdings between 8-40 hectares, and on large holdings or estate plantations of more than 40 hectares. The focus of this section is on the management of natural rubber cultivation of small-scale farmers.

2.3.1 Natural Rubber Cultivation

Thailand is located between the latitudes 6^{o} and 13^{o} N. The peninsular part of the South and the coastal area of the East, which are traditional rubber areas, have a monsoon climate which is appropriate for rubber tree cultivation. Figure 2.2 shows Thailand's rubber producing areas. Following guidelines for rubber cultivation (Department of Agriculture, n.d.; Rubber Research Institute Department of Agriculture, 2010), the process starts from land selection and preparation until obtaining products as follows.

Figure 2.2 Rubber Growing Areas in Thailand

Source: adapted from www.maps-thailand.com (n.d.)

i) Land Selection and Preparation

The desirable area for rubber cultivation should be located not higher than 600 metres above sea level, not be subject to flooding, land must be flat or undulating and hilly with slopes of less than 35^o. In areas with slopes of more than 15^o, trees should be planted in rows across the slope following contour lines. On account of protection against soil erosion, terraces along trees must be built while cover crops at the side of the rows can increase effectiveness. Annual rainfall is to be not lower than 1,250 mm with 120-150 rainy days. Providing well-aerated and good drainage conditions, rubber growing soils should have a clay-loam to sandy clay-loam texture and should be fertile with topsoil deeper than one metre; additionally, without a hardpan or a high stoniness within one meter depth, the finest soils for rubber should have a ground water table deeper than one metre. The most favourable pH range of soils varies from 4.5-5.5. After areas are cleared of wild growth, planting in lines on the East/West direction is employed. In general, the planting density is 418 to 475 plants per hectare.

ii) Planting Material

Planting using a variety of enhanced rubber budding or clones is generally utilised. Selected clones are the key factor concerning the success of rubber cultivation in terms of productivity. Each clone is suitable for different locations. Farmers receiving a financial grant from the government must plant only recommended clones.

iii) Growth

There are two growing stages. The immature stage ranges from planting to the tappable size. Depending on growing conditions, the rubber tree takes approximately seven years to come to the mature stage, when the girth of the tree is 50cm at 150cm above ground level. The mature or yielding period covers the time when the trees start to be tapped for latex until the time when they become unprofitable. In March and April, the tree’s leaves die and drop and new leaves develop, and this affects the metabolism of the tree and latex production and rubber production fluctuates during this time. Production is also low in the rainy season.

iv) Fertilisation

Soil quality in rubber areas is normally poor as organic matter falls due to soil erosion and natural decomposition. Therefore, the application of fertilisers is necessary for the growth of rubber trees and productivity. To increase yield by fertiliser use, factors such as the type of soils, rubber tree variety, and tree age should be considered. Most fertilisers used in rubber cultivation are inorganic, but organic fertiliser is also recommended as a complement to improve soil quality. Fertilisers are normally applied during the rainy season and are broadcast beneath the canopy. Fertilisers can also be applied by digging holes between trees and placing fertilisers in the holes.

v) Intercropping

During the immature period, crops such as rice, banana, maize, pineapple, and other food crops may be grown between rubber rows, and it is possible to nurture animals such as poultry, sheep, pigs, and cows. Intercropping can give extra income for farmers particularly in the first three years. It is difficult to grow arable crops due to decreased light from rubber tree growth. Farmers may be concerned about a possible reduction in rubber yield and additional cost of intercropping. To protect farmers from the negative effects of intercropping on rubber tree growth, legume cover crops, consisting of *Pueralia Phaseolides, Calopogonium Muconoides* and *Centrosema Pubecens*, are recommended to be cultivated instantly after the intercrops are harvested. In addition, legumes could be grown continuously throughout the first period of rubber cultivation where intercropping is not adopted.

2.3.2 Harvesting

After the immature period, the harvested period generally starts at the beginning of the eighth year of planting. The rubber tree is tapped (cut) for latex, which is the sap or liquid generated by cells in the tree. To get a high return and lengthen productive life, farmers start the tapping process when the tree reaches 50cm girth at 150cm above ground level. Traditionally, rubber farmers tap between 3.00–6.00am; they believe that tapping outside this time, especially at noon or in high temperature, produces low yields due to the flowing period being shortened. However, following the half-spiral tapping system every two days, tapping should be done in the early morning from 6.00-8.00am because it is more comfortable, secure, and low-cost than at night. At the height of 150cm, a special knife is used to cut a thin layer from the intact section of bark at an angle of 30^{o} from the top left to the bottom right to get an optimum amount of latex into the vessels. Cutting should be performed deeply but should not reach the wood and be too thick because it may negatively affect productive life. Latex flows from vessels into a small cup below the cut and farmers return to collect it within a few hours.

Natural rubber can be produced throughout most of the year except in the rainy season and the deciduous season when trees are losing leaves. On average, there are 180 tapping days per year in the North and the North East, 150-180 days in the East, 100-

120 days in the upper South, and 150-180 days in the lower South. Each farmer can tap up to 500 trees per day. At present, as a result of the success in reducing tree damage, skilled farmers are able to tap trees for approximately 25 years.

2.3.3 Rubber Wood Sawing

Before 1989, rubber trees past their productive life were mainly used as fuel on farms and in factories producing ribbed smoked sheet or material for charcoal production. In 1989, the Thai government banned natural forest logging to reduce environmental degradation, and wood imports significantly increased. Old rubber trees became an attractive source of raw materials for the wood industry. Currently, rubber wood is used by the furniture and construction industry and it is an important source of additional income to rubber farmers. In general, farmers sell their rubber wood to dealers or middlemen, who trade them to sawmills. The wood dealers offer farmers a stumpage price based on various factors including distance from sawmill and to main road, season of the year, size of the trees, quality of tapping and variety of the trees. Chain saws are normally used to fell trees and process logs. Tractors or small bulldozers are sometime used to uproot trees. The wood dealer gets all the saleable wood from the field. Costs of processing and transportation are paid by the wood dealer. In 2009, the rubber wood price received by rubber farmers varied between 4,556.72 and 9,113.44 US$/hectare.

2.3.4 Labour System and Costs of Production

Natural rubber cultivation is labour-intensive and all cultivation and harvesting practices are carried out by manpower. Family labour is traditionally employed on smallholdings but a shortage of labour usually occurs in the South and immigrant workers are employed from the North East (and from Myanmar). Farmers also adopt an output (crop)-sharing system where tappers in particular earn income by sharing outputs (and risk) with owners (Puapongsakorn *et al.*, 2001, p.66). In the past, sharing is on a 50-50 basis, but when rubber yield is higher, sharing is on a 60-40 basis where owners get the higher share, and the proportion sometimes changes to a 55-45 or 50-50 basis as trees get older.

Average production costs during 2004-2006 are shown in Table 2.1. Excluding rents, the largest cost is labour, especially the costs of tapping and rubber collection, which are more than half total cost. Other essential costs are materials, interest, and rent.

Table 2.1 Costs of Natural Rubber in Thailand (US$/hectare), 2004-2006

	Year		
	2004	**2005**	**2006**
Variable costs	1,300	1,340	1,558
Labour costs	1,011	1,037	1,229
Management	204	216	234
Tapping and collection	807	822	995
Materials	170	181	188
Fertilisers	74	85	89
Weedicides and pest control	18	19	20
Other	79	77	79
Interest expense	118	122	142
Fixed costs	220	207	207
Land rents	71	67	67
Other	149	140	140
Total cost per hectare	1,520	1,547	1,765
Average cost per tonne	838	887	958

Source: adapted from Centre for Agricultural Information Office of Agricultural Economics(2006).

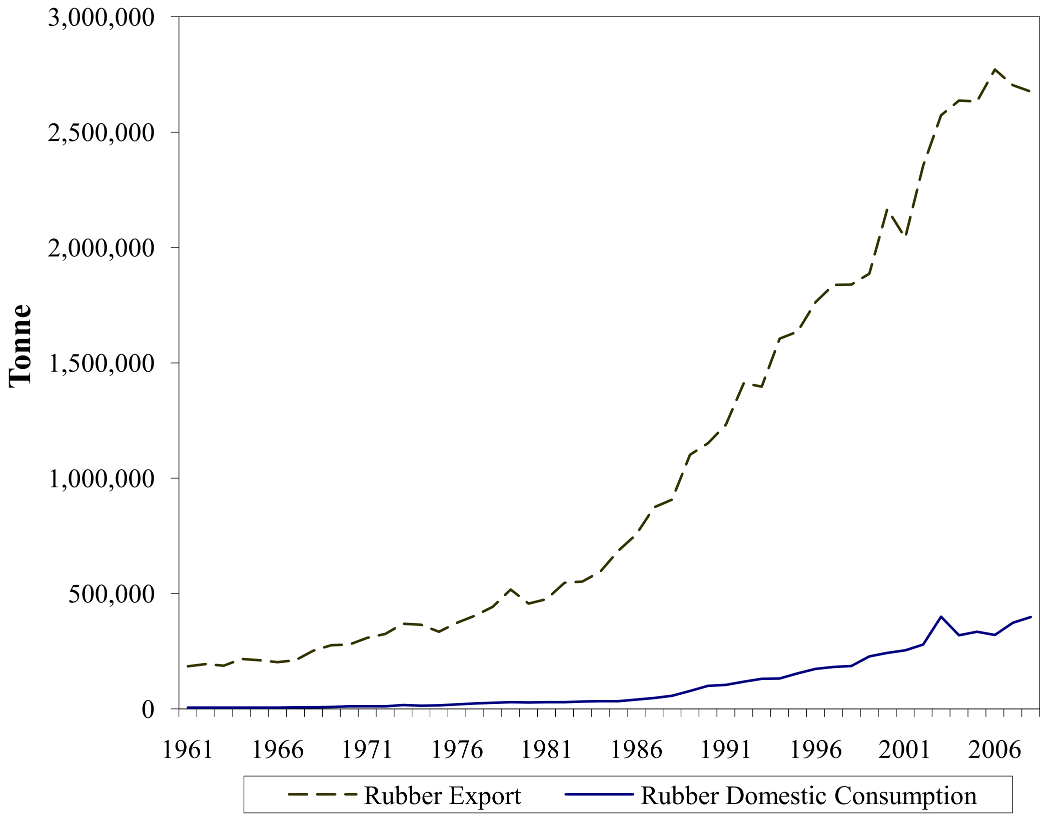
2.3.5 Market Flows and Distribution of Natural Rubber

The domestic market for natural rubber in Thailand can be separated into local markets, central markets, and a futures market. Most farmers sell to a local market. Products are transported from farmer to factory to manufacture concentrated latex or dry rubbers. These products are sold in an original form as freshly tapped latex or an initial processed product such as raw or unsmoked rubber sheets. Various groups are involved: (1) mobile dealers or hawkers, (2) village shops, (3) district dealers, (4) town dealers, and (5) packers or processors or exporters. In the past, most rubber smallholders, especially those who lived in deep rural areas, sold to hawkers or village shops. Mobile dealers went from smallholder to smallholder on a bicycle or motorcycle and were either self-employed or bought on behalf of town or village dealers. But most mobile dealers collected rubber for selling at village shops. Rubber accumulated at village shops was in turn sold to either district or town dealers. Finally, rubber sheet or latex from district and town dealers would be sold to packers/processors/exporters who would process for export.

Since the improvement of roads, the situation has changed. Most rubber smallholders, who live in areas where rural roads exist, make use of motorcycles or cars to bring latex or rubber sheets to sell directly in the nearest district market or in town, while those who do not own vehicles bring their rubber on small buses. The role of mobile dealers and village shops has drastically declined. In addition, due to support from the government to reduce the role of medium traders such as district or town dealers, several rubber factories, which are operated by groups of farmers or agricultural co-operatives, have been established to purchase and process rubber products from their members or other farmers. These co-operatives and other large farmers can sell products directly to packers/processors/exporters by auction at central markets and receive higher prices. Several central markets have been established in production areas. The first central market was established in 1991 in the South. Four further central markets, two in the South and two in the North East, have been established. These central markets are managed by the Rubber Research Institute (RRI), Department of Agriculture (see below). Since 2000, rubber farmers can sell through a number of local central markets operated by the Office of the Rubber Replanting Aid Fund (ORRAF). Even though a majority of farmers still sell their products in a traditional market, trading in a central market is increasingly important. There is also a futures market for rubber in the Agricultural Future Exchange of Thailand (AFET), which was established in 2004 but volume is small.

Most rubber is exported as raw material. Figure 2.3 shows that natural rubber exports increased from 184,500 tonnes in 1961 to 2,675,283 tonnes by 2008. The major importers of Thai rubber are China, the USA, Japan, and Malaysia. China’s imports increased to more than 836,000 tonnes in 2008, and it has become the most important customer replacing Japan. By contrast, domestic consumption increased slowly until 1986, but since has increased substantially to 397,595 tonnes in 2008. Nevertheless, it is still relatively small, accounting for 15% of production. Domestic consumption is mainly used in the production of tyres, elastic bands, rubber gloves, and condoms. Thus, Thailand's rubber industry depends on the world market and exports and is dependent on the fluctuating world price.

Figure 2.3 Thai Natural Rubber Export and Domestic Consumption, 1961-2008



Source: adapted from Rubber Research Institute (various years) and Rubber Research Institute (n.d.).

2.4 The Role of Government in the Natural Rubber Sector

The Thai government encourages rubber production and marketing, as well as rubber processing for exports. Since the first-economic Development Plan in 1961, several measures have been implemented through government agencies, which are mainly under the Ministry of Agriculture and Cooperatives. The major government agencies involved with rubber production are described below.

i) The Rubber Research Institute (RRI), Department of Agriculture

This institution emerged from the Rubber Division which was established in 1938. Its objective is to manage and undertake research and development in production, distribution, marketing, processing, and the production of natural rubber products.

According to the Rubber Control Act 1999, RRI's task is to make sure that production, distribution, marketing and consumption develop according to world standards. RRI is responsible for developing technology which includes the teaching of new technology to farmers and gathering of new information to use in developing the sector. RRI is also responsible for the operation of central markets.

ii) The Office of the Rubber Replanting Aid Fund (ORRAF)

Since the first economic Development Plan, replanting of old rubber trees with high yielding clones has been the main goal of rubber development policies. Under the Rubber Replanting Aid Fund Act of 1960, the ORRAF was established as a government enterprise under the administration of the Ministry of Agriculture and Cooperatives to assist replanting with high yielding varieties, and to introduce modern methods of cultivation via the rubber replanting scheme. The main objective of the ORRAF is to encourage farmers to replace low-yielding rubber trees by high yielding rubber tree clones or other high-value economic perennial trees. The ORRAF also aims to help farmers to establish new rubber growing areas. Funds for the operation in the rubber replanting scheme are normally from two sources: (1) cess tax[4] levied on rubber exports is the main source where at least 85% of cess tax must be paid to the fund every year; (2) government budget, where necessary. In addition, the ORRAF may obtain interest income on deposits and grants and foreign loans from international organisations (Office of the Rubber Replanting Aid Fund, n.d.-b).

There are certain preconditions for farmers to apply to the replanting fund (Office of the Rubber Replanting Aid Fund, n.d.-c):

---

[4] Cess tax is the tax obtained from natural rubber exporters.

a) Farmers must own at least two rais.[5] The minimum rubber tree for any rai is 10 trees, and overall there must be an average of 25 trees which are over-aged rubber trees (more than 25 years). However, it is acceptable if the trees are in bad condition or low yielding and at least 15 years old;

b) Farmers must have clear rights to the produce of rubber trees to be replanted; and

c) Qualification for planting in new areas is that farmers must own a new area of at least 15 rais.

After selection, farmers obtain grant payments consisting of materials provided in kind and cash payments before the trees come into production. The cash component, including fixed grants for labour on the completion of specified tasks, aims to alleviate the problem of a temporary shortfall in smallholders' income after deforestation of old trees. This incentive is considered necessary to induce replanting with new more productive varieties by smallholders who depend on rubber for cash income. Material inputs include high-yielding clonal varieties, fertiliser, and chemicals in amounts determined by agronomic and economic considerations. Lower production costs are expected to stimulate more production. Following complaints of late arrival of inputs and poor quality of fertilisers, the ORRAF stopped providing fertilisers but pays money for purchasing fertilisers directly (Suzuki, 2009, p.12).

Grants are determined by the Board of the Fund. To keep up with rising costs and inflation, the ORRAF has raised the grant from an initial level of 1,500 baht per rai in 1961 to 7,300 baht per rai at present. Farmers get support until they conduct the first

[5] 1 hectare = 6.25 rais.

rubber tapping activities. Full payment of benefits is delivered to small-scale farmers in seven instalments. The allocation of each instalment is conditional on satisfactory completion of specified tasks certified by inspectors who perform yearly auditing visits. If irregularities or difficulties are found, direct instructions are given to farmers.

Farmers are expected to participate fully in the replanting project. The main restriction on farmers is that tapping cannot be done until the seventh year after planting seedlings. This tapping restriction is compensated with an economic allowance to small-scale farmers in the form of low interest loans. These loans are to establish intercropping or animal husbandry activities. The largest loan is 30,000 baht at 3% interest. During 1962-2008, the amount of rubber growing areas granted under replanted programme is 8,771,299 rais or 1,403,407 hectares.

Another essential task of the ORRAF is to promote the formation of rubber processing cooperatives. The ORRAF informs farmers about the advantages of producing higher and more uniform qualities of rubber sheets, and group bargaining. If a group of farmers decides to form a processing cooperative, the government provides free production facilities to construct a Rubber Smoked Sheet factory or a house for producing raw rubber sheets.

iii) The Department of Agricultural Extension (DAE)

Extension services had been one of various functions of the Rubber Division. In 1968, the Ministry of Agriculture transferred that job to a new institution, DAE, which is responsible for the dissemination of information about production, processing, and quality control for all crops including rubber trees out of those in the replanting programme.

iv) The Rubber Estate Organisation (REO)

Established in 1961 under the Rubber Estate Organisation Act, the REO was founded as a government enterprise under the administration of the Ministry of Agriculture and Cooperatives. It is responsible for natural rubber production in its own plantations. Its operations cover various tasks varying from seedlings to processing to a number of natural rubber products. The REO trades rubber on both domestic and foreign markets. Even though REO is essentially a commercial organisation, it is a major means for the government to stabilise rubber production and price and provides information about good practices on rubber cultivation to farmers.

Formerly, the Thai government concentrated on production policies, i.e., rubber research activities by the RRI and rubber replanting scheme by the ORRAF, to increase productivity. The cess tax imposed on rubber exports has created substantial funds to support replanting activities. Since rubber production involves large numbers of workers especially farmers, if there is a large decrease in the rubber price, the government may intervene in the market. In the past, the government had not intervened in rubber markets directly but operated through instruments such as export tax and cess tax.[6] In 1992-2003, the rubber price fell and costs of production increased and this put an downward pressure on farm income, particularly when price was lower than average cost. To increase farm prices, the government intervened directly by purchasing natural rubber from farmers. Funds were mainly sourced by loans from a

---

[6] Due to the decrease of rubber price, the export tax rate was decreased to zero by the end of 1990. Thus, currently, there is only cess levied on rubber export.

government enterprise bank (Suzuki, 2009, pp.4-7). However, Puapongsakorn *et al*. (2001) note that these interventions were not successful as the raised farm price was lower than an unrealistically high target price and there was a limited government budget. This scheme also suffered losses from corruption (Suzuki, 2009, p.14).

To improve productivity and profitability in the sector and to increase the benefits from value-added production in the long run, the government established the first comprehensive rubber development strategies in 1999-2006. The plans aimed to improve productivity, stabilise prices, develop rubber products, process rubber wood, and strengthen the business capacity of farmers. One of the most important projects was the One Million Rais Project where the ORRAF established new rubber areas. The total target acreage was 1m rais (160,000 hectares) with 700,000 rais (112,000 hectares) in the North East and 300,000 rai (48,000 hectares) in the North. In 2006-2008, a plan for restructuring rubber and rubber products was created, but it was never adopted due to political instabilities. In 2009-2013, comprehensive rubber development strategies have been developed to increase competitiveness (National Natural Rubber Committee, 2010).

To help rubber farmers to access capital for improving production, the government operated the Populist Rubber Plantation Project during 2004-2010 which enabling farmers to take out loans from financial institutes to increase income and add value to their products, and farmers who join the project can use rubber wood as collateral. Further, it is the first time that farmers in the National Forest Reserves are granted documents which can be used as collateral to take out loans and they can receive replanting subsidies from the ORRAF.[7]

Until 1999, the Thai government played a significant part in the world rubber market by supporting international buffer stock schemes. This action affected the world price by purchasing rubber to stock when the price is low and selling when the price is high. Thailand was a member of the International Natural Rubber Organization (INRO) which was established in 1980 as a result of the UN Conference on Trade and Development (UNCTAD) held in 1976 on the fall of commodity prices.[8] The objective of INRO was to balance demand and supply to stabilise price. However, the success of INRO's intervention was limited, and the failure of market interventions during 1998-1999 was due to the collapse of cooperation among its members in making payments to the buffer stock. As a result, the world price was below the minimum guaranteed price. Further, the rubber market was more beneficial to importing countries than to exporters which encouraged INRO members to withdraw. After the withdrawal of Malaysia, Thailand left INRO in 1999 when the organization was disbanded.

In 2001, Thailand, Indonesia and Malaysia established the International Tripartite Rubber Council (ITRC). Its role is to manage rubber production and export to ensure fair and remunerative income for domestic producers of the three countries. In 2004, the three governments also established a joint venture, the International Rubber Consortium Limited (IRCo), as the organisation responsible for managing the

---

[7] In the past, rubber farmers in the National Forest Reserves could not sell wood and replant.

[8] Members of INRO consisted of rubber exporting countries, i.e., Indonesia, Ivory Coast, Malaysia, Nigeria, Sri Lanka, and Thailand, and rubber importing countries, i.e., China, Austria, Belgium/Luxembourg, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Spain, Sweden, the UK, Japan, and the USA.

implementing of the rubber supply measures, i.e., the Supply Management Scheme (SMS) and the Agreed Export Tonnage Scheme (AETS), to control rubber production and export. Later, Vietnam was invited to become a member of this council and company. IRCo would intervene to buy rubber when prices decreased. However, negotiation of prices is complicated since Malaysia, which has now become an importing country, will not agree to be disadvantaged. Moreover, it seems that each member is not vigorously necessitated to abide by the agreement, especially that on the reduction of rubber areas, to avoid the surplus supply (Kaiyoorawong and Yangdee, 2008, p.22).

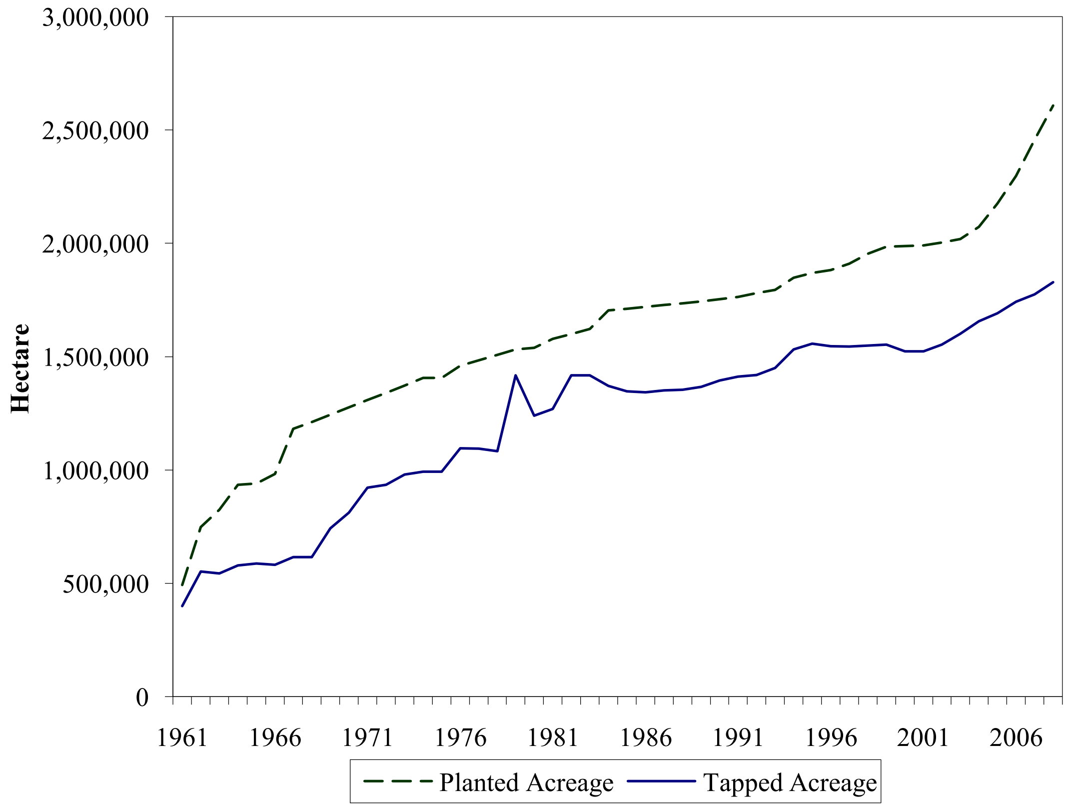
2.5 Trends in the Natural Rubber Sector

This section describes trends in acreage (planted and harvested or tapped), yield, production, and price of natural rubber. Alternative crop prices of paddy and palm oil, and fertiliser prices are also described.

2.5.1 Acreage

Most rubber acreage in Thailand is located in the traditional region, but in the last two decades there has been a rapid expansion into the North East and North where soils and topography are less suited to growing rubber trees. This expansion has been caused by the continuing high price of rubber and government support programmes. Figure 2.4 shows planted and tapped acreages of natural rubber from 1961-2008. Planted acreage expanded from 492,800 hectares in 1961 to 1,244,000 hectares in 1969, whereas the tapped acreage normally increased later due to the time lag in cultivation. However, tapped acreage significantly increased in some years, e.g., 1979, possibly due to substantial rises in the rubber price. Since the 1960s, planted acreage increased continually while tapped acreage fluctuated because of drought, heavy rain, and low prices. Since 2003, planted acreage rose substantially from 2,018,611 hectares to 2,608,106 hectares in 2008, and tapped acreage increased from 1,553,214 hectares in 2002 to 1,827,890 hectares in 2008.

Figure 2.4 Natural Rubber Planted and Tapped Acreages in Thailand, 1961-2008

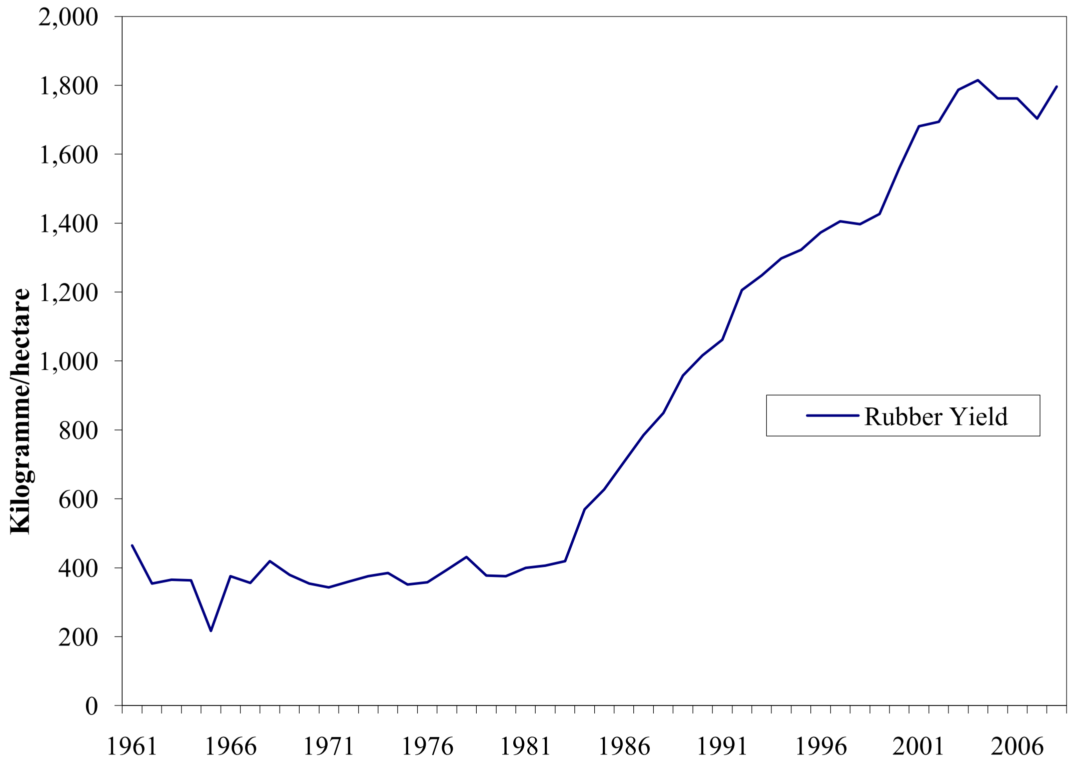


Source: adapted from Centre for Agricultural Information Office of Agricultural Economics (n.d.).

2.5.2 Yield

Average yield per hectare is total production divided by tapped acreage. Production was low until the early 1980s because of low-yielding varieties. Afterwards, yield increased because of the expansion of high-yielding acreages encouraged by the replanting programme. Steady improvements in technology such as breeding methods which involves selection of new clonal rubber tree varieties and budgrafting, new tapping techniques, and the use of fertilisers, played a key role in increasing productivity. Figure 2.5 shows the increase in yield in 1961-2008. From 1961-1983, overall natural rubber production generated an average yield of 400 kgs. per hectare although it fell to its lowest of 217 kgs. in 1965. Since 1984, the yield improved from 570 kgs. to a peak of 1,815 kgs. in 2004 and then slightly decreased to 1,796 kgs. in 2008.

Figure 2.5 Average per Hectare Yield of Natural Rubber Production in Thailand, 1961-2008

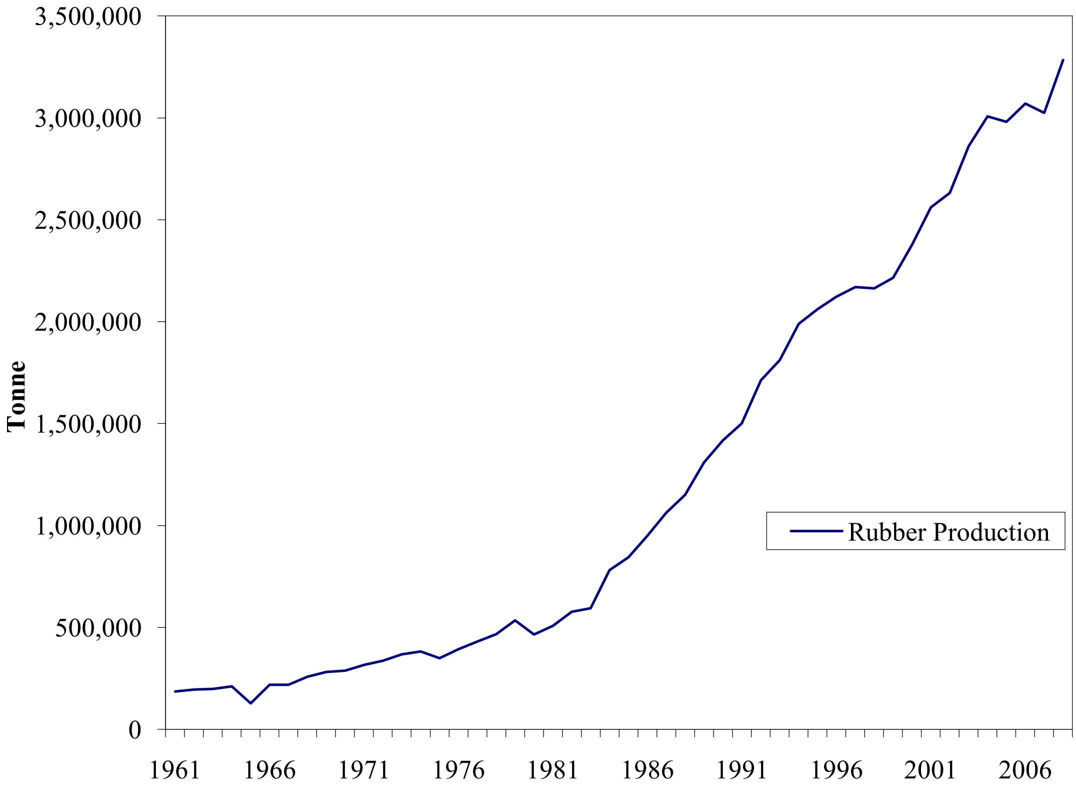


Source: adapted from Centre for Agricultural Information Office of Agricultural Economics (n.d.).

2.5.3 Production

Although production fluctuates due to price variations, drought, and heavy rains, it generally increased throughout the sample period as shown in Figure 2.6. Output slowly increased from 186,100 tonnes in 1961 to 534,300 tonnes in 1979. Since 1980, production dramatically rose to more than 3m tonnes in 2008. The increased production is attributed to both acreage and yield increases.

Figure 2.6 Natural Rubber Production in Thailand, 1961-2008



Source: adapted from Centre for Agricultural Information Office of Agricultural Economics (n.d.).

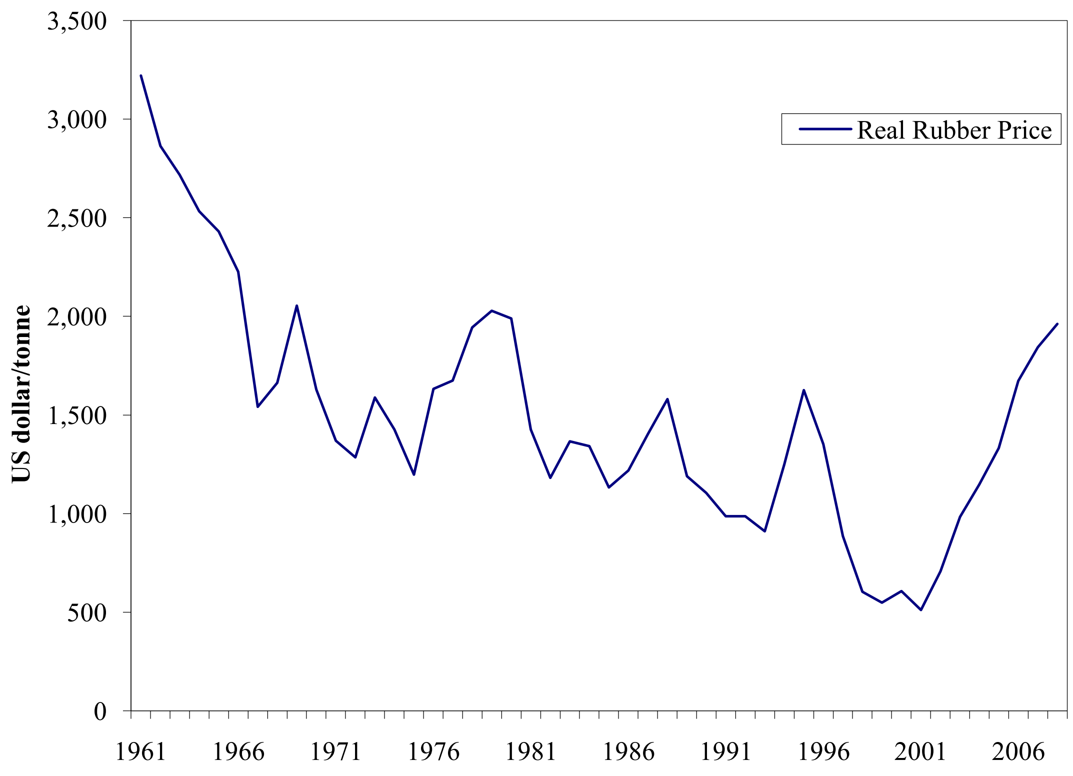
2.5.4 Natural Rubber Prices

Figure 2.7 shows the domestic price of natural rubber in Thailand during 1961-2008 in real terms. Specifically, this is the real farm gate price of RSS-3[9] which is normally used as the reference price for natural rubber in Thailand. The deflator used to determine real rubber price and other prices in this study is the GDP deflator with the base year (2005=100). In the 1960s after the end of the Korean War, the price fell from 3,220 US$/tonne to 1,541 US$/tonne in 1967 mainly due to substitution by

[9] RSS-3 is Ribbed Smoked Sheet Grade 3 natural rubber.

synthetic rubber. From the second part of the 1960s, prices fell and fluctuated. In particular, when the oil price increased during the oil shock in 1970s and 1980s, the production cost of synthetic rubber increased; this stimulated the demand for natural rubber and its price increased. Similarly, in 1990s, the rubber price significantly increased due to the effects of the Gulf War before continually decreased due to the world economic crisis. This general trend of falling prices continued to a low of 511 US$/tonne in 2001 and in 2006 it recovered to 1,673 US$/tonne. This recent increase is caused by growth of global demand especially from China. This increase appears to have caused farmers to expand production or switch from other crops to rubber.

Figure 2.7 The Real Natural Rubber Prices in Thailand, 1961-2008



Source: adapted from Centre for Agricultural Information Office of Agricultural Economics (n.d.).

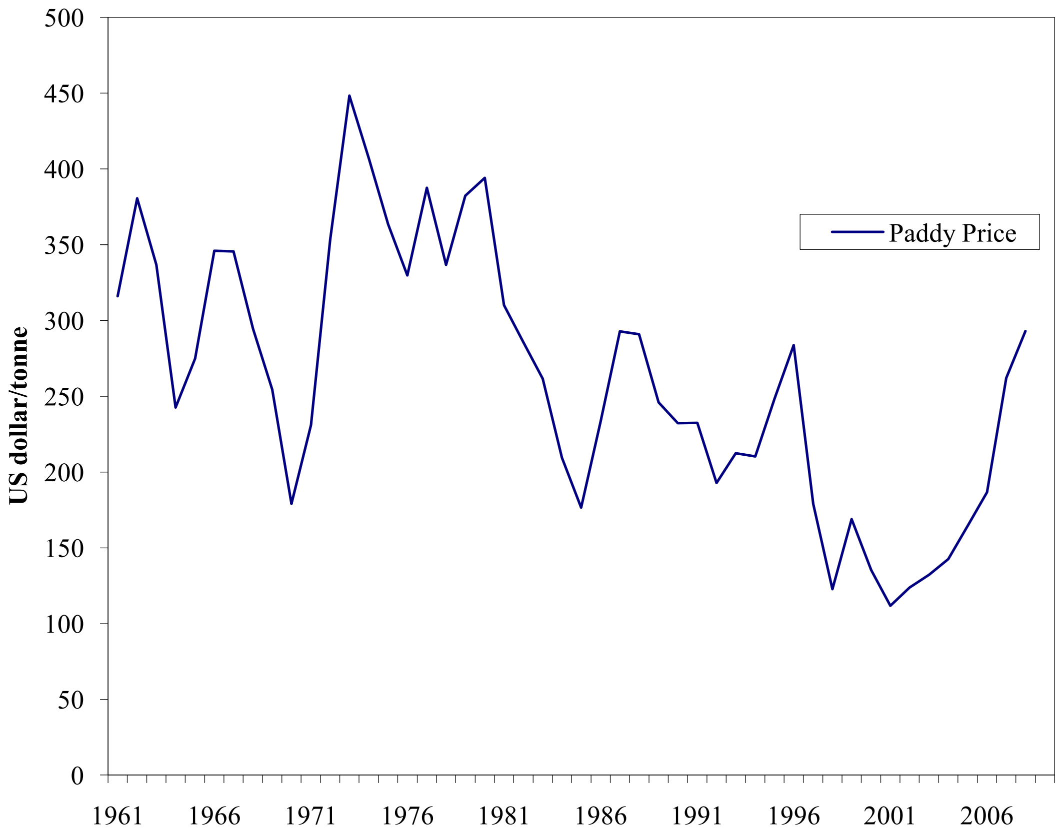
2.5.5 Alternative Crop Prices

Theoretically, competition between crops for land area exists. If the prices of alternative crops relative to the rubber price increase, more land is allocated to other crops. We focus on two alternative crops, rice and oil palm.

i) Rice

Rice is a traditional crop in Thailand which is cultivated mainly for household consumption. When rubber was first introduced, some marginal rice land and uncleared forest areas switched to rubber since rubber was more profitable and underemployed labour could be relocated to rubber production from less productive rice activities. Thus, the expansion of rubber production in the South in the early stage of rubber development can be described as a process of employing surplus capacity (Stifel, 1973). More recently, however, rice lands were still changed to rubber growing areas. After the South was transformed into a market-oriented economy particularly since 1960s, both rice and rubber seems to be more area-specific single cash crops. Rice growing areas are generally located in the plain near the coast while rubber is mainly cultivated in upland areas near mountains. However, there is still a competition among rice and rubber for land and labour especially in the marginal rice land. In Figure 2.8, the real paddy price varies substantially with a downward trend during 1961-2008. Price decreased from 316 US$/tonne in 1961 to 179 US$/tonne in 1970, then rose to 448 US$/tonne in 1973, and dropped to 177 US$/tonne in 1985. The paddy price fell to its lowest at 112 US$/tonne in 2001. Since then, price continually increased to 293 US$/tonne in 2008.

Figure 2.8 Real Paddy Prices, 1961-2008 in Thailand

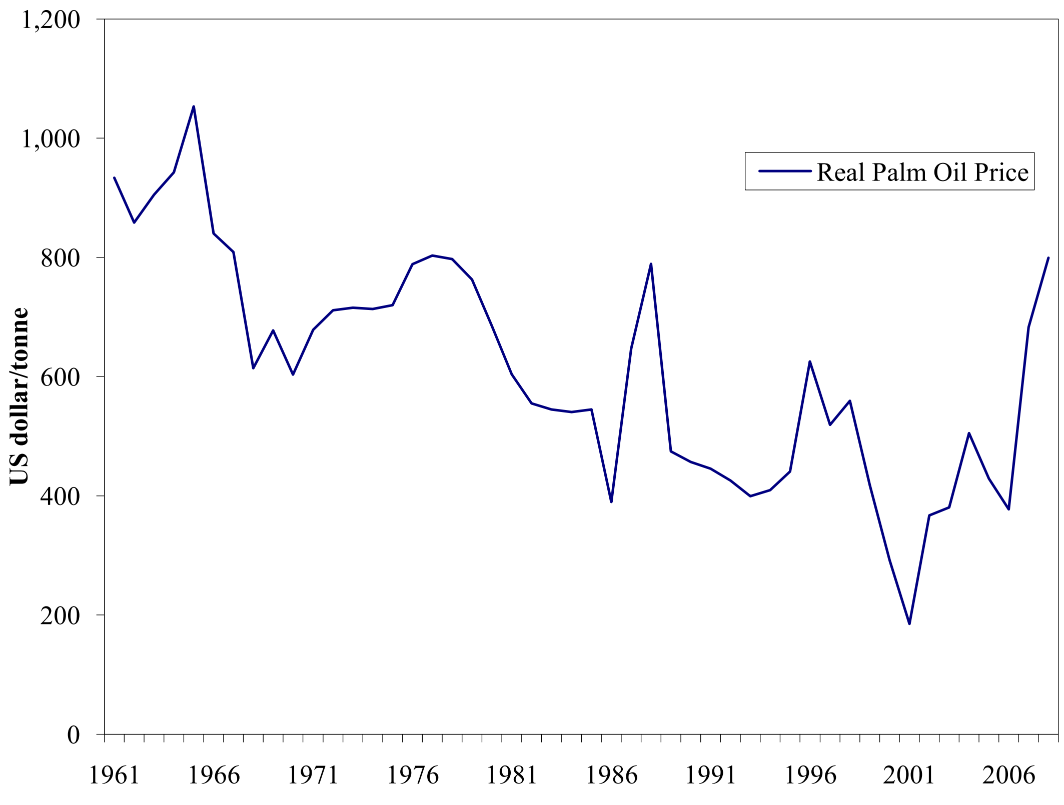


Source: adapted from IRRI (n.d.) and Centre for Agricultural Information Office of Agricultural Economics (n.d.).

ii) Oil Palm

There is evidence of commercial oil palm plantations in Southern Thailand before World War II when cultivation ceased. The major factor contributing to the establishment of the oil palm sector in Thailand was the fall of rubber prices when natural rubber was substituted by synthetic rubber during the 1960s. As a result, there was a desire to reduce reliance on rubber and diversify agricultural production to other commercial crops. Oil palm became an alternative for Thailand following its success in Malaysia which shifted from rubber to oil palm in the 1960s and later became the world's leading producer and exporter. It was expected that with a similar climate, soils and topography, Southern Thailand could produce oil palm. Accordingly, palm acreage expanded through the South and the East especially during the second part of 1970s partly a result of the relative attractiveness of the palm oil price. Moreover, in comparison to rubber, palm cultivation has two advantages. First, oil palm has a lower gestation period: three years after it is planted, palm starts its yield while rubber growers have to wait another three or four years for first tapping. Second, oil palm production requires less labour and this is particularly important given the labour shortage in the South. Figure 2.9 shows that real palm oil price[10] significantly fluctuated from a peak at 933 US$/tonne in 1961 to the lowest price at 558 US$/tonne in 2001. However, there is a downward trend until 2001 before it increased to 800 US$/tonne in 2008.

Figure 2.9 Real Palm Oil Prices in Thailand, 1961-2008



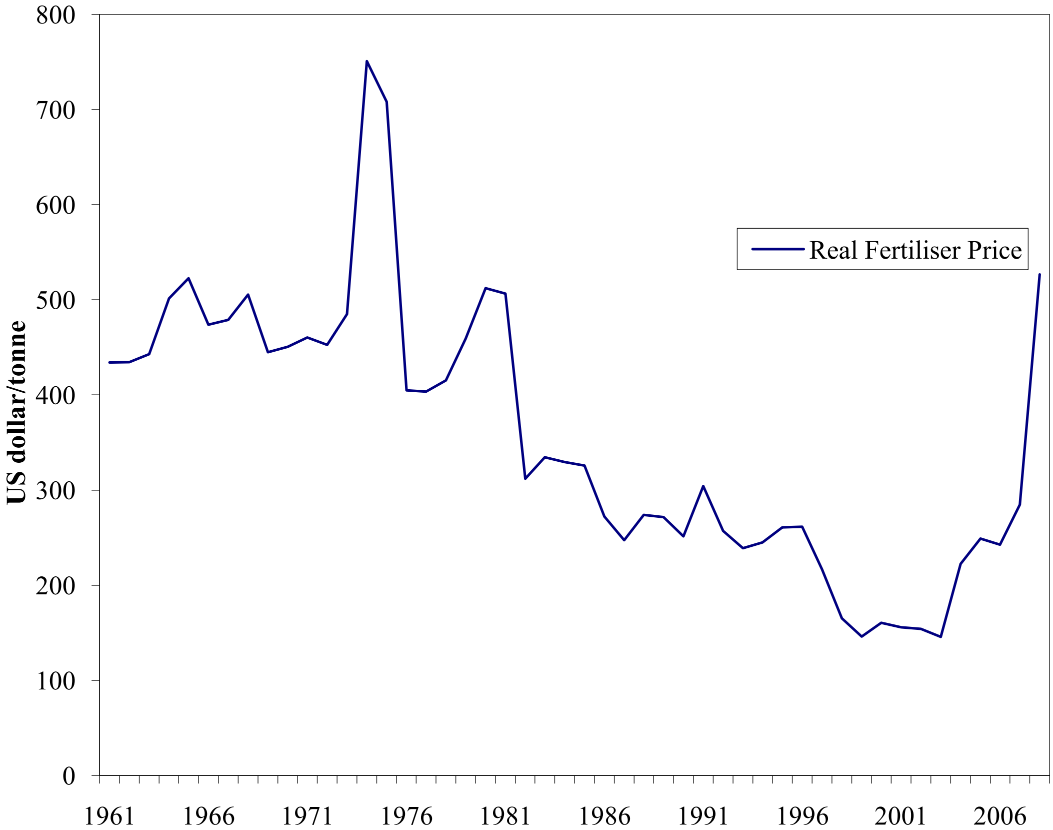
Source: adapted from FAO (n.d.) and Centre for Agricultural Information Office of Agricultural Economics (n.d.).

[10] No data are available on the palm oil price in Thailand between 1961-1968 and the export price from Malaysia is used as a proxy.

2.5.6 Fertiliser Prices

Fertiliser is an essential input for rubber cultivation and fertiliser expenditure is an important part of total cost. Most fertilisers are imported and the real average import price is shown in Figure 2.10 for 1961-2008. In 1961-1973, it varied from 434 US$/tonne to 485 US$/tonne, and reached a peak of 751 US$/tonne in 1974. It then fell to 405 US$/tonne in 1976 before increasing to 512 US$/tonne in 1980. These two high prices reflect global oil shocks. After that, the fertiliser price has a downward trend to its lowest of 146 US$/tonne in 2003 before increasing to 527 US$/tonne in 2008.

Figure 2.10 Real Fertiliser Prices in Thailand, 1961-2008



Source: adapted from Centre for Agricultural Information Office of Agricultural Economics (2009) and Office of Agricultural Economics (various years).

2.6 Summary

Originated from the Amazon area, the rubber tree was first introduced into Southern Thailand in 1901, subsequently spreading to Southern and Eastern regions. Rubber cultivation in Thailand is mainly on smallholdings. Since the 1960s, rubber areas have continually increased and have expanded to the North East and the North. Thailand developed into the world's largest manufacturer of natural rubber in 1990. Rubber is an important source of both foreign revenue and domestic employment.

Most natural rubber is from the tropical rubber tree, *Hevea Brasiliensis.* The peninsular part of Southern Thailand and the coastal area of the East are traditional rubber areas which have a monsoon climate suitable for rubber cultivation. As a perennial, the rubber tree is usually replanted when latex yields become unprofitable. Depending on growing conditions, the rubber tree takes approximately seven years to come to the mature stage when farmers can then tap for approximately 25 years. Natural rubber production is labour-intensive and labour consists of both family members as owners and paid workers. Paid workers, particularly tappers, earn income by crop-sharing. Rubber farmers sell products in original form as freshly tapped latex or as an initial processed product such as the raw or unsmoked rubber sheet. In general, farmers sell in local markets for export. The Thai government plays an important role through its agencies. The Rubber Replanting Aid programme plays an important in replanting low-yielding trees by high-yielding trees. The government occasionally intervenes in the market to control prices.

Rubber acreage is mainly located in the traditional region. The last decade has seen a rapid expansion of acreage in new regions. The expansion of high-yielding rubber acreages and better technology has led to increasing yields since the 1980s. Although production fluctuates because of price fluctuations, drought, and heavy rains, it increased during 1961-2008 due to the acreage expansion and the yield improvements.

This chapter provides a background to natural rubber production in Thailand and "sets the scene" for an analysis of natural rubber supply response. The next chapter discusses the literature on supply response, particularly previous studies in Thailand.

Appendix 2.1 Natural Rubber Data, 1961-2008

Year	Planted Acreage (ha)(1)	Tapped Acreage (ha)(2)	Yield (tonne/ha)(3)	Production (tonne)(4)	Nominal Price ($/tonne)(5)	Real Price ($/tonne)(6)
1961	492,800	400,160	465	186,100	455.88	3,220.41
1962	748,320	551,840	354	195,400	405.65	2,863.56
1963	824,320	544,000	365	198,300	379.08	2,717.77
1964	935,040	579,520	363	210,600	363.33	2,531.96
1965	941,120	588,320	217	127,400	364.86	2,429.85
1966	983,040	581,600	375	218,100	358.24	2,226.01
1967	1,181,600	615,200	356	219,300	245.73	1,540.82
1968	1,212,160	615,200	419	257,800	263.67	1,663.23
1969	1,244,000	742,720	379	281,800	332.10	2,053.30
1970	1,276,160	811,520	354	287,200	273.32	1,628.24
1971	1,308,320	922,560	343	316,300	227.88	1,369.07
1972	1,340,320	934,720	360	336,900	227.92	1,285.52
1973	1,372,320	979,840	375	367,700	334.77	1,588.41
1974	1,405,760	992,640	385	382,100	362.21	1,426.61
1975	1,405,760	992,640	351	348,700	315.03	1,197.51
1976	1,460,160	1,096,320	358	393,000	448.53	1,632.31
1977	1,484,000	1,094,720	394	431,000	487.74	1,675.18
1978	1,508,160	1,082,720	431	467,000	620.08	1,943.97
1979	1,532,160	1,417,120	377	534,300	703.27	2,028.47
1980	1,538,400	1,240,480	375	465,200	780.41	1,989.72
1981	1,578,720	1,269,280	400	507,700	606.31	1,426.41
1982	1,600,160	1,417,920	406	576,000	527.39	1,181.00
1983	1,622,880	1,418,240	419	593,900	632.61	1,366.75
1984	1,703,745	1,371,057	570	781,283	629.88	1,341.44
1985	1,711,158	1,347,020	627	844,070	543.10	1,131.98
1986	1,719,790	1,343,537	707	949,834	594.70	1,219.37
1987	1,727,969	1,351,909	785	1,061,435	716.48	1,402.82
1988	1,735,906	1,354,858	849	1,150,722	854.75	1,580.02
1989	1,743,871	1,366,633	958	1,309,531	683.22	1,190.14

Appendix 2.1 Natural Rubber Data, 1961-2008 (continued)

Year	Planted Acreage (ha)(1)	Tapped Acreage (ha)(2)	Yield (tonne/ha)(3)	Production (tonne)(4)	Nominal Price ($/tonne)(5)	Real Price ($/tonne)(6)
1990	1,753,702	1,395,096	1,016	1,417,666	671.08	1,105.20
1991	1,763,440	1,411,846	1,062	1,500,012	633.31	986.31
1992	1,779,924	1,419,483	1,206	1,712,488	661.81	986.40
1993	1,794,017	1,450,701	1,248	1,810,826	630.74	910.17
1994	1,848,289	1,531,979	1,298	1,988,872	910.54	1,248.89
1995	1,870,001	1,558,033	1,323	2,061,577	1,251.85	1,626.13
1996	1,882,447	1,545,807	1,373	2,122,045	1,082.76	1,352.26
1997	1,910,089	1,544,157	1,405	2,169,219	738.10	885.82
1998	1,954,721	1,548,317	1,397	2,162,789	549.57	603.79
1999	1,985,151	1,552,879	1,427	2,215,365	479.19	548.62
2000	1,987,357	1,523,899	1,560	2,377,789	536.75	606.35
2001	1,990,401	1,523,407	1,681	2,561,120	461.83	511.14
2002	2,003,964	1,553,214	1,694	2,631,605	644.55	707.59
2003	2,018,611	1,601,353	1,787	2,860,966	910.22	983.23
2004	2,072,039	1,656,686	1,815	3,007,612	1,097.15	1,147.13
2005	2,175,331	1,691,761	1,762	2,980,318	1,331.92	1,331.92
2006	2,294,087	1,743,513	1,762	3,071,218	1,748.59	1,672.83
2007	2,456,561	1,775,338	1,703	3,024,207	1,989.96	1,843.60
2008	2,608,106	1,827,890	1,796	3,283,572	2,211.13	1,961.98

Sources: (1), (2), (3), (4) and (5) derived from Centre for Agricultural Information Office of Agricultural Economics (n.d.).
(6) derived from calculation.

Appendix 2.2 Data on Alternative Crops, Fertiliser, and GDP Deflator, 1961-2008

Year	Real Paddy Price ($/tonne)[7]	Real Palm Oil Price ($/tonne)[8]	Real Fertiliser Price ($/tonne)[9]	GDP Deflator[10]
1961	316.00	933.39	434.16	0.14
1962	380.68	858.2	434.6	0.14
1963	336.80	905.12	442.75	0.14
1964	242.49	942.6	501.54	0.14
1965	274.96	1053.31	522.77	0.15
1966	346.00	840.17	473.71	0.16
1967	345.63	808.85	478.87	0.16
1968	294.47	613.94	505.6	0.16
1969	254.44	677.53	444.91	0.16
1970	179.05	603.47	450.63	0.17
1971	231.07	678.76	460.28	0.17
1972	353.31	711.48	452.8	0.18
1973	448.27	715.48	484.97	0.21
1974	406.72	713.3	750.9	0.25
1975	363.54	720	708.01	0.26
1976	329.85	788.5	404.86	0.27
1977	387.56	803.08	403.36	0.29
1978	336.69	797.01	415.22	0.32
1979	382.39	762.8	459.52	0.35
1980	394.08	684.82	512.4	0.39
1981	310.08	603.77	506.46	0.43
1982	285.95	554.96	311.85	0.45
1983	261.61	544.82	334.52	0.46
1984	209.46	540.54	329.39	0.47

Appendix 2.2 Data on Alternative Crops, Fertiliser, and GDP Deflator (continued)

Year	Real Paddy Price ($/tonne)(7)	Real Palm Oil Price ($/tonne)(8)	Real Fertiliser Price ($/tonne)(9)	GDP Deflator(10)
1985	176.59	544.89	325.83	0.48
1986	233.43	389.82	272.25	0.49
1987	292.74	646.99	247.38	0.51
1988	290.86	789.28	273.77	0.54
1989	245.96	474.43	271.56	0.57
1990	232.24	457.01	251.36	0.61
1991	232.42	445.55	304.08	0.64
1992	192.82	425.95	257.18	0.67
1993	212.41	399.57	238.97	0.69
1994	210.35	409.35	244.86	0.73
1995	248.38	440.81	260.8	0.77
1996	283.66	625.25	261.33	0.80
1997	179.04	518.96	216.64	0.83
1998	122.75	559.49	165.03	0.91
1999	168.91	418.2	146.13	0.87
2000	135.41	292.19	160.53	0.89
2001	111.69	185.26	155.71	0.90
2002	123.68	367.34	153.99	0.91
2003	132.28	380.82	145.73	0.93
2004	142.48	505.27	222.55	0.96
2005	164.27	428.89	248.9	1.00
2006	186.73	377.23	242.5	1.05
2007	261.98	682.73	284.65	1.08
2008	292.99	799.50	526.76	1.13

Sources: (7) derived from IRRI (n.d.) and Centre for Agricultural Information Office of Agricultural Economics (n.d.).
(8) derived from FAO (n.d.) and Centre for Agricultural Information Office of Agricultural Economics (n.d.).
(9) derived from Centre for Agricultural Information Office of Agricultural Economics (2009) and Office of Agricultural Economics (various years).
(10) obtained from IMF (n.d.).

Chapter 3 Literature Review on Supply Response of Natural Rubber in Thailand

3.1 Introduction

Agricultural supply response is an important topic in agricultural economics. Its main aim is to derive output and input elasticities which can then be used to develop agricultural policies. The effectiveness of those policies on production is mainly determined by the supply elasticities and policy-makers must therefore have a precise knowledge of them. Previous literature reviews on agricultural supply response, such as Askari and Cummings (1976), Colman (1983), Rao (1989) and Hennebery and Tweeten (1991), have concentrated on methodology highlighting strengths and weaknesses. These methods, which rely on different aspects of the theory of the firm to surmount obstacles in the estimation process (Colman, 1983, p.202), can be categorised into two major groups: econometric and programming approaches. This chapter reviews the literature on supply response and is structured as follows: Section 3.2 and 3.3 reviews econometric and programming approaches, Section 3.4 examines econometric approaches for perennial crops, Section 3.5 examines the literature on the supply response of natural rubber in Thailand, and Section 3.6 summarises.

3.2 Econometric Approaches to Agricultural Supply Response

Econometrics develops and applies mathematical and statistical techniques to analyze economic data to generate empirical content to economic theories. It is used to test economic relationships which are useful for making economic decisions and policy-making. Econometric approaches to examine agricultural supply response can be separated into three groups: direct estimation of the supply function, the indirect or two-stage approach, and the cointegration approach.

3.2.1 Direct Estimation of the Supply Function

Direct estimation of the supply function is adopted in the majority of empirical supply response studies. Most examine a single commodity but the literature also includes both models containing several supply functions which are estimated separately and models involving a system of supply equations which are estimated simultaneously. In general, parameters are estimated directly from time-series data at the aggregate (market) level.

Supply response is described by a set of explanatory variables based on the knowledge of economic theory and the technical conditions of production (Colman, 1983, p.219). Agricultural production, particularly of a perennial, is affected by past decisions, which can be a function of both current and future expectations of economic circumstances. An essential question in agricultural supply response analysis involves modelling expectations, and how to derive appropriate functional forms, variables, and the estimating method to integrate various sources of postulated expectations. Key are the models of Koyck (1954) and Nerlove (1958), the distributed lag model of Almon (1965), and Muth's (1961) model of rational expectations. Further, the inclusion of variables corresponding to expectations of prices, revenues or profits into supply functions is a short-cut procedure to acknowledge the role of investment which is an important factor in explaining the supply response of livestock and perennial crops (Colman, 1983, pp.210-211).

Alternative theories have been developed to explain the dynamics of agricultural supply response. Two of the most important are Nerlove's (1958) adaptive expectations and partial adjustments models. The latter is one of the simplest specifications reflecting the underlying investment decision. These models, or modifications of them, have been used extensively in the literature (Hennebery and Tweeten, 1991; Askari and Cummings, 1976).

In the adaptive expectations model,[11] assume that the output in period t, Q_t, is a function of expected price in the same period, P_t^*:

$$Q_t = \beta_0 + \beta_1 P_t^* + u_t \tag{3.1}$$

where u_t is an error term. Since the expected price is not an observable variable, Nerlove (1958, p.53) hypothesizes that "... [in] each period people revise their notion of 'normal' price in proportion to the difference between the then current price and their previous idea of 'normal' price". In other words, the producer in each period adjusts his expected price to the degree of previous errors. Accordingly, the current market price influences the decision of how much to produce in several forthcoming periods (Colman and Young, 1989, pp.36-37). The expected price can be illustrated in terms of the expected price in the previous period plus some fraction of the difference between the actual and expected prices in the previous period, that is:

[11] This derivation is based on Gujarati and Porter (2009, pp.629-630) and Sadoulet and de Janvry (1995, pp.86-89).

$$P_t^* = P_{t-1}^* + \delta(P_{t-1} - P_{t-1}^*) + v_t \qquad 0 < \delta \leq 1 \tag{3.2}$$
[12]

where P_t denotes the actual price in period t, δ is the coefficient of expectation, and v_t is an error term. If $\delta = 0$, the expected price in the present period remains the same as in the last period, and actual price has no effect on expectations. This is inconsistent with the adaptive expectations hypothesis and we restrict $\delta > 0$. Conversely, if $\delta = 1$, expected price equals actual price in the previous period and expectations are naïve since past price behaviour is completely ignored (Colman and Young, 1989, p.36). Rearranging (3.2) gives:

$$P_t^* = \delta P_{t-1} + (1-\delta)P_{t-1}^* + v_t \tag{3.3}$$

Here, the expected price at time t is a weighted average of the actual price at time t and the expected price in the previous period, with weights of δ and $1-\delta$, respectively. If $\delta = 0$, $P_t^* = P_{t-1}^*$ and expectations are static, and expected price is the same in all periods. On the other hand, if $\delta = 1$, $P_t^* = P_{t-1}$ and expectations are realized completely and without delay in the same period.

Substituting (3.3) into (3.1) gives:

$$Q_t = \beta_0 + \beta_1 \delta P_{t-1} + \beta_1(1-\delta)P_{t-1}^* + u_t + \beta_1 v_t \tag{3.4}$$

---

[12] The model can be expressed as $P_t^* = P_{t-1}^* + \delta(P_t - P_{t-1}^*) + v_t$ (Gujarati and Porter, 2009, p.629).

Next, lag (3.1) one period, and multiply it by $(1-\delta)$:

$$(1-\delta)Q_{t-1} = \alpha_0(1-\delta) + \alpha_1(1-\delta)P^*_{t-1} + (1-\delta)u_{t-1} \tag{3.5}$$

Subtract (3.5) from (3.4) and after some simple algebraic manipulation:

$$Q_t = \beta_0\delta + \beta_1\delta P_{t-1} + (1-\delta)Q_{t-1} + \omega_t \tag{3.6}$$

where $\omega_t = u_t - (1-\delta)u_{t-1} + \beta_1 v_t$. Consider the difference between (3.1) and (3.6). In (3.1), the price coefficient, β_1, measures the average change of output response to a change in expected price, P^*_t, while in (3.6), $\beta_1\delta$, measures the average response of output to a change in price last period, P_{t-1}. These responses are the same if $\delta = 1$ when expected and observed prices are equal.

The partial adjustment model postulates that long-run equilibrium or desired output in period t, Q^*_t, is a function of actual price in the same period:[13]

$$Q^*_t = \beta_0 + \beta_1 P_t + u_t \tag{3.7}$$

Long-run output is not directly observable and Nerlove (1958, p.62) proposes a relationship between the long-run and actual output which holds for any point in time: "In each period actual output is adjusted in proportion to the difference between the output desired in long run equilibrium and actual output …", that is:

$$Q_t - Q_{t-1} = \lambda(Q^*_t - Q_{t-1}) + w_t \qquad 0 < \lambda \le 1 \tag{3.8}$$

[13] The derivation of the model is based on Gujarati and Porter (2009, p.632) and Sadoulet and de Janvry (1995, pp.86-89).

where Q_t is the actual output in period t, λ is the coefficient of adjustment, and w_t is an error term. Thus the actual output in period t is revised by a portion of the difference between the long-run equilibrium or desired output and the actual output in the previous period. If $\lambda = 0$, the output in the present time period remains unchanged from that in the previous period. This is inconsistent with the partial adjustment hypothesis and we restrict $\lambda > 0$. Conversely if $\lambda = 1$, actual output equals desired output, that is, adjustment to long-run equilibrium is realised immediately. Generally, $0 < \lambda < 1$ and the adjustment to long-run equilibrium is likely to be incomplete in one period for a number of reasons such as rigidity, inertia, institutional factors, technical constraints, and so forth. Inertia arising from investment adjustment costs and technical constraints reflect the role of investment in the dynamics of supply response. Equation (3.8) can be rewritten as:

$$Q_t = \lambda Q_t^* + (1-\lambda)Q_{t-1} + w_t \qquad 0 < \lambda \leq 1 \tag{3.9}$$

and actual output in period t is a weighted average of desired output at the same time and actual output in the previous period, weighting by λ and $(1-\lambda)$ respectively. If $\lambda = 0$, actual output in period t is the same as in the previous period. Conversely, if $\lambda = 1$, actual output adjusts to long-run equilibrium within one period. Now substituting (3.7) into (3.9) gives:

$$Q_t = \beta_0\lambda + \beta_1\lambda P_t + (1-\lambda)Q_{t-1} + \upsilon_t \tag{3.10}$$

where $\upsilon_t = \lambda u_t + w_t$. This model is a short-run function where short-run output, Q_t, may be different from its long-run level, Q_t^*.

Although the adaptive expectations and partial adjustment models seem similar, they are different in theory: the former is based on uncertainty about the formulation of expected price, while the latter is based on technical or institutional rigidities, inertia, cost of change, and so on. In empirical studies, the two models might be appropriate for different situations. Adaptive expectations with no partial adjustment ($\lambda = 1$) is appropriate to study crop production where there are no significant fixed factors, and adaptation can be completed in a single period; that is, $Q_t^* = Q_t$. Partial adjustment with no adaptive expectations ($\delta = 1$) is suitable for situations where crop prices are known at the planting stage (Sadoulet and de Janvry, 1995, p.88). If variables are in logarithmic form, the short-run price elasticities of supply response of these models are $\beta_1\delta$ and $\beta_1\lambda$, respectively, while the long-run price elasticity for both is β_1.

A third Nerlovian model is a combination of the two. Since long-run equilibrium output and expected price are both unobservable, a relationship between the two variables connects observed output with observed price from different periods that is:[14]

$$Q_t^* = \beta_0 + \beta_1 P_t^* + u_t \tag{3.11}$$

In estimating a reduced-form equation of the model consisting of (3.3), (3.8), and (3.11), an identification problem arises. It is impossible to identify the coefficients of expectation and adjustment, that is, there is no way to distinguish the difference between long- and short-run supply elasticities from the distinction between current actual price or price in last time period and expected prices in the future (Nerlove,

[14] The derivation of the model is based on Gujarati and Porter (2009, p.634) and Sadoulet and de Janvry (1995, pp.86-89).

1958, p.64). To overcome this problem, Nerlove suggests that an additional variable, Z_t, is incorporated into (3.12) which denotes all other observed exogenous variables:[15]

$$Q_t^* = \beta_0 + \beta_1 P_t^* + \beta_2 Z_t + u_t \tag{3.12}$$

Combining (3.12) with the partial adjustment model in (3.9) gives:

$$Q_t = \beta_0\lambda + \beta_1\lambda P_t^* + \beta_2\lambda Z_t + (1-\lambda)Q_{t-1} + \lambda u_t + w_t \tag{3.13}$$

The expected price, P_t^*, in (3.3), is substituted into (3.13) to give:

$$Q_t = \beta_0\lambda + \beta_1\lambda(1-\delta)P_{t-1}^* + \beta_1\lambda\delta P_{t-1} + \beta_2\lambda Z_t + (1-\lambda)Q_{t-1} + \lambda u_t + w_t + \beta_1\lambda v_t \tag{3.14}$$

Rearranging (3.13) gives:

$$P_t^* = \frac{1}{\beta_1\lambda}\left[Q_t - \beta_0\lambda - \beta_2\lambda Z_t - (1-\lambda)Q_{t-1} - \lambda u_t - w_t\right] \tag{3.15}$$

Lagging (3.15) one period gives:

$$P_{t-1}^* = \frac{1}{\beta_1\lambda}\left[Q_{t-1} - \beta_0\lambda - \beta_2\lambda Z_{t-1} - (1-\lambda)Q_{t-2} - \lambda u_{t-1} - w_{t-1}\right] \tag{3.16}$$

Substitution of (3.16) into (3.14) gives:

---

[15] This variable can be included in the adaptive expectations or partial adjustment models.

$$Q_t = \beta_0\delta\lambda + \beta_1\delta\lambda P_{t-1} + [(1-\delta) + (1-\lambda)]Q_{t-1} - (1-\delta)(1-\lambda)Q_{t-2}$$

$$+ \beta_2\lambda Z_t - \beta_2\lambda(1-\delta)Z_{t-1} + w_t - (1-\delta)w_{t-1} + \lambda u_t - \lambda(1-\delta)u_{t-1} + \beta_1\lambda v_t \quad (3.17)$$

Equation (3.17) can be rewritten to give the reduced and estimable form:

$$Q_t = \alpha_0 + \alpha_1 P_{t-1} + \alpha_2 Q_{t-1} + \alpha_3 Q_{t-2} + \alpha_4 Z_t + \alpha_5 Z_{t-1} + z_t \quad (3.18)$$

where $\alpha_0 = \beta_0\delta\lambda$, $\alpha_1 = \beta_1\delta\lambda$, $\alpha_2 = (1-\delta) + (1-\lambda)$, $\alpha_3 = -(1-\delta)(1-\lambda)$, $\alpha_4 = \beta_2\lambda$, $\alpha_5 = -\beta_2\lambda(1-\delta)$, and $z_t = w_t - (1-\delta)w_{t-1} + \lambda u_t - \lambda(1-\delta)u_{t-1} + \beta_1\lambda v_t$. There are three difficulties in estimating (3.18) by ordinary least squares (OLS). First, the estimates are inefficient because the disturbance term is likely to be serially correlated. Second, the estimates are inconsistent due to the lagged dependent term. Third, this reduced form is overidentified because there are six reduced-form coefficients, i.e., $\alpha_0,...,\alpha_5$ and five structural parameters, i.e., β_0, β_1, β_2, δ, and λ (Sadoulet and de Janvry, 1995, p.87; Askari and Cummings, 1976, p.48). We can obtain a unique solution for structural parameters by imposing a non-linear constraint on the parameters of the reduced form:

$$\alpha_5^2 - \alpha_3\alpha_4^2 + \alpha_2\alpha_4\alpha_5 = 0 \quad (3.19)$$

Non-linear, maximum likelihood methods should be used for estimation, and serial correlation in the error terms need to be corrected. If the parameters are estimated in logarithmic form, the short run price elasticity is $\beta_1\delta\lambda$ and the long-run price elasticity is $\alpha_1 / \delta\lambda$ or β_1 (Sadoulet and de Janvry, 1995, pp.87-88).

Nerlove's supply response models have been applied to the production behaviour of agricultural producers in a variety of empirical studies which examine different crops in different countries. However, Nerlove's framework has attracted several criticisms. First, the theoretical postulations employed in partial adjustment models are *ad hoc* (Nerlove, 1979), that is, in each period, if we are dealing without discrete time, a portion of the difference between the current period and long-run equilibrium is eliminated (McKay *et al.*, 1999, p.111).[16] Second, both short- and long-run supply responses with respect to price tend to be underestimated due to the formulation of price expectations, that is, producers' price expectations may remain constant if they consider these changes to be temporary. Therefore, expected price changes based on the adaptive expectation model may be overestimated and the aggregate supply elasticity is underestimated. Further, the supply elasticity may be biased downward since price expectations variable do not include all relevant past prices (Hennebery and Tweeten, 1991, p.52). Third, difficulties arise from choosing the most appropriate non-market factor, Z. A common choice is weather, but others include technological progress, infrastructure improvement, growth in demand for output, or simply a time trend (Askari and Cummings, 1976, p.44).

A further criticism of directly estimating the supply function arises from the question, "what appropriate price should be used?" From production theory, output is a function of profitability or relative profitability in the case of multiple products. But price variables which enter independently or as simple price ratios may not generally satisfy their expected meaning, and it is difficult to obtain appropriate enterprise profitability

---

[16] This hypothesis is related to the concept of a fixed long-run equilibrium or desired value of a specified variable, which is considered as unrealistic in the framework optimising behaviour under dynamic conditions (Hallam and Zanoli, 1993, p.154).

(Colman, 1983, p.223). The influence of risk on the decisions of a producer to invest and supply has received little attention (Colman, 1983, p.222).

Several criticisms also refer to intrinsic limitations of econometrics. First, the estimation procedure is under pressure of degrees of freedom, and consequently time-series analysis may not distinguish the partial influence of individual variables if they change together over time (Colman, 1983, pp.223-224). A failure to include relevant variables leads to misspecification which may cause biased supply elasticities estimates (Hennebery and Tweeten, 1991, p.53). Moreover, time-series estimates are subject to the Lucas critique which suggests that the estimated parameters depend on the policy prevailing at the time the model is estimated, and they change when a policy change occurs. Thus, it is impossible to forecast the effect of policy transformation (McKay *et al*., 1999, p.112). Finally, OLS is based on the assumption that the underlying data generating processes are stationary but most economic variables are non-stationary and applying OLS to non-stationary data may produce spurious results (Granger and Newbold, 1974). A key advantage of estimating supply functions directly is that data requirements and estimation procedures are simple. This approach is also less prone to specification errors than programming and indirect, two-stage procedures because there are fewer steps in estimating supply elasticities. Further, dynamic adjustment and the formulation of price expectations are simple to deal with compared to other methods (Hennebery and Tweeten, 1991, p.53; Colman, 1983, pp.223-224).

3.2.2 Indirect Estimation of the Supply Function

A second method of estimating supply response is the indirect, two-stage or duality approach. From duality principles, there exists a relationship between the production, profit and cost functions, and the supply function. One of the production, profit and cost functions is econometrically estimated in the first stage using either time-series or cross-sectional data and then the results are used to derive supply response functions by algebraic manipulation in the second stage (Colman, 1983, pp.203-204).

In deriving estimates of supply response from a production function, the procedure involves imposing the first-order profit-maximising conditions on the production function which are used to determine profit-maximising input levels; then, by substituting these input demand functions into the production function, the supply function estimates with the same exogenous variables can be obtained (Colman, 1983, pp.204-205). Estimates of supply response can also be derived from a profit function. This procedure is based on estimating the indirect profit function which is derived from a profit maximisation problem. The indirect profit function is defined as the maximum profit associated with given output and input prices. This is obtained by substituting input demand and output supply functions from a profit-maximising primal solution into the direct profit function. This function is expressed in terms of output and input prices, and quantities of inputs from the Hotelling-Shepherd Lemma. The output supply and input demand functions can then be obtained by taking the partial derivative of the indirect profit function with respect to output and input prices (Hennebery and Tweeten, 1991, pp.56-59). Finally, estimates of supply response can be derived from estimating an indirect cost function which is derived from a constrained cost-minimisation problem. This function is the minimum cost needed to produce a certain level of output at particular input prices and is expressed in terms of variable input prices and output. Using the Hotelling-Shepherd Lemma, partial differentiation of the indirect cost function with respect to input prices yields the conditional input demand functions from which the supply function can be derived.

Although there are a number of studies generating supply response functions using these duality relationships, there are five limitations. First, it is theoretically grounded in a single-commodity framework which is unreasonable for estimating supply functions under circumstances where different products compete for available inputs (Colman, 1983, p.216). Second, simultaneous bias in the production function is caused by including inputs as determinants of output since these variables are jointly determined. Estimation through profit or cost functions however overcome this problem because the profit, output supply, and input demand functions are expressed in terms of exogenous variables such as output price, input prices and quantities of inputs. Third, two-stage procedures are appropriate at the micro-firm level, but the application at the aggregate level is questionable. Fourth, difficulties arise when an attempt is made to distinguish between short- and long-run elasticities. Finally, the derivations of input demand and output supply functions from profit or cost functions are based on the assumption of profit maximisation, cost minimisation, and perfect competition which may not hold (Hennebery and Tweeten, 1991, pp.58-59).

The major advantage of using the indirect procedure is the simplicity in deriving input demand and output supply functions by partial differentiation. Moreover, because this method involves less algebraic manipulations, more complicated functional forms with few restrictions on the estimating equations can be employed giving a close relationship between economic theory and empirical model.

3.2.3 Cointegration Approach to Estimate the Supply Function

When OLS is used to estimate a Nerlovian supply response equation, an implicit assumption is that each data series is stationary. Economic variables, including agricultural time-series data, are generally non-stationary and OLS may produce spurious or meaningless regressions. Modern time series techniques, cointegration approach, can be used to avoid this problem since it can be used with non-stationary data (McKay *et al*., 1999, p.113).

The concept of cointegration proposes that if two (or more) series are associated to create an equilibrium relationship over the long run, then although the series may be non-stationary, they tend to move closely together over time and the variation between them is unchanged, i.e., stationary. Here, a meaningful regression on the levels of the variables can be obtained, and any important long-run information is still present. From the Granger representation theorem, a dynamic model of these integrated series can be converted into an error correction model (ECM) which contains information on both the short- and long-run properties of the model.[17] Short-run disequilibrium is indicated by a process of adjustment to long-run equilibrium (Engle and Granger, 1987). The essential implication of this theorem is that cointegration and ECM can be exploited to establish an integrated practical and conceptual structure to investigate short- and long-run performance, that is, this method becomes a way of acquiring consistent and separate estimates of both short-

[17] The error correction model is theoretically considered as a better approach to partial adjustment models for studying agricultural supply response (Hallam and Zanoli (1993, p.154).

and long-run supply elasticities (McKay *et al*., 1999, p.113). Hendry and von Ungern-Sternberg (1981), Salmon (1982), Nickell (1985) and Hallam and Zanoli (1993) demonstrate that ECMs can be derived from the dynamic optimising behaviour of economic agents and represents forward-looking behaviour. This theoretical basis of the ECM can be used to model agricultural supply response, and the ECM also nests the partial adjustment model (Hallam and Zanoli, 1993, p.152).

An ECM of agricultural supply response in its simplest form comprises of output and price, Q_t and P_t, can be represented as:

$$\Delta Q_t = \alpha \Delta P_t - \psi(Q_{t-1} - \phi P_{t-1}) + \nu_t \tag{3.20}$$

where ν_t is a disturbance term with zero mean, constant variance, and zero covariance. The term α is the short-run effect of P_t on Q_t, and ϕ is the long-run equilibrium relationship between Q_t and P_t:

$$Q_t = \phi P_t + u_t \tag{3.21}$$

that is, $(Q_{t-1} - \phi P_{t-1})$ evaluates the 'errors' or the divergences from long-run equilibrium. The term ψ measures the speed of adjustment, that is, the degree to which Q_t adjusts to long-run equilibrium where a negative sign means that adjustment restores the long-run relationship.

Engle and Granger (1987) suggest a two-stage procedure to estimate the ECM. In the first stage, the static long-run cointegrating regression in (3.21) is estimated and then cointegration is tested by testing for stationarity of the residuals, u_t. If the residuals are stationary, cointegration is present and the lagged residuals from (3.21) are used in the second stage to estimate the ECM in (3.20) because they are the error-correction term, $(Q_{t-1} - \phi P_{t-1})$. OLS produces consistent estimators of all parameters (Hallam and Zanoli, 1993, p.153).

Since the Engle-Granger procedure implies a unique cointegrating vector, it is not efficient for systems containing more than two variables. An alternative approach is the reduced rank procedure of Johansen (1988) which is a system approach for testing the existence of all possible cointegrating relationships among the variables. This procedure is preferred to the Engle-Granger approach and is the *de facto* procedure in the applied cointegration works, and it is discussed in Chapter 5.

There are at least two major advantages of cointegration over more traditional methods. First, the problem of spurious regression is avoided. Second, both levels and differences of variables can be incorporated into the ECM so that distinct estimates of both short- and long-run relationships among integrated variables can be derived (McKay *et al.*, 1999, pp.113-114; Hallam and Zanoli, 1993, pp.151-152). Third and based on the equilibrium concept in cointegration, we can directly examine the dynamics of supply while that in the Nerlovian models are merely deduced from theoretical assumptions. Further, only the reduced form Nerlovian models can be estimated whereas in cointegration analysis, we can estimate the equilibrium relationship (McKay *et al.*, 1999, p.114). However, the cointegration approach can be criticised because it lacks a theoretical economic basis (McKay *et al.*, 1999, p.114; Maddala, 1998, p.75). Nevertheless, cointegration is widely used to estimate agricultural supply response at a commodity level in both developed and developing countries and examples include Hallam and Zanoli (1993), Townsend and Thirtle (1997), Abdulai and Rieder (1995), Weliwita and Govindasamy (1997), McKay *et al*. (1999), Alias *et al.* (2001), Alemu *et al*. (2003), Mesike *et al*. (2010), and Alias and Tang (2010).

3.3 Programming Approaches to Agricultural Supply Response

Linear programming (LP) models are an important approach to estimating supply response. Colman (1983, pp.202-203) states that LP develops a complete linear model which explains the production system of each reference farm by means of constructing a set of linear, additive production functions for each possible output that each farm is able to generate, given constraints on resource availability. A profit function is usually used as an objective function but other objectives, such as risk aversion may also be incorporated. After assuming given technology and product and input prices, LP is used to calculate the endogenous variables, that is, the profit-maximizing output and input levels for each farm. Supply-price relationships are then constructed for each output and farm by solving the problem for various groups of prices. The market level supply response relationship is obtained by aggregating the supply-price function from the farm level in the reference groups.

There are three main advantages of LP. First, it depends on the quality of the data and the ability to integrate psychological and institutional factors to restrict the rapid adjustment of farmers to prices by the use of flexibility constraints. Second, LP can avoid data problems that exist in econometric models such as the requirement that the number of times-series observations exceeds the number of estimated parameters and the larger the difference the better. However, it cannot guarantee that behavioural parameters remain unchanged for long periods which may cause unstable estimates through model misspecification (Colman, 1983, p.224). Third, the use of cross-sectional farm budget data is normally more reliable than aggregate time series data employed in econometric models (Hennebery and Tweeten, 1991, p.56).

LP has four main disadvantages. First, the supply response relationships are generally of a partial character, and there is no summary of the relationship between outputs and prices in terms of a formal functional statement. Second, there is a difficulty in estimating supply elasticities due to the uneven relationship linking output and price derived from the models (Hennebery and Tweeten, 1991, p.56). Third, it is difficult to both acquire an appropriate classification of farms and identify the performances and limitations of reference farms. Fourth, data collection at the farm level is costly (Colman, 1983, p.214-215).

3.4 Econometric Approaches to Supply Response of Perennial Crops

The supply of perennial crops has four distinctive characteristics. First, perennial crops have a biologically-determined gestation period between planting and harvesting. Second, current production depends on previous output levels. Third, there are significant costs of adjustment which restrict the planting and removal of trees. Fourth, planting and removal decisions are restricted by both past decisions and the existence of binding non-negativity constraints about the adjustment process, i.e., technical conditions of production, the availability of suitable land and labour, and credit market conditions. Separately and collectively, these characteristics imply that producers must have foresight or long-term planning with reference to investment. Further, the first two characteristics imply that the theory of perennial crops is dynamic. In particular, the productivity of such yield-bearing perennials as trees for any given level of inputs generally depends on a biologically-determined life-cycle. The total stock of trees and different maturities or age-cohort is an important factor affecting production, as are improvements of new varieties or clones which raise yields of a given age group significantly (Akiyama and Trivedi, 1987b, pp.138-139). The theory and empirical methods of analysing the supply response of perennials is therefore different from methods employed to analyse annual crops.

Empirical studies of aggregate supply response of perennials first appeared in the literature in the early 1960s and most use an econometric approach. Nerlovian supply response models are used in a number of studies (see Askari and Cummings, 1976) but they face several criticisms on both theoretical and empirical grounds since they were not developed for perennial crops. Several studies provide separate estimates of new planting, removal, and harvesting equations but most encounter empirical problems due to data availability related to new planting, removal, replacement, and age distribution. Therefore, the single-equation regression models are commonly used where dependent variables include aggregate output, aggregate acreage, and their changes. We now review some studies of the supply response of perennial crops which use econometric approaches and time-series data.

The study of cocoa production in Ghana by Bateman (1965) seems to be the first attempt to adopt the Nerlovian supply response framework to perennial crop production. Since decisions to plant cocoa are based on expectations of income streams spread over the life of the tree and maintenance costs, Bateman assumes that farmers maximise the present value of expected profits with respect to area planted. Area planted thus becomes a function of the present value of expected prices, expected marginal yields per acre, expected total yields per acre, and expected marginal costs. Assuming that the producer price is the most important factor affecting income expectations, Bateman postulates that area planted is a function of the mean value of discounted expected own and substitute prices, and adaptive Nerlovian price expectations are assumed. The dependent variable is output due to a lack of data on area planted. After taking first differences and combining the result with a planting equation, Bateman derives a reduced-form equation where output is a function of lagged own and substitute prices, lagged rainfall, lagged humidity, and lagged output:

$$\Delta Q_t = a_0 + a_1 P_{t-k} + a_2 P_{t-s} + a_3 PA_{t-k} + a_4 PA_{t-s} + a_5 \Delta R_{t-1} + a_6 \Delta H_{t-1} + a_7 \Delta P_t$$

$$+ a_8 Q_{t-1} + a_9 \Delta R_{t-2} + a_{10} \Delta H_{t-2} + a_{11} \Delta P_{t-1} + w_t \tag{3.22}$$

where ΔQ_t is the change in output in period t, P_t and PA_t are producer prices of cocoa and coffee in period t, k is the age at which trees first yield, s is the age at which the second distinct increase in yield occurs, ΔR_{t-1} is the change in rainfall in t-1, ΔH_{t-1} is the change in humidity in t-1, ΔP_t is the change in output price in period t, Q_{t-1} is the amount of cocoa harvested in period t-1, and w_t is a disturbance term. In a modified model, Bateman postulates that producers encounter constraints to adjust the actual stock of trees to the desired level given a change in price. Here, the desired stock of trees is a function of the expected own price, the expected price of an alternative crop, and the stock of trees.

Behrman (1968) uses a similar model for cocoa production in major producing countries. Instead of modelling actual planted acreage, Behrman models desired acreage which is a function of expected own and cross prices. Nerlovian area adjustment is applied. Due to a lack of data, Behrman transforms this acreage hypothesis to one in terms of output which is now a function of both current and lagged owns prices and an infinite sum of the product of yield and lagged area. In first differences, output is a function of lagged own and cross prices and lagged output.

Ady (1968) analyses the supply response of cocoa and coffee production in a planting equation similar to Bateman's model. This model is also comparable to that of Behrman where the planting equation has the stock of trees as the dependent variable. Nerlovian price expectations are hypothesised. Again due to a lack of data on new planting and acreage, Ady develops a single, reduced-form equation in terms of first differences of output. Additional variables include a world price, an index of agronomic factors, and an index of other economic factors.

A significant development in supply response analysis of perennials was the theoretical model of French and Mathews (1971) who formulate a general framework within which new plantings and acreage adjustments occur. They apply the model to the US asparagus industry. Their model consists of five components. First, two functions involve the desired quantity of output and bearing acreage. The output equation is:

$$Q_t^d = Q_{t-1}^e + a_1(\pi_t^e - \pi_t^*) + a_2(\pi_{At}^e - \pi_{At}^*) + u_{1t} \tag{3.23}$$

where Q_t^d is desired production in period t, Q_{t-1}^e is expected average production in t-1, π_t^e and π_{At}^e are expected long-run profits for the crop and an alternative crop in period t, π_t^* and π_{At}^* are normal long-run profits for the crop and the alternative crop in period t, and u_{1t} is a disturbance term. The acreage equation is:

$$A_t^d = A_{t-1} + b_1(\pi_t^e - \pi_t^*) + b_2(\pi_{At}^e - \pi_{At}^*) + b_3 \Delta Y_t^e + u_{2t} \tag{3.24}$$

where A_t^d is desired bearing acreage in period t, A_{t-1} is actual bearing acreage in t-1, Y_t^e is the expected normal or average yield in period t, $\Delta Y_t^e = Y_t^e - Y_{t-1}^e$, and u_{2t} is a disturbance term.

Second, the Nerlovian partial adjustment hypothesis is adopted for new plantings where acreage adjusts the desired level:

$$N_t = c_1(\pi_t^e - \pi_t^*) + c_2(\pi_{At}^e - \pi_{At}^*) + c_3 \Delta Y_t^e + c_4 A_{t-1}^o + c_5 N_{t-k-1} + c_6 A_{t-1} + u_{3t} \tag{3.25}$$

where N_t is actual planted acreage in period t, A_{t-1}^o is the acreage of plants removed due to declining productivity in t-1, N_{t-k-1} is the total acreage planted after t-k-1 or the non-bearing acreage in t-1, k is the period between initial planting and bearing, and u_{3t} is a disturbance term.

Third, the equation that explains acreage removals is:

$$R_t = d_0 + d_1 A_t^o + d_2 A_t^o(\pi_t^s - \pi_t^*) + d_3 A_t^o(\pi_{At}^s - \pi_{At}^*) + d_4 Z_t + d_5 A_t + u_{4t} \tag{3.26}$$

where R_t is acreage removed in period t, π_t^s and π_{At}^s are short-run profit expectations for the crop and for an alternative crop in period t, Z_t is a variable to account for institutional or physical factors, and u_{4t} is a disturbance term. The change in bearing acreage is:

$$\Delta A_t = A_t - A_{t-1} = (1-\alpha)N_{t-k} - R_{t-1} + u_{5t} \tag{3.27}$$

where α is a proportion of planting removed because of disease and insect damage during gestation period interval k and is typically small, and u_{5t} is a disturbance term. Substituting (3.25) and (3.26) into (3.27) gives:

$$\begin{aligned}\Delta A_t = {} & g_0 + g_1(\pi_{t-k}^e - \pi_{t-k}^*) + g_2(\pi_{At-k}^e - \pi_{At-k}^*) + g_3 \Delta Y_{t-k}^e + g_4 A_{t-k-1}^o + g_5 A_{t-1}^o \\ & + g_6 A_{t-1}^o(\pi_{t-1}^s - \pi_{t-1}^*) + g_7 A_t^o(\pi_{At-1}^s - \pi_{At-1}^*) + g_8 Z_{t-1} + g_9 N_{t-2k-1} + g_{10} A_{t-k-1} \\ & + g_{11} A_{t-1} + u_{6t}\end{aligned} \tag{3.28}$$

where g_i, i=1,…,11 are parameters to be estimated.

Fourth, relationships that clarify the transformation of unobservable expectation variables into observable variables are constructed. The yield expectation is related to a long-term trend with unusual discrete jumps:

$$\Delta Y_t^e = f(Y_{m_{t-1}}, Y_{m_{t-2}}, \ldots) \tag{3.29}$$

where Y_m denotes the yield of mature plants. Under competitive conditions, long-run profitability per unit of product tends towards zero. Normal profit in the minds of producers could change over time as the structure of the industry and average cost change. Without some observable measures, it is possible to estimate π_t^* and π_{At}^* as:

$$\pi_t^* = h_0 + h_1 C_t + u_{7t} \tag{3.30}$$

$$\pi_{At}^* = m_0 + m_1 C_{At} + u_{8t} \tag{3.31}$$

where C_t and C_{At} are average costs of the product and the alternative in period t, and u_{7t} and u_{8t} are disturbance terms. Short- and long-run profit expectations of both the crop and the alternative are similarly specified as functions of past profits, which depend on price and cost:

$$\pi_t^e = g(\pi_{t-1}, \pi_{t-2}, ..., v_{1t}) \tag{3.32}$$

$$\pi_{At}^e = g_A(\pi_{At-1}, \pi_{At-2}, ..., v_{2t}) \tag{3.33}$$

where v_{1t} and v_{2t} permits the inclusion of any temporary modification of expected profits to account for unusual events such as changes in legislation. Finally, an equation that describes variation in average yield is:

$$\overline{Y}_t = \sum_{i=k}^{H} w_i A_{it} + m_1 T + u_{7t} \tag{3.34}$$

where $\overline{Y}_t$ is the average yield, A_{it} is the acreage of the *i*th age in period t, w_i are the weights for past planting of the *i*th age, H is a maximum age of the plant, and T is a time trend. The weights could vary depend on the age distribution of the trees. However, since normal average yield is relatively stable for a long period in the life cycle, using the complete distribution of ages can be avoided. Bearing stages thus may be classified into three or four groups with a different average yields in each group. If data on age distribution are unavailable, yield could be specified as a function of time. However a time trend would not account for yield variation due to age distribution.

By substituting (3.29), (3.30), (3.31), (3.32), and (3.33) into (3.25), a planting equation is obtained. In the same way, an acreage removed equation is derived by specifying π_t^s and an observable variable, such as $\pi_t^s = \pi_t$. The major limitation of this model is data availability, and estimating (3.28) may encounter a degrees of freedom problem, loss of information about planting and removals, and complexity of the disturbance terms. Accordingly when applying the model to the US asparagus industry, French and Mathews (1971) specify the acreage adjustment equation as:

$$\Delta A_t = \beta_0 + \beta_1 P_{t-1}^r \overline{A}_{t-1} + \beta_2 \overline{P}_{t-k-1} + \beta_3 \overline{A}_{t-1} + \beta_4 \overline{A}_{t-k-1} + \beta_5 D_t + s_t \tag{3.35}$$

where $\mathbf{P}_{t-1}^r$ is the ratio of grower price to an index of farm wage rate in t-1 which reflects profitability, $\overline{A}_{t-1}$ is the average harvested acreage during the previous five periods thereby accounting for the acreage of old asparagus, $\overline{P}_{t-k-1} = (P_{t-k-1} + P_{t-k-2})/2$, D is a dummy for changes in legislation pertaining to the source of harvest labour, and s_t is a disturbance term. Since various alternative crops are available to farmers, it is difficult to develop meaningful measures of π_{At}^e and it is omitted. Also ΔY_t^e is omitted because average yield did not vary much over the sample period, and N_{t-2k-1} is omitted due to its unavailability. In estimating the structural system, a single reduced-form equation is obtained by solving the structural system. This overcomes data limitations relating to new plantings, removals, and the age distribution of existing asparagus. However, the structural parameters are under-identified and French and Matthews could not retrieve the structural coefficients.

Developments of the basic model of French and Matthews (1971) include Rae and Carman (1975), Minami *et al*. (1979), Alston *et al*. (1980), Carman (1981), French *et al*. (1985), Bushnell and King (1986), Kinney *et al*. (1987), French and King (1988), French and Willet (1989), French and Nuckton (1991), and Carman and Craft (1998). These studies mainly concentrate on acreage response. The following considers them briefly in turn.

Rae and Carman (1975) study the supply response for New Zealand apples. Equations for new plantings, removals, yields and adaptation of innovations are specified and estimated. A modified measure of yield expectations given technical change (plantings on the semi-intensive system) is formulated and estimated.

Minami *et al*. (1979) study the production and acreage adjustment for Californian cling peaches. New planting and removal equations are specified in terms of expected profits (where price and cost variables are transformed into a single measure of profitability) and other determinants. Separate variables for young and old bearing trees are used to capture the effects of age distribution on tree removals and plantings. The removal equation also includes dummy variables to reflect the effects of a tree-removal incentive programme. Yield variation is explained by varieties of trees, districts of designation, ages, and time trends.

Alston *et al.* (1980) analyse the supply response of Australian oranges to assess the effects of changes in prices received by growers on tree numbers and production. Investment in trees is included in an input demand framework which focuses on the influence of the age composition on planting decisions. Different hypotheses concerning the process of adjustment are evaluated. Separate planting, removal, and yield equations are specified and estimated. Plantings are influenced by a moving average of past profitability levels which is used to represent expected profitability, the number of trees in the age classes and the number of trees removed. Because of data limitations on the age distribution of trees, removals are estimated as a function of bearing acreage. The yield equation is specified as a function of the proportion of bearing trees less than 10 years old and a time trend.

Carman (1981) uses a supply response model to estimate the impact of tax reform involving changing cost capitalization provisions on the acreage, production, and prices of Californian navel oranges, valencia oranges, lemons, almonds, walnuts, avocados and grapes. New plantings and changes in total acreages are specified as a function of identical independent variables including lagged average prices, lagged average total revenues, a dummy for income tax reform, farm labour availability, and lagged bearing acreages. Average yields are specified as a function of time.

To extend Minami *et al.* (1979), French *et al.* (1985) reformulate and apply a supply response model of plantings and removals by age category to California cling peaches. The model includes new planting and removal equations. New plantings are a function of actual past net returns, the potential future production from trees standing, the risk caused by a market intervention programme, and lagged total acres less acres removed in the same period. This study also suggests that the area of trees removed is determined by the productivity of trees which varies with age, short-run profit expectations, and variables representing market intervention. Because of data availability, the removal equation is estimated by age of trees. Explanatory variables are the existing area of trees, current average return, and a variable to account for intervention measures.

Bushnell and King (1986) formulate a supply response model of Californian almonds by specifying planting, removal, and yield estimation. The removal and new planting function have similar variables: the expected revenue per hectare of the perennial crop and its alternative, the expected variance in revenue per hectare, the bearing area of almonds, the non-bearing area, and farm labour. The variance and expected gross revenue for walnuts as the alternative crop are deleted from the estimation due to perverse signs. To account for yield variability, yield is specified as a function of a lagged yield and a time trend.

Kinney *et al*. (1987) develop a supply response model for lemons in California and Arizona. The acreage response to changes in economic conditions is examined through planting and removal relationships. The area planted is specified as a function of farm level total revenue per acre for lemons, a dummy to measure the impact of cost capitalization caused by tax reform, and the variance of past prices. The removals equation is specified as a function of farm level total revenue per acre for lemons, and the variance of past prices. Due to data limitations, the planting and removal equations could not be estimated directly, and the change in bearing acreage incorporating planting and removal relationships is estimated instead.

French and King (1988) examine the acreage response of Californian cling peaches to changes in prices, costs and other relevant variables by reformulating the model of French *et al.* (1985). The model consists of new plantings, removals, and yield equations. New plantings are determined by average profitability, total net acres, a dummy for market intervention, and a time trend, but potential future production is deleted in favour of the ratio of expected future to current production. It is difficult to reflect the influence of the age on tree removals in one equation due to non-linear relationships between age and tree removals and the removal equation for each age class is applied. This is similar to removal equations in French *et al*. (1985) except that dummies for market interventions are included. For projection purposes, yield is specified as a function of a time trend.

French and Willet (1989) modify the acreage response model of French and Mathews (1971) by taking account more fully of the lag distribution of profit expectation and structural changes in the industry. The modified model starts with the acreage-change identity of French and Mathews, and removals are specified as a function of the previous year's profitability and the acreage in various age classes. Due to data limitations, the weighted sum of acreage by age class is replaced by the unweighted total bearing acreage. New plantings are specified as a function of the expected long-run profitability with two modifications from the original model. First, profit expectations follow the adaptive expectations model, and second, even though the size of the industry might be expected to affect the planting response, acreage variables are omitted from the planting equation because they are insignificant.

French and Nuckton (1991) study the production of raisin-type grapes in California. The model for estimating plantings and removal functions are adapted from French *et al.* (1985) and French and King (1988). Plantings are determined principally by the net existing acreage and estimates of net returns throughout the expected life of the trees. Acreage removed is a function of declining productivity determined by biological factors, and farmers' expected returns.

Carman and Craft (1998) analyse the supply response of Californian avocados. The model includes equations for plantings, removals, changes in both bearing acreage and total acreage, and yield. The yield equation includes the effects of alternate bearing[18] and time trends. New plantings are a function of expected profitability which is measured by a moving average of farm-level total revenue per acre, changes in income tax law, and total acreages. Removals are determined by expected profitability and bearing acreages. The estimated equation for the change in total acres or net investment includes independent variables used to estimate plantings and removals. The formulation of the change in bearing acreage is similar to the net investment equation but with extensive lags on new plantings because of the time required to reach bearing age. Lagged average price and costs are used to proxy expected profit.

An alternative to the French and Mathews' (1971) perennial crop supply response framework is that of Wickens and Greenfield (1973) who argue that the application of the Nerlovian supply response model causes difficulties in quantifying investment and harvesting decisions independently. Instead, they propose a structural model for

[18] Alternate bearing, also called biennial or uneven bearing, is the inclination of fruit trees to produce a heavy crop one year, and then a light crop or no crop on the following year.

Brazilian coffee, consisting of a vintage production function along with investment and harvesting functions.

The vintage production function is:

$$q_t^P = \sum_{i=0}^{n} \delta_i I_{t-i} \tag{3.36}$$

The investment function is:

$$I_t = \alpha_o + \alpha_1 I_{t-1} + \alpha_2 P_t \tag{3.37}$$

The short-run harvesting function is:

$$q_t = \gamma_o + \gamma_1 q_t^P + \sum_{i=0}^{m} \gamma_{i+2} P_{t-1} + \bar{\gamma} q_{t-1} \tag{3.38}$$

where q_t^P is production potential in period t, q_t is actual production in period t, I_t is investment in period t, and P_t is producer price in period t. The vintage production function in (3.36) represents potential production in terms of investment and a yield term, δ_i. The former is the number of trees planted i years ago which have survived to year t, while the latter is the average yield of these trees. Taking the number of trees to be capital, it is assumed that labour and land are used in fixed proportions to capital, and that labour and land are unrestricted. The investment function in (3.37) is derived from a formal optimising model where the expected discounted net revenue is maximised with respect to production function constraints. Investment lasts until the marginal cost of investing in one more tree equals the expected discounted net revenue of investment. Equation (3.38) is a short-run harvesting equation where output is a function of potential production reflecting past investment and a distributed lag on own prices indicating the harvesting decision. The term, $\bar{\gamma}q_{t-1}$, denotes the biennial bearing cycle. The reduced-form model is obtained by solving (3.36)-(3.38) for output in terms of a distributed lag function of price and a lagged dependent variable:

$$q_t = \sum_{i=0}^{n} \tau_i p_{t-i} + (\bar{\gamma} + \alpha_1) q_{t-1} - \bar{\gamma}\alpha_1 q_{t-2} + \text{constant} \tag{3.39}$$

where

$$\begin{aligned}
\tau_i &= \gamma_2 + \alpha_2\gamma_1\delta_0 && i = 0 \\
&= \gamma_{i+2} + \alpha_2\gamma_1\delta_0 - \alpha_1\gamma_{t+1} && i = 1,\ldots,m \\
&= \alpha_2\gamma_1\delta_{m+1} - \alpha_1\gamma_{m+1} && i = m+1 \\
&= \alpha_2\gamma_i\delta_i && i = m+2,\ldots,n
\end{aligned}$$

Equation (3.39) shows that lagged output is related to the dynamics of the investment function and the biennial cycle. The coefficient on lagged price depends on the short-run adjustment coefficient, γ_i, and is proportional to the yield pattern in the long run. To estimate (3.39), Wickens and Greenfield model the price coefficients by an Almon (1965) polynomial distributed lag function, and the lag shape is similar to a yield pattern of coffee after three years; and then, the reduced form is simplified in a first-difference form. The model has a number of limitations. First, the coefficients in the three structural equations cannot be derived from the reduced form. Second, a difficulty arises when including a non-price variable in the planting equation since it becomes a distributed lag term in (3.39). Third, the yield pattern of perennial crops may not be correctly estimated by the polynomial used as weights of lagged prices could diverge from the yield pattern. Finally, the sum of the coefficients of lagged output is rarely close to unity which is inconsistent with theory (Akiyama and Trivedi, 1987b). Nevertheless, the model has been widely applied with little or no modification, including Dowling (1979) on rubber in Thailand, Tan (1984) on rubber in several major producer countries including Thailand, and Hartley *et al*. (1987) on rubber in Sri Lanka.[19]

Hartley *et al*. (1987) examine a supply response for rubber in Sri Lanka by modifying Wickens and Greenfied's model to emphasize the uprooting/replanting decision. The available data on the age distribution of the stock of trees (area under cultivation), area newly planted and replanted, and age-yield profiles over a long period of time permit the estimation of a system rather than a single reduced-form supply equation. The model contains both a replanting equation and a new planting equation, corresponding to the single investment function of Wickens and Greenfield, and a harvesting equation. The estimated results suggest that the model cannot explain new plantings in Sri Lanka and is not suitable for studying the supply response of a mature industry in which adjustment is dominated by removal and replanting activities.

Akiyama and Trivedi (1987b) examine the supply response of tea in major producing countries including India, Sri Lanka, and Kenya.[20] To resolve difficulties of identifying long- and short-run aspects of the supply decision, they provide a framework in which actual output, feasible output, and planed output are distinguished. A structural model is developed consisting of new planting, uprooting, and replanting equations which highlight the role of producer price expectations which determine investment. These equations are useful for analysing long-run supply

[19] The literature on rubber supply response in Thailand is presented in Section 3.5.

[20] In earlier work, Akiyama and Trivedi (1987a) examine the supply response of tea not only in the three major producing countries but also in Malawi, USSR, Bangladesh, Indonesia, China, the rest of Asia, and the rest of Africa.

response. An ECM is applied. The estimated equations for Sri Lanka (new plantings, uprootings, and removals), India (extensions and replantings), and Kenya (smallholder new plantings and estates yield) are presented. For Sri Lanka for example, new plantings depend on lagged values of new plantings, a moving average producer price, the cost of production, and the change in current and moving average prices. While planned replantings and uprootings are assumed to be jointly determined, actual uprootings are determined by lagged values of uprootings and replantings, lagged and the change in the moving average producer price and replanting subsidies, whilst actual replantings are specified as a finite distributed lagged on current and lagged values of uprootings. In the supply equation, new plantings and the average age-yield profile are combined to construct a measure of feasible output. Tea production is influenced by total estimated feasible production, lagged production, the ratio of current price to costs of production, and a dummy for supply shocks caused, for example, drought. A major difficulty is the identification problem since some unknown parameters in the production equation cannot be estimated.

Dorfman and Heien (1989) develop a model of investment behaviour by incorporating uncertainty and adjustment costs to investment in the US almond industry using pooled data. This framework yields investment as a function of the expected present value of investment (EPVI) which is a distributed lag of current, and past present values of an acre of almond trees, and the variance of this expected value. Almond production is specified as a function of bearing acreage, dummies for location and alternate year, and rainfall. Dorfman and Heien also show that the EPVI model without uncertainty is basically the model of Wickens and Greenfield (1973).

Alston *et al.* (1995) analyse the supply relationship of Californian almonds. To predict production from a given bearing acreage, estimated yield is determined by the effects of alternate bearing cycles, the effects of age classes of trees, rainfall, and a time trend. Planting and removal equations are modelled in two ways. The first is based on French and Bressler (1962), French and Mathews (1971), French *et al*. (1985) and Alston *et al*. (1980). Annual plantings are a linear function of expected annual profitability, the previous year's acreage, and current removals. Likewise, removals are determined by expected annual profits, the previous year's acreage, and a time trend. The second model is the expected net present value investment model and is derived from Dorfman and Heien (1989). Assuming that investment depends on the expected present value of a stream of net profits derived over the productive life of an investment, investment is a function of the expected net present value of an investment made in year t, ENPV. Due to lags in investment decisions and adjustment costs, the investment is expressed as a partial adjustment investment model. The removals equation becomes a function of ENPV and the acres of trees nearing the end of their productive life.

To examine supply response dynamics of perennial crops, structural models have been developed with separate equations for new planting, removal/replanting, and output. A major disadvantage of these studies is the scarcity of data, particularly on new plantings, removals, age distribution, and yield profiles. To overcome this problem, an alternative approach - a state-space model - has been used. This system models dynamics with (possibly) unobservable state variables and measurement equations, which connect the state variables to observable variables and applications include Knapp and Konyar (1991) and Kalaitzandonakes and Shonkwiler (1992).

Knapp and Konyar (1991) use state-space models and the Kalman filter, which is the most common method to estimate the unknown states of a dynamic process, to examine Californian alfalfa production. Data on total acreage, production, and various exogenous factors are available, but new plantings, removals, and acreage by age category are not. Accordingly, new plantings and removals are modelled in state space form. Estimation is then carried out using a Kalman filter combined with an iterative search over the parameters. New plantings and removals are specified as a function of existing acreage, expected profits of growing alfalfa which depends on expected revenue, expected production costs, and the opportunity cost of using land for alfalfa production as represented by expected prices of competing crops. Expected revenue is the product of expected price and expected yield. Naïve expatiations are applied to price and production costs.

Kalaitzandonakes and Shonkwiler (1992) develop a state-space model where the structural equation can be estimated separately without complete data on new plantings and replantings. They apply the model to grapefruit in Florida. Total plantings is the observable variable, and new plantings and replantings are unobserved states. Under restrictive assumptions, i.e., deterministic initial state and the absence of an error term in the measurement equation, estimation is carried out by maximum likelihood methods. New plantings and replantings are formulated in a dynamic unobserved components model, which is a special case of state-space model. New plantings are a function of the stock of trees in the previous period, expected prices constructed as the ratio of the expected grapefruit price and expected opportunity costs, the industry's potential future output, tax considerations, and losses from severe weather. The expected orange price is used as the opportunity cost of grapefruit investment. Potential future output is measured as a ratio of non-bearing to total acres in t-1, and a dummy is used to proxy tax. Replantings are affected by expected prices and severity of weather. Rational expectations are applied. Even though the state-space methods are useful in estimating perennial supply structural systems, these models are not popular because of the disadvantages relating to a comparative lack of information and appropriate statistical software (Durbin and Koopman, 2001, pp.52-53).

Modern time series analysis addresses the problem of spurious regression when using non-stationary data. ECMs can then be applied to model the dynamics of adjustment to long-run equilibrium. Empirical applications on the supply response of perennial crops using this approach include Abdulai and Rieder (1995), Mesike, Okoh and Inoni (2010), and Alias and Tang (2010).

Abdulai and Rieder (1995) use cointegration to analyse cocoa production in Ghana for 1960-1989. The Engle-Granger approach is used where the long-run cointegrating regression is:

$$SC_t = a_0 + a_1 SM_t + a_2 PC_t + u_t \tag{3.40}$$

where SC_t is the cocoa output in period t, SM_t is the supply of manufactured goods in period t, PC_t is the producer price of cocoa in period t. The supply of manufactured goods is used to show that the farmer is motivated by both money he received and by the goods and services he can buy. The Phillips-Ouliaris (1990) test shows that cointegration exists. Then, the Johansen-Juselius (1990) procedure with the maximum eigenvalue and trace tests are used to examine the possibility of more than one cointegrating vector. Both tests suggest the existence of a unique cointegrating vector. To examine the effect of the real exchange rate, RER_t, which is a measure of the competitiveness of agriculture, another cointegrating regression is estimated:

$$SC_t = b_0 + b_1 SM_t + b_2 RER_t + v_t \tag{3.41}$$

Again, the Phillips-Ouliaris (1990) and the Johansen-Juselius (1990) procedures show one cointegrating vector. A Granger causality test is conducted to examine the direction of causality and suggests that PC_t, RER_t, and SM_t are Granger prior to SC_t. Next, a simple ECM is estimated and the significance of added lags of variables are tested. In (3.42), the producer price of maize variable, PM_t, is included as an exogenous variable to capture the impact of a competing crop. The estimated ECM is:

$$\Delta SC_t = \alpha_1 \Delta SC_{t-1} + \alpha_2 \Delta PC_t + \alpha_3 \Delta PC_{t-1} + \alpha_4 PM_t + \alpha_5 \Delta SM_t + \gamma EC1_{t-1} + w_t \tag{3.42}$$

where ΔSC_t is the change in cocoa supply, ΔPC_t is the change in cocoa price, ΔSM_t is the change in the supply of manufactured goods, $EC1_{t-1}$ are lagged residuals or the error correction term from(3.40). From (3.41), the estimated ECM is:

$$\Delta SC_t = \beta_1 \Delta SC_{t-1} + \beta_2 \Delta ER_t + \beta_3 \Delta ER_{t-1} + \beta_4 \Delta ER_{t-2} + \beta_5 \Delta SM_t + \delta EC2_{t-1} + z_t \tag{3.43}$$

where ΔER_t is the change in real exchange rate, $EC2_{t-1}$ are lagged residuals or the error correction term from (3.41). Abdulai and Rieder (1995) suggest that the ECM is preferable to the partial adjustment model.

Alias *et al.* (2001) examine the supply of Malaysian perennial crops, using annual data for palm oil and rubber from 1975-1997 and annual data for cocoa from 1977-1997. The Engle-Granger approach is used to test for cointegration in:

$$\ln PO_t = a_0 + a_1 \ln POPI_{t-5} + a_2 \ln GE_{t-4} + a_3 T_t + e_t \tag{3.44}$$

where PO_t is palm oil output in period t, $POPI_{t-5}$ is the palm oil price index in period t-5, GE_{t-4} is the government expenditure on agriculture and rural development in period t-4 , and T is a time trend.

$$\ln NR_t = b_0 + b_1 \ln NRPI_t + a_2 \ln POPI_t + b_3 \ln GE + b_4 T_t + u_t \tag{3.45}$$

where NR_t is rubber output in period t, $NRPI_t$ is the rubber price index in period t, $POPI_t$ is the palm oil price index in period t.

$$\ln CO_t = c_0 + c_1 \ln RCPP_{t-2} + c_2 \ln INT_{t-2} + c_3 \ln GE_{t-4} + c_4 T_t + v_t \tag{3.46}$$

where CO_t is cocoa output in period t, $RCPP_{t-2}$ is the ratio of cocoa price index to palm oil price index in period t-2, INT_{t-2} is the interaction term between cocoa price index and government expenditure on agriculture and rural development in period t-2. The augmented Dickey-Fuller and Phillips-Perron tests are applied and show that cointegration exists in each model. The general form of ECM for each model is estimated and tested down sequentially based on the general-to-specific procedure. The preferred ECM obtained for palm oil, rubber, and cocoa are:

$$\Delta \ln PO_t = d_0 - d_1 \Delta \ln PO_{t-1} + d_2 \Delta \ln GE_{t-2} + d_3 \Delta \ln POPI_{t-1}$$

$$+ d_4 \Delta \ln POPI_{t-5} - EC_{t-1} + w_t$$

(3.47)

$$\Delta \ln NR_t = f_0 - f_1 \Delta \ln NR_{t-1} + f_2 \Delta \ln NRPI_{t-1} - f_3 \Delta \ln NRPI_{t-1}$$

$$+ f_4 \Delta \ln NRPI_{t-2} - f_5 \Delta \ln POPI_{t-2} - EC_{t-1} + y_t$$

(3.48)

$$\Delta \ln CO_t = g_0 + g_1 \Delta \ln RCPP_{t-1} + g_2 \Delta \ln INT_{t-1} - EC_{t-1} + z_t$$

(3.49)

where EC_{t-1} is the error correction term. In these VECM models, general-to-specific modelling is used to obtain a parsimonious model.

Mesike, Okoh and Inoni (2010) analyse rubber supply response in Nigeria using cointegration and vector error correction methods for 1970-2008. The Johansen procedure is used to test for cointegration in:

$$Q_t = a_0 + a_1 Q_{t-1} + a_2 PNR_{t-1} + a_3 PE_{t-1} + a_4 ER_{t-1} + a_5 T_t + a_6 TD_t + v_t$$

(3.50)

where Q_t is the output at time t, PNR_t is the producer's price at time t-1, PE_t is the export price at time t-1, ER_t is the exchange rate at time t-1, T_t is a time trend, and TD_t is a structural break. The model is then estimated in VECM form as:

$$\Delta Q_t = b_0 + b_1 \Delta Q_{t-1} + b_2 \Delta PNR_{t-1} + b_3 \Delta PE_{t-1} + b_4 \Delta ER_{t-1} + b_5 \Delta T_t + b_6 \Delta TD_t$$

$$-\alpha(Q_t - a_0 - a_1 Q_{t-1} - a_2 PNR_{t-1} - a_3 PE_{t-1} - a_4 ER_{t-1} - a_5 T_t - a_6 TD_t) + w_t$$

(3.51)

where α measures the speed of adjustment towards long-run equilibrium. This study confirms that cointegration analysis can overcome the spurious regression problem and it provides a more general dynamic structure than Nerlovian models.

Alias and Tang (2010) examine the supply of Malaysian palm oil using the Johansen procedure for 1967-2002. The cointegrating relationship is:

$$\ln PO_t = d_0 + d_1 \ln RPOR_{t-3} + d_2 \ln IR_{t-3} + d_3 \ln G_{t-3} - d_4 T_t + e_t \tag{3.52}$$

where PO_t is palm oil production in period t, $RPOR_t$ is the relative price of palm oil to rubber in period t, IR_t is the interest rate in period t which is used to represent the cost of borrowing, G_t is government expenditure in period t, and T is a time trend. A three-year lag length is based on justifications of parsimony. Cointegration is confirmed and an ECM is estimated:

$$\Delta \ln PO_t = c_0 + \sum_{i=1}^{n} c_{1i} \Delta \ln RPOR_{t-i} + \sum_{i=1}^{n} c_{2i} \Delta \ln IR_{t-i} + \sum_{i=1}^{n} c_{3i} \Delta \ln G_{t-i} - EC_{t-1} + v_t \tag{3.53}$$

where EC_{t-1} is the error correction term. In this VECM model, general-to-specific modelling is used to obtain a parsimonious model.

3.5 Empirical Studies of Supply Response of Natural Rubber in Thailand

Natural rubber is an important crop in the Thai economy and an understanding of farmers' behaviour is necessary to formulate effective policies. Existing studies on supply response include of Behrman (1971), Stifel (1973), Dowling (1979), Grilli

(1979), Sakarindr (1979), Man and Blandford (1980), Jumpasut (1981), Hataiseree (1983), Meyanathan (1983), Tan (1984), Suwankul and Wailes (1987), Yibngamcharoensuk (1988), Aroonsiriporn (1989), Division of Agricultural Economic Research (1989), Changkid (1982), Arthannarong (1994), Burger and Smit (1978), and Pipitkul (2003). Each has analysed the response of natural rubber production to price and non-price variables. We consider each in turn.

Behrman (1971) estimates the supply response of natural rubber production by using annual data at the national level for 1947–1965. Both short-run and combined short- and long-run supply behaviour are examined. For the short-run analysis, where the tappable area (or total area) is assumed to be given, the supply equation is:

$$SN_t = a_0 + a_1 PN_t + a_2 [TA \, or \, A]_t + a_3 [E(YLD) \, or \, TIME]_t + a_4 RAIN_t + u_{1t} \tag{3.54}$$

where SN_t is the supply (or production) of natural rubber, PN_t is own price, TA_t is the tappable area, A_t is the total area, $E(YLD)_t$ is the expected yield per unit area, $TIME_t$ is a time trend, and $RAIN_t$ is rainfall. $E(YLD)_t$ is the forecast of actual yield per unit area from a linear regression of YLD_t on rainfall and a time trend:

$$YLD_t = b_0 + b_1 RAIN_t + b_2 TIME_t + u_{2t} \tag{3.55}$$

Equations (3.54) and (3.55) are estimated by OLS. Only PN_t and TA_t are significant and the short-run price elasticity of supply is estimated to be 0.409 and significant. Behrman then estimates a combination of short- and long-run responsiveness under the assumption that the tappble area is determined by past planting and replanting decisions, and by current removal and abandonment decisions. Planted and replanted area is not removed or abandoned before it becomes cultivated and a first-order difference of (3.54) is estimated:

$$\Delta SN_t = c_0 + c_1 \Delta PN_t + c_2 \Delta TA_t + c_3 \Delta E(YLD)_t + c_4 RAIN_t + \Delta u_{1t} \tag{3.56}$$

The tappable area is defined as the difference between the area planted or replanted during the gestation period from planting until initial tapping (LAG years), PLT_{-LAG}, and the current removal and abandonment of tappable trees, $RMVL_{t,}$:

$$\Delta TA_t = PLT_{-LAG} - RMVL_t \tag{3.57}$$

and:

$$PLT_{-LAG} = d_0 + d_1 E(PN)_{-LAG} + d_2 E(YLD)_{-LAG} + u_{3t} \tag{3.58}$$

$$RMVL_t = h_0 + h_1 E(PN)_t + h_2 E(YLD)_{-LAG} + u_{4t} \tag{3.59}$$

Price expectations, E(PN), are represented by a distributed lag function of all past prices, with the weighted average of all such past prices from $-\infty$ to the year preceding the sample period, t_0, denoted by $SMPN_{t_0}$:

$$E(PN)_t = \sum_{i=0}^{t-t_o} (1-\gamma)^i \gamma PN_{-i} + (1-\gamma)^{t-t_0} SMPN_{t_o} + u_{5t} \tag{3.60}$$

where γ is the expectation adjustment coefficient. Substituting (3.60) into (3.58) and (3.59) and substituting the result into (3.57) gives the change in the tappable area. Substituting this into (3.56) gives the combined short- and long-run model:

$$\Delta SN = b_0 + b_1\Delta RAIN + b_2\Delta PN + b_3 \sum_{i=0}^{t-t_0-LAG} (1-\gamma)^i PN_{-i-LAG} + b_4 E[YLD]_{-LAG}$$
$$+ b_5 \sum_{i=0}^{t-t_0} (1-\gamma)^i \gamma PN_{-i} + \left\{b_3 (1-\gamma)^{t-t_0-LAG} + b_5 (1-\gamma)^{t-t_0}\right\} SMPN_{t_0} + v_t \qquad (3.61)$$

where v is a disturbance term. Maximum likelihood methods are adopted to estimate (3.61). Behrman argues that the results are unsatisfactory because the estimated short- and long-run price elasticities of supply are too low at 0.037 and 0.189. Nevertheless, while the estimated long-run elasticity of supply is somewhat inelastic, it is higher than the estimated short-run elasticity of supply due to input adjustment in the long run. The estimates are also thought to be inadequate because the estimates of the weighted sum of all past prices from $-\infty$ to the year preceding the sample period, t_0, are insignificant which causes unreasonable estimates of expected prices. Further, the gestation lag between planting and initial tapping is too short. Accordingly, Behrman suggests that this method should be discarded and new approaches should be adopted.

Stifel (1973) directly estimates a new planting equation with annual data for 1913-1941 and 1948-1962, and a supply function with quarterly data for 1926-1937 and 1950-1968:

New planting equation:

$$\ln NP_t = \alpha_0 + \alpha_1 \ln PR_t + \alpha_2 \ln Q_{t-3} + u_t \qquad (3.62)$$

Supply equation:

$$\ln S_t = \beta_0 + \beta_1 \ln PR_t + \beta_2 \ln PP_t + \beta_3 T_t + \beta_4 S_{2t} + \beta_5 S_{3t} + \beta_6 S_{4t} + v_t \tag{3.63}$$

where NP_t is new planting in period t, PR_t is own price, Q_{t-3} is annual production in period t-3, S_t is output in period t, PP_t is the price of rice as the competitive crop, T_t is a time trend, and S_{2t}, S_{3t} and S_{4t} are quarterly dummies. Although the acreage response with respect to price is significant and the elasticity of new planting area is estimated to be 0.80, a low R^2 and an unsatisfactory Durbin-Watson statistic indicate that price is only a partial explanation. The short-run price elasticities of supply for the two samples are estimated to be 0.771 and 0.15.

Dowling (1979) estimates the supply response of natural rubber using annual time series data at the national level for 1915-1939, 1950-1971, and 1950-1975. The structural model of tree crop supply response developed by Wickens and Greenfield (1973) is adopted. Dowling applies Almon lags and estimates a number of regressions for different order polynomial lag lengths. Due to the existence of residual autocorrelation, the Cochrane-Orcutt technique is used. From the estimate of the coefficients on price, estimated short-, medium-, and long-run price elasticities of supply are obtained. The short-run elasticity is the mean elasticity for the current period when $i = 0$; the medium-run elasticity is the sum of mean elasticities for $i = 1,...,4$; and the long-run elasticity is the sum of mean elasticities for $i=1,\ldots,11$ or $i=1,\ldots,14$. For 1915-1939 and 1950-1971 when the rubber:rice price ratio is used and rubber exports proxy pre-war production, a third-order polynomial is chosen, and the short-, medium-, and long-run elasticities are estimated to be 0.092, 0.639, and 1.205. When a fourth-order polynomial is chosen, corresponding elasticities are estimated to be 0.126, 0.759, and 1.522. For 1950-1975 when the London rubber price is used with a fourth-order polynomial, the elasticities are estimated to be 0.165, 1.556, and 2.641. For an equation that uses the Malaysian rubber price, the elasticities are estimated to be 0.180, 1.664, and 1.751. Also estimated is a structural equation and the elasticities are estimated to be 0.265, 1.917, and 2.132. Dowling concludes that output responsiveness in the long-run is fairly elastic and is somewhat higher in the post-war period; and the short-run response is rather inelastic.

Grilli (1979) estimates the supply response of natural rubber using the Nerlovian model and OLS with time series data at the national level for 1955–1975. The estimated supply equation is:

$$THANRS_t = \alpha_0 + \alpha_1 THANRS_{t-1} + \alpha_2 THANRP_t + \alpha_3 TIME_t + u_t \qquad (3.64)$$

where $THANRS_t$ is output in period t, $THANRP_t$ is own price (for RSS-3 in Malaysian currency), and $TIME_t$ is a time trend. The price elasticity of supply is estimated to be 0.25.

Sakarindr (1979) analyses the supply response of natural rubber by 2SLS using a simultaneous equation model with annual data at the national level for 1955–1972. Acreage and production equations are estimated in two models including domestic and world rubber market models. While the former is applied to examine the domestic market behaviour, the latter is used to determine the characteristic of production and export supply of natural rubber in producing countries and their relationships in the world market. Also, the domestic model can be separated into two sub-models, which differ in the specification of price. In the first model, natural rubber price is a function of the main domestic economic variables that affect the rubber price; and in the second, it is a function of the world rubber price. The acreage and production equations in the domestic rubber market are:

Acreage equation:

$$TAPAREA_t = a_0 + a_1 PRNR_t + a_2 PRNR_{t-1} + a_3 YLDNR_{t-1} + a_4 PLNTAREA_{t-8} + u_t \quad (3.65)$$

Production equation:

$$PRODNR_t = b_0 + b_1 PRNR_t + b_2 TAPAREA_{t-1} + b_3 TIME_t + v_t \quad (3.66)$$

Production equation in the world rubber is:

$$PRODNR_t = c_0 + c_1 PRNR_t + c_2 TAPAREA_{t-1} + c_3 TIME_t + w_t \quad (3.67)$$

where $TAPAREA_t$ is the tappable area in period t, $PRODNR_t$ is production in period t, $PRNR_t$ is the domestic price of rubber in Bangkok, $YLDNR_{t-1}$ is average yield in period t-1, $PLNTAREA_t$ is the planted area in period t-8, TIME is a time trend, and u_t and v_t are disturbance terms. In the first model of the domestic rubber market, the current and lagged price elasticities with respect to tappable area are estimated to be 0.105 and 0.198, respectively. The estimated lagged yield elasticity of tappable area is 0.977, and the estimated elasticity of tappable area with respect to planted area (lagged eight years) is 1.130. The estimated price elasticity of supply is 0.117, and the estimated elasticity of supply with respect to tappable area is 0.579. In the second model, the elasticity of the current price of tappable area is estimated to be perversely negative (but insignificant) at -0.100 whilst the estimated lagged price elasticity is 0.197 which suggest that farmers plan to harvest in advance. The estimated lagged yield elasticity of tappable area is 0.973, and the estimated elasticity of tappalbe area with respect to planted area (lagged eight years) is 1.135. The estimated price elasticity of supply is 0.113, and the estimated elasticity of supply with respect to tappable area is 0.572. These results differ only slightly between the two models. In the world rubber market model, the estimated price elasticity of supply is 0.19 while the estimated elasticity of supply with respect to tappable area is 0.581.

Man and Blandford (1980) use two–stage least squares (2SLS) and a simultaneous equation model to estimate the supply response of natural rubber with time series data at the national level for 1960-1977. Based on the Nerlovian model used by Ady (1968), the estimated supply equation is:

$$\Delta Q_t = a_0 + a_1 \Delta P_t + a_2 \Delta RN_t + a_3 \Delta P_{t-6} + a_4 \Delta P_{t-7} + a_5 D_1 + a_6 Q_{t-1} + u_t \tag{3.68}$$

where ΔQ_t is the change in production, ΔP_t is the change in the current domestic price, ΔRN_t is the change in rainfall, D_t accounts for technological improvement in production, and Q_{t-1} is production in t-1. All variables have appropriate signs and the short- and long-run price elasticities of supply are estimated to be 0.644 and 1.452. Man and Blandford note that the estimated long-run elasticity is higher than the estimated short-run elasticity as expected because investment in response to price is important in natural rubber production. In addition, the high degree of responsiveness in the long run reflects the aggressive promotion of replanting and new varieties programme over the period studied.

Jumpasut (1981) uses OLS to estimate a supply function directly for natural rubber at both aggregate and regional levels using the Nerlovian framework. The aggregate model uses quarterly data for 1947-1979 while the model for the South East and South regions uses monthly data for 1970-1979. The estimated equations are the same in both cases, namely:

$$\Delta Q_t = a_0 + a_1 P_{t-7} + a_2 C_{t-7} + a_3 Q_{t-1} + a_4 R_{t-2} + a_5 P_{t-1} + a_6 T_{t-1} + a_7 Y_{t-8} + a_8 \Delta R_{t-1}$$

$$+ a_9 \Delta P_t + a_{10} C_{t-1} + a_{11} \Delta C_t + u_t \qquad (3.69)$$

where ΔQ_t is the change in production, P_t is own price, C_t is the price of rice, Q_{t-1} is production in t-1, R_{t-2} is the deviation of rainfall from the trend in t-2, T_t is a time trend, Y_{t-8} is farmer's income in t-8, ΔR_{t-1} is the change in deviation of rainfall from the trend from t-1 to t-2, ΔP_t is the change in own price from t-1 to t, C_{t-1} is the rice price in t-1, and ΔC_t is the change in the rice price. Several coefficients are not statistically significant at the aggregate level. The estimated short- and long-run supply elasticities of P_{t-1}, which involves tapping intensity, are 0.59 and 0.25, while those of P_{t-7}, which influences the planting decision, are 0.05 and 0.02. In the South East, the short- and long-run elasticities of P_{t-1} are estimated to be -0.22 and -0.12 while those of P_{t-7} are estimated to be 1.65 and 0.93. In the South, corresponding elasticities are estimated to be 0.17 and 0.08, and 0.67 and 0.31. The estimated short- and long-run elasticities of ΔP_t, which also involves tapping intensity, at both aggregate and regional levels are approximately zero. Rice is used as a substitute crop for natural rubber. At the aggregate level, the short- and long-run cross-price elasticities of C_{t-1} and ΔC_t are estimated to be -0.12 and -0.05, and the estimated short- and long-run cross-price elasticities of C_{t-7} are 0.06 and 0.03. In the South East, the short- and long-run cross-price elasticities of the current price of rice are estimated to be -0.99 and -0.56 and the short- and long-run cross-price elasticities of C_{t-7} are estimated to be -0.86 and -0.36. In the South, the estimated short- and long-run cross-price elasticities of the current rice price are -3.78 and -1.78, whilst the estimated short- and long-run cross-price elasticities of C_{t-7} are -0.99 and -0.47. Jumpasut also calculates farmers' income elasticities. At the aggregate level, the short- and long-run income elasticities of Y_{t-8} are estimated to be -0.03 and -0.01; corresponding estimates in the South East are estimated to be -0.29 and -0.17, and in the South are estimated to be -0.06 and -0.03. Estimated price and income elasticities in the South are less than those in the South East since producers in the South depend more on rubber production. All other estimated elasticities have the correct sign, with the exception of a negative sign for the estimated rubber price elasticities in the South East and a positive sign for the estimated cross-price elasticities of C_{t-7} at the aggregate level. Estimated price elasticities of natural rubber are quite inelastic in both the short and long run, and estimated long-run elasticities are generally smaller than estimated short-run elasticities. Jumpasut concludes that the long-run lagged price of natural rubber may have less of an effect on production than the current price, while the substitute crop's price has no effect on production; rainfall and technological factors affect production to a certain degree; and natural rubber production is little affected by past income levels.

Hataiseree (1983) estimates the supply response of natural rubber by 2SLS using a simultaneous equation model with annual data at the national level for 1964–1980. The estimated equation is:

$$PN_t = \alpha_0 + \alpha_1 HP_t + \alpha_2 PP_{t-1} + \alpha_3 T_t + \alpha_4 TAP_t + u_t \tag{3.70}$$

where PN_t is total production, HP_t is the Had Yai natural rubber price of RSS-3, PP_{t-1} is the average wholesale price of rice for grade one at Bangkok in period t-1, T_t is a time trend, and TAP_t is the tappable area of natural rubber. The results indicate that the supply elasticity with respect to the domestic price is estimated to be 0.21, and the estimated cross-price elasticity of supply is low at -0.108.

Meyanathan (1983) uses OLS to estimate the short-run response of natural rubber with monthly data for 1972-1976. The explanatory variables are lagged price, a trend reflecting technological factors that affect yield, and weather especially the effect of rainfall which are proxied by dummies for seasonal adjustments in each month. The estimated equation is:

$$S_t = \alpha_0 + \alpha_1 X_{2t} + \alpha_2 X_{3t} + \alpha_3 X_{4t} + \alpha_4 X_{5t} + \alpha_5 X_{6t} + \alpha_6 X_{7t} + \alpha_7 X_{8t} + \alpha_8 X_{9t}$$
$$+ \alpha_9 X_{10t} + \alpha_{11} X_{12t} + \alpha_{12} P_{t-2} + \alpha_{13} T_t + u_t \tag{3.71}$$

where S_t is output, P_{t-2} is own price in t-2, T_t is a time trend, and X_{2t}, …, X_{12t} are monthly dummies. The short-run supply elasticity is estimated to be 0.02.

Tan (1984) directly estimates the supply function of natural rubber using OLS for 1956-1978. Like Dowling (1979), the model of Wickens and Greenfield (1973) is applied with the Singapore f.o.b. natural rubber price. Third- and fourth-degree polynomials are experimented with Almon distributed price lags. The short-, medium- and long-run elasticities of supply are estimated to be 0.395, 3.955, and 6.714.

Estimated elasticities of area and change in area in response to price have perverse negative signs at -0.097 and -0.029.

Suwanakul and Wailes (1987) present a simultaneous equation model to analyse the world rubber market and OLS and 2SLS estimators are applied to data at the national level for 1954–1983. A partial adjustment model is applied. For Thailand, the estimated tappable area response model is:

$$TA_t = a_0 + a_1 TA_{t-1} + a_2 UNTA_{t-6} + a_3 P_{t-1} + u_t \tag{3.72}$$

where TA_t is the tappable area in period t, $UNTA_{t-6}$ is the untappable area in period t-6, P_{t-1} is own price, lagged one year. The results reveal that the estimated price elasticity of area tapped is very low at 0.03 in the short run and is 0.31 in the long run. The estimated price elasticity of rubber yield is inelastic at 0.18 in the short run and is 0.25 in the long run. The estimated output elasticity is 0.21 in the short run and 0.56 in the long run.

Yibngamcharoensuk (1988) uses the Nerlovian model of Bateman (1965) to estimate the supply response of natural rubber using OLS and data at the national level for 1964–1983, 1966–1983, and 1969–1983. Four equations are estimated:

Area planted equation:

$$A_t = a_0 + a_1 \ln PFN_{t-1} + a_2 \ln A_{t-1} + a_3 \ln TEH_t + u_t \tag{3.73}$$

where A_t is area planted, PFN_{t-1} is the farm price in t-1, and TEH_t is technological progress.

Yield equation:

$$\ln Y_t = b_0 + b_1 PFN_t + b_2 PFP_t + b_3 R_t + b_4 TEH_t + v_t \tag{3.74}$$

where Y_t is yield, PFN_t is the farm price, PFP_t is the farm price of oil palm (a competing crop), and R_t is a rainfall index.

Farm gate price equation:

$$\ln PFN_t = c_0 + c_1 PEN_t + c_2 CESS_t + c_3 DP_t + w_t \tag{3.75}$$

where PEN_t is the current export price of natural rubber, $CESS_t$ is the value of cess of natural rubber,[21] and DP_t is a dummy representing government policy.

Production equations:

$$\ln Q_{1t} = \alpha_0 + \alpha_1 PFN_t + \alpha_2 R_t + \alpha_3 TEH_t + \alpha_4 N_{1t} + u_{1t} \tag{3.76}$$

$$\ln Q_{2t} = \beta_0 + \beta_1 PFN_t + \beta_2 R_t + \beta_3 TEH_t + \beta_4 N_{2t} + u_{2t} \tag{3.77}$$

where N_{1t} is potential output which is computed from the area equation multiplied by the yield equation using the actual farm price, N_{2t} is the potential output which is estimated in a similar way except that the actual farm price in both equations are replaced by the estimated farm price from the farm price equation. Q_{1t} and Q_{2t} are actual outputs corresponding to N_{1t} and N_{2t}. Results show that the elasticity of area planted with respect to the previous farm price is estimated to be 0.047. The elasticity of area planted with respect to the area planted in the previous period is estimated to be 0.406. The own price yield elasticity is estimated to be 0.137. The elasticity of yield with respect to the price of palm oil is estimated to be -4.379. The elasticity of

[21] Cess is a tax paid by the natural rubber exporter to the government.

yield with respect to lagged rainfall is estimated to be 0.245. The elasticities of production with respect to farm price are estimated to be 0.114 for N_{1t} and 0.112 for N_{2t}. The elasticities of production with respect to rainfall are estimated to be 0.095 for N_{1t} and 0.093 for N_{2t}. The elasticities of production with respect to the potential output are estimated to be 0.021 for N_{1t} and 0.020 for N_{2t}. Finally, the elasticity of farm price with respect to cess is estimated to be -0.315.

Aroonsiriporn (1989) uses three-stage least squares (3SLS) and a simultaneous equation model to estimate the acreage response of natural rubber using data for 1966–1986 at the aggregate level. The estimated supply equation is:

$$\ln ATT_t = \alpha_0 + \alpha_1 \ln WSP_t + \alpha_2 \ln AT_{t-6} + \alpha_3 \ln ATT_{t-1} + u_t \tag{3.78}$$

where ATT_t is the tappable area, WSP_t is the wholesale price of RSS–3, and AT_{t-6} is planted area in t-6. Although the coefficient of WSP_t is insignificant, the elasticities of tappable area with respect to the wholesale price of RSS–3, the planted area lagged six periods, and the tappable area in t-1 are estimated to be 0.002, 0.403, and 0.471. This study also indicates that government pricing policy and export tax reduction encourages production and export expansion.

The Division of Agricultural Economic Research (1989) uses 2SLS and a simultaneous equation model to estimate the supply response of natural rubber using data at the national level for 1961–1976. The estimated supply equation is:

$$Q_t = a_0 + a_1 BKKPR_t + a_2 TAP_t + a_3 T_t + u_t \tag{3.79}$$

where Q_t is output, $BKKPR_t$ is the Bangkok wholesale price for RSS-1,[22] TAP_t is the tappable area, and T_t is a time trend. The estimated price elasticity of supply is 0.236.

Changkid (1982) estimates the supply response of natural rubber using OLS and data at the national level for 1973–1987. The estimated supply equation is:

$$\ln S_t = \alpha_0 + \alpha_1 \ln P_t + \alpha_2 \ln TA_t + u_t \tag{3.80}$$

where S_t is output in period t, P_t is the farmer's price in period t, TA_t is planted area in period t, and u_t is an error term. The price elasticity of rubber supply is estimated to be 0.41 while the elasticity of supply in response to planted areas is estimated to be 0.94. However, the estimates suffer from autocorrelation.

Arthannarong (1994) uses OLS and data at the national level for 1977-1993 to analyse the supply response of natural rubber production in the long run using Bateman's (1969) model. The estimated equation is:

$$A_t = \alpha_0 + \alpha_1 P_{t-1} + \alpha_2 A_{t-1} + \alpha_3 A_{t-2} + u_t \tag{3.81}$$

where A_t are cultivated area, and P_{t-1} is own price in t-1. Arthannarong then applies OLS and national level data for 1984–1994 to study the short-run supply response using the model of Wickens and Greenfield (1973). The estimated equation is:

$$Q_t = \beta_0 + \beta_1 P_{t-1} + \beta_2 Q_{t-1} + u_t \tag{3.82}$$

[22] RSS-1 is Ribbed Smoked Sheet Grade 1 natural rubber.

where Q_t is output. Arthannarong does not calculate elasticities, but the results are used to forecast the future planted area and output.

Burger and Smit (1978) analyse the supply response of natural rubber production using national level data for 1974-1993. The estimated equation is:

$$\ln(Q/QN)_t = a_0 + a_1 \ln PN_t + a_2 \ln(Year - 1900)_t + u_t \tag{3.83}$$

where Q_t is production in year t, QN_t is normal production in year t, PN_t is own price in year t, and $(Year\text{-}1900)_t$ is a time trend. The level of normal production is constructed to realise the effects of new planting, uprooting and replanting, yield profiles, embodied technical progress in quality of clones, and other variables such as labour availability. The long-run elasticity of production with respect to price is estimated to be 0.25.

Pipitkul (2003) estimates the supply response of natural rubber using a simultaneous equation model with annual data at the national level for 1975–2002. The estimated supply equation is:

$$\ln Q_t = \alpha_0 + \alpha_1 \ln PQ_t + \alpha_2 \ln PNR_{t-6} + u_t \tag{3.84}$$

where Q_t is actual production in period t, PQ_t is potential production in period t, and PNR_{t-6} is the farmer's price of rubber graded RSS-3 in period t-6. The estimated supply elasticity with respect to price is low at 0.08 while the estimated elasticity of supply with respect to potential output is 2.08.

In summary, all studies of natural rubber supply response in Thailand use time series data. Most use direct, single-equation methods to estimate the supply function except Sakarindr (1979), Man and Blandford (1980), Hataiseree (1983), Suwanakul and Wailes (1987), Aroonsiriporn (1989), Division of Agricultural Economic Research (1989), and Pipitkul (2003) which use simultaneous equation models. All studies use OLS except Behrman (1981) who uses maximum likelihood methods and Dowling (1979) who also uses the Cochrane-Orcutt iterative procedure to address the problem of autocorrelation. Most studies use production or output as the dependent variable for evaluating the supply response; Stifel (1973) uses new planting together with production; Burger and Smit (1978) uses the proportion of actual production to normal production; Sakarindr (1979), Suwanakul and Wailes (1987) and Aroonsiriporn (1989) use the tappable area; Yibngamcharoensuk (1988) uses both area planted and yield together with production; and Arthannarong (1994) uses area planted in a short-run analysis. The results of these studies are summarised in Table 1.

The estimated short- and long-run price elasticities of supply, acreage, or yield vary because of differences in estimated models, periods of study, and explanatory variables. The estimated short-run price elasticities of supply are generally relatively inelastic. The highest estimated short-run price elasticity of supply is 0.771 in Stifel (1973) which covered the early development of rubber production in Thailand during 1926-1937. The second highest estimated short-run price elasticities of supply is 0.664 in Man and Blanford (1980) for 1960-1977. However, the latest study of Pitikul (2003) for the period 1975-2002 shows that the estimated short-run price elasticity of supply is only 0.08. In the medium and long runs, estimated price elasticities of supply are generally higher than those in the short run. However, Jumpasut (1981) covering the period 1947-1979 at the aggregate level and 1970-1979 at the regional level shows that the estimated short-run price elasticity of supply at the aggregate level is 0.59 while that in the long run is higher at 0.25. Further, at the regional level (in the South), the estimated short-run price elasticity of supply is 0.17, but the estimate in the long run is 0.08.

In acreage response models, estimated short-run price elasticities of rubber acreage are normally inelastic. Similar to supply response models, the highest estimated price elasticity of new planting rubber area is 0.80 in Stifel (1973) which covered the period from 1913 to 1941. However, Sakarindr (1979) finds that the elasticity of tapplable area with respect to the current price is estimated to be perversely negative (but insignificant) at -0.1002. Further, Yibngamcharoensuk (1988) shows that estimated elasticities of area and change in area in response to price have perverse negative signs at -0.097 and -0.029. In the long run, Suwankul (1987) finds that the estimated price elasticity of acreage is 0.31, which is higher than in the short run. In yield response models, estimated short-run yield price elasticities are also inelastic. Suwankul (1987) and Yibngamchroensuk (1988) find that the short-run yield elasticity is 0.18 and 0.137, respectively. Competitive crop price are included in models. Stifel (1973), Jumpasut (1981), and Hataiseree (1983) use the rice price in supply response models while Yibngamcharoensuk (1988) uses palm oil price in a yield response model. Rainfall is included in several studies to reflect the effects of weather. These competitive crop prices and non-price factors, like rainfall, have negative influences on the response of natural rubber production.

Table 3.1 Summary of Studies on Supply Response for Natural Rubber in Thailand

Author	Period of study	Method of estimation	Type of supply equation	Dependent variable	Elasticities		
					Short Run	**Medium Run**	**Long Run**
Behrman (1971)	1947-1965	OLS and ML	Single	Production	0.409 and 0.037	-	0.189
Stifel (1973)	1913-1941 1948-1962	OLS	Single	New planting	0.80	-	-
	1926-1937 1950-1968	OLS	Single	Production	0.771 0.15	-	-
Dowling (1979)	1915-1939 1950-1971 1950-1975	OLS Cochrane-Orcutt	Single	Production	0.092-0.176 0.165-0.265	0.639-0.906 1.556-1.917	1.205-1.533 1.752-2.641
Grilli (1979)	1955-1975	OLS	Single	Production	0.25	-	-
Sakarindr (1979)	1955-1972	2SLS	Simultaneous	Tappable area	0.1052, -0.1002, and 0.5805	-	-
				Production	0.1173, 0.1127, and 0.1292		
Man and Blandford (1980)	1960-1977	2SLS	Simultaneous	Production	0.644	-	1.452
Jumpasut (1981)	1947-1979 1970-1979	OLS	Single	Production	Aggregate: 0.59 South East: -0.22 South: 0.17	-	0.25 -0.12 0.08
Hataiseree (1983)	1964-1980	2SLS	Simultaneous	Production	0.21	-	-
Meyanathan (1983)	1972-1976	OLS	Single	Production	0.02	-	-
Tan (1984)	1956-1978	OLS	Single	Production Area planted	0.395 -0.097 and -0.029	3.954	6.714
Suwanakul and Wailes (1987)	1954-1983	OLS 2SLS	Simultaneous	Tappable area Yield Production	0.03 0.18 0.21	- - -	0.31 0.25 0.56
Yibngamcharoensuk (1988)	1964-1983 1966–1983 1969-1983	OLS	Single	Area planted Yield Production	0.047 0.137 0.114 and 0.112	-	-
Aroonsiriporn (1989)	1966-1986	3SLS	Simultaneous	Tappable area	0.002	-	-

Table 3.1 Summary of Studies on Supply Response for Natural Rubber in Thailand (continued)

Author	Period of study	Method of estimation	Type of supply equation	Dependent variable	Elasticities		
					Short Run	**Medium Run**	**Long Run**
Division of Agricultural Economic Research (1989)	1961-1976	2SLS	Simultaneous	Production	0.236	-	-
Changkid (1982)	1979-1987	OLS	Single	Production	0.41	-	-
Arthannarong (1994)	1977-1993	OLS	Single	Area cultivated Production	-	-	-
Burger and Smit (1997)	1974-1993	OLS	Single	Production ratio	-	-	0.25
Pipitkul (2003)	1975-2002	2SLS	Simultaneous	Production	0.08	-	-

Previous studies can be criticised on four main grounds. First, a number of studies apply Nerlovian models which are criticised on several aspects, particularly that of the *ad hoc* theoretical postulations employed in partial adjustment models. Second, OLS is generally applied to potentially non-stationary data and results may be spurious (Granger and Newbold, 1974) Third, omitted relevant variables may cause biased results: other price variables such as competitive crop prices and the prices of inputs are rarely incorporated. Competitive crop prices are used by Stifel (1973), Jumpasut (1981), Hataiseree (1983), and Yibngamcharoensuk (1988), but none have included input prices especially the fertiliser price and wage rate although it could be argued that most studies incorporate these effects implicitly through the use of a cost of living index as the price deflator. Even though rainfall is a significant factor affecting rubber cultivation, only four studies - Behrman (1971), Man and Blandford (1980), Jumpasut (1981), and Yibngamcharoensuk (1988) - include it. Furthermore, the tappable area, which reflects not only short-run capacity constraints but also past planting and replanting decisions and a long-run removal abandonment decision, is used by Behrman (1971), Hataiseree (1983), and Aroonsiriporn (1989). Natural rubber supply response is also influenced by a number of other non-price variables such as the role of government, infrastructure, R&D, the use of modern techniques including fertilisers, and improved varieties. It is difficult to incorporate these variables into a supply response model directly, and most studies proxy their impacts collectively through a time trend. Finally, one further factor influencing farmers' decisions is risk, but no study includes this.

3.6 Summary and Conclusions

Econometric and programming approaches have been developed to examine the dynamics of supply response. Econometric approaches can be divided into direct methods, indirect or two-stage duality approaches, and cointegration approaches. Direct estimates, often using Nerlove's model, involve estimating supply equations where supply is typically defined as a function of own price, other relevant prices, and non-price factors. This method is applied in many empirical studies of agricultural supply response due to simple data requirements and estimation procedures, lower chance of specification errors, and fewer difficulties in formulating price expectations. Disadvantages include criticisms of the Nerlovian models, especially the *ad hoc* specification, choosing an appropriate price variable, little attention on the influence of risk, and intrinsic limitations of econometric methods particularly spurious regressions. In the indirect approach, the supply response function is derived in a second stage from results obtained from econometric estimation of the production, profit or cost functions in a first stage via duality relationships. An advantage of this method is the opportunity to use more complex functional forms with few restrictions. However the method is more suitable for micro-firm level analysis and its application at the aggregate level is questionable, and it is also difficult to distinguish between short- and long-run elasticities. The cointegration approach overcomes the problem of spurious regression, and both short- and long-run elasticities can be estimated, but it can be criticized for lacking a theoretical basis. The linear programming approach models production with given resource availability. Its main advantage stems from the quality of data used since psychological and institutional constraints can be included by using flexibility constraints, while disadvantages are difficulties of calculating elasticities and the high cost, and difficulties of collecting data. Most studies of perennial crop supply response use econometrics and the Nerlovian models, but difficulties arise from an inadequate dynamic structure, spurious results, biased results due to omitted relevant variables, and no consideration on the influence of risk.

In summary, it is clear that there are gaps in our understanding of the supply response of natural rubber production in Thailand. It therefore is necessary to undertake further research using a contemporary dataset and modern methods such as cointegration approaches which can be used with non-stationary data to address the problem of spurious regression to obtain consistent estimates of both short- and long-run supply elasticities.

Chapter 4 The Theoretical Framework

4.1 Introduction

Production concerns the technical relationships between inputs that are used to generate outputs. Decisions that underlie production processes are taken by social units such as firms and farms. The economic theory of production involves the allocation of scarce resources (what to produce, how much to produce and how to produce). It is often based on the objective of maximizing profits subject to a production function. In agriculture, farmers are involved with the allocation of inputs to crop cultivation, the kinds of crops to grow, and so on (Ellis, 1988, p.6). One major issue that has dominated the analysis of agricultural production concerns supply response where the supply of a commodity responds to changes in both price and non-price variables. This chapter presents the main elements of agricultural supply response. These are then used as a basis for constructing an economic model of farmers' supply response for rubber. Only the case of perfect competition in both output and input markets is considered.

This chapter is organised as follows. Section 4.2 introduces fundamental concepts of production, focusing on the single-variable factor case. The production function with two variable inputs is then introduced. Section 4.3 focuses on some economic aspects of production from an output perspective. Conditions for profit maximisation and comparative statics are derived. Section 4.4 extends the model to the multiple-output case. Section 4.5 discusses the influence of prices and non-price variables. Section 4.6 considers the modelling of natural rubber supply response.

4.2 Some Concepts of Production Economics[23]

We begin with some basic economic concepts of production based on the neoclassical theory of the firm. The production function and some technical aspects of production are introduced.

4.2.1 The Production Function

The production function describes the technical production process of how inputs (factors of production) are transformed into outputs (commodities). It represents the maximum physical output produced from combinations of physical inputs with given technology (Debertin, 1986, pp.14-15; Doll and Orazem, 1984, pp.20-21). The production function is:

$$y = f(x_i) \qquad i = 1,...,k \tag{4.1}$$

where y denotes output and x_i are inputs. The distinction between fixed and variable inputs is important. If all inputs but one are constant, the production function is:

$$y = f(x_1 \mid x_2,....,x_k) \tag{4.2}$$

where x_1 is the variable input, and $x_{2,....,}$ x_k are fixed inputs. In a given production period, a variable input can be adjusted whereas a fixed input cannot be modified. Land is often considered as a fixed input in the short run but is variable in the long run. Thus, the distinction between fixed and variable inputs depends on the length of

[23] This section draws on Beattie and Taylor (1985, pp.9-29) and Debertin (1986, pp.14-38, and 81-96).

the production period: all inputs are variable in the long run, whilst the period of time where at least one input is fixed is the short run (Debertin, 1986, p.19). The production function is usually based on the assumption that technology is constant or at least exogenously specified. However, the fixed technology assumption becomes increasingly erroneous as the length of run increases because it is possible that production parameters could change, and changing technology is sometimes included in the model (Beattie and Taylor, 1985, p. 3).

The relationship between output and a variable input can be described by the law of diminishing marginal returns which states that as amounts of a variable input are added to a production process while all other inputs are held constant, the additional units of output added per unit of variable input will finally decline (Debertin, 1986, p.21; Doll and Orazem, 1984, p.35). The production function is sometimes referred to as the total product, TP, function to highlight other important aspects of the factor-product relationship, that is the marginal product, MP, of the variable input and its average product, AP. MP is the change in output resulting from an incremental or unit change in the use of the variable input expressed per unit of the input and can be either positive or negative. Geometrically, MP is the slope of the production function (Debertin, 1986, p.24; Doll and Orazem, 1984, p.35):

$$MP_1 = \frac{\partial TP}{\partial x_1} \tag{4.3}$$

AP is the average amount of the total product per unit of the variable input:

$$AP_1 = \frac{TP}{x_1} \tag{4.4}$$

The physical relationship between output and a variable input can also be expressed as the input elasticity or the elasticity of production, E_p, which measures the response of output to a change in the use of an input. It is defined as the ratio of the percentage change in output in response to a one percent change in an input with other inputs constant:

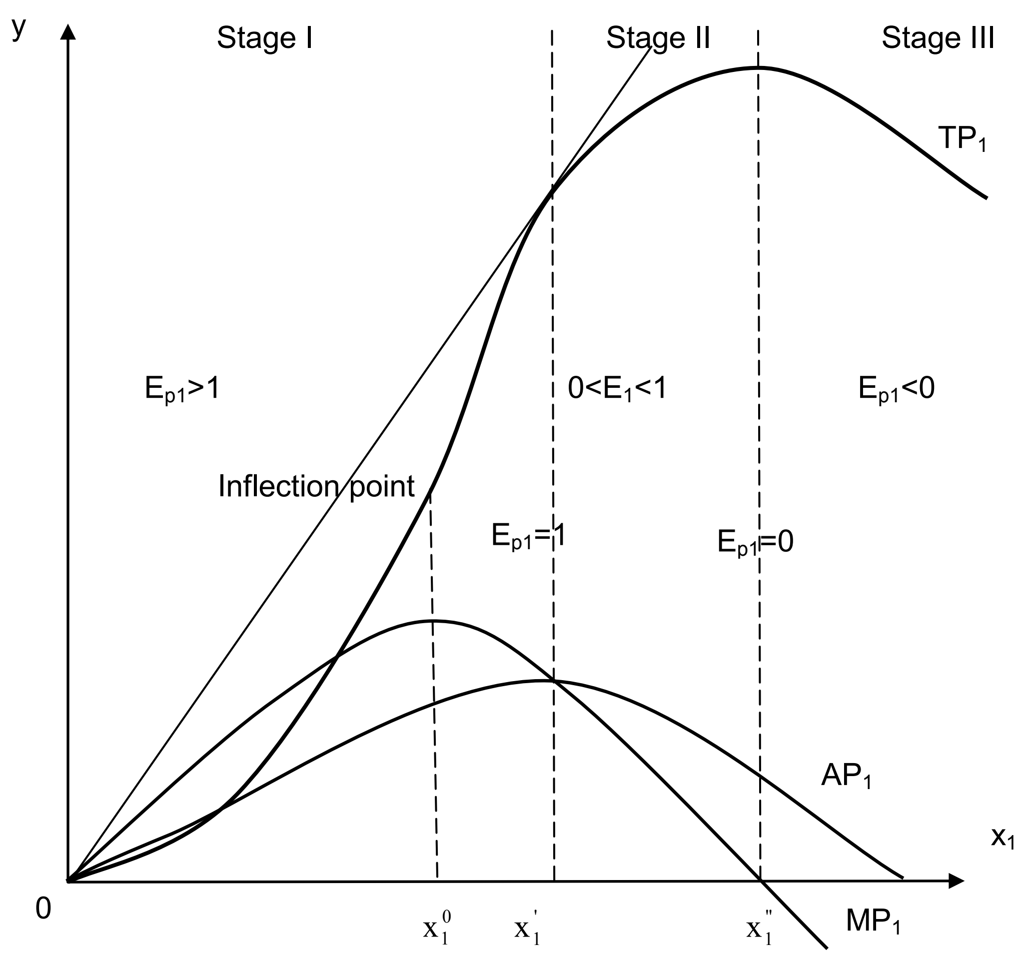
$$E_{p1} = \frac{\%\,\text{change in output}}{\%\,\text{change in input } x_1} = \frac{\partial y / y}{\partial x_1 / x_1} = \frac{\partial y}{\partial x_1} . \frac{x_1}{y} = \frac{MP_1}{AP_1} \tag{4.5}$$

If $E_p>1$, output responds more than proportionately to increases in the use of the input; if $0<E_p<1$, output increases less than the increase in the input; if $E_p<0$, output decreases as the input increases, and if $E_p=1$, the proportionate increases are equal.

4.2.2 The Three Stages of Production Function

The neoclassical production function has been used widely in the economic analysis of agricultural production. Consider an one-output, two inputs production function where one of the inputs, x_1, is variable and the other, x_2, is fixed - see Figure 4.1. The function initially increases at an increasing rate, as the use of input x_1 increases until it reaches the inflection point at x_1^0; thereafter it changes to increasing at a decreasing rate. The inflection point is where increasing marginal returns ends and where diminishing marginal returns starts. The production function reaches a maximum at x_1'' beyond which output decreases (Debertin, 1986, pp.28-29).

Figure 4.1 The Three Stages of Production Function



Source: adapted from Beattie and Taylor (1985, p.13).

An important characteristic of the production function is that changes in x_1 lead to changes in MP_1, AP_1, and E_{p1}. The value of E_{p1} can be divided into three stages of production. Stage I includes input levels from zero units to x_1' (where $MP_1=AP_1$) and over this range, $E_{p1}>1$. Stage II is the region from x_1' to the point where the production function reaches its maximum at x_1'' where $MP_1=0$ and $E_{p1}=0$. $E_{p1}<0$ beyond x_1''. Stage III is the region where the production function is declining and $MP_1<0$ and $E_{p1}<0$ (Debertin, 1986, pp.53-55). The elasticity of production is greatest when the ratio $MP_1:AP_1$ is greatest which occurs when MP_1 reaches its maximum at

x_1^0. Stages I and III are irrational stages of production because rational firms would never operate here as production is inconsistent with profit maximisation. Stage II is the rational or economic stage of production.

4.2.3 Production with Two Variable Inputs

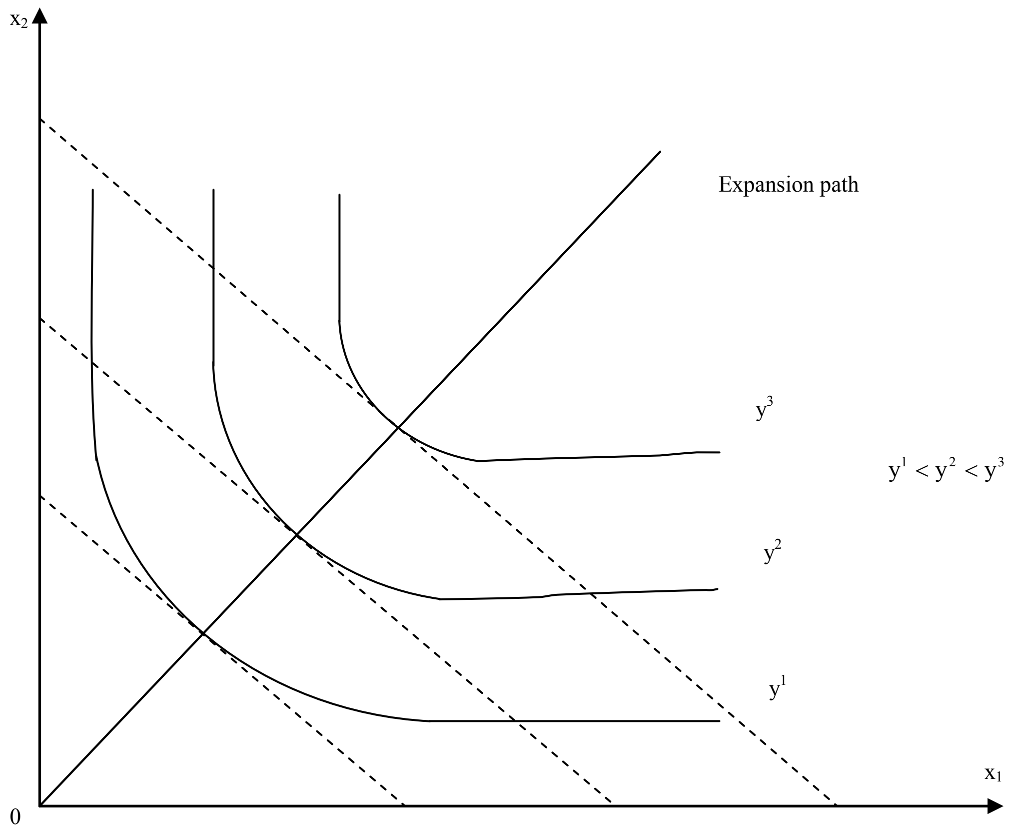
The discussion in the previous sub-section, which focussed on a single variable input, yields some powerful concepts about resource allocation. However, the use of a single variable input model is inadequate because it does not allow interaction between inputs or a comparison of input-input relationships. Now consider a model in which two inputs are allowed to vary. The production function becomes:

$$y = f(x_1, x_2 \mid x_3, ..., x_k) \tag{4.6}$$

where x_1 and x_2 are variable inputs and x_3,…, x_k are fixed. Here, various different combinations of inputs can produce the same level of output, and they can be shown by a family of isoquants – see Figure 4.2. An isoquant is a line representing the combinations of x_1 and x_2 that produce equal quantities of output and its equation is derived from (4.6) when output is held constant:

$$x_2 = f^{-1}(x_1, y) \tag{4.7}$$

Figure 4.2 A Family of Isoquants



Isoquants are convex to the origin, and, if the marginal products of both inputs are positive, are downward sloping. However, if the marginal product of one of the inputs is negative, it is possible for isoquants to slope upward. The slope of an isoquant is the marginal rate of substitution, MRS, which is a measure of how one input substitutes for another to maintain the same output. MRSx_1x_2 is the slope of the isoquant assuming that input x_1 is increasing and x_2 is decreasing:

Consider the total differential of the production function:

$$\begin{aligned} dy &= (\partial f / \partial x_1)dx_1 + (\partial f / \partial x_2)dx_2 \\ &= f_1 dx_1 + f_2 dx_2 \end{aligned} \tag{4.8}$$

Since $dy = 0$ along an isoquant, we get

$$0 = f_1 dx_1 + f_2 dx_2 \tag{4.9}$$

Then, we can derive $MRS_{x_1x_2}$ as the ratio of marginal products in positive terms; that is,

$$MRS_{x_1x_2} = -\frac{dx_2}{dx_1} = \frac{f_1}{f_2} \tag{4.10}$$

Similarly, we can derive $MRS_{x_2x_1}$ as

$$MRS_{x_2x_1} = -\frac{dx_1}{dx_2} = \frac{f_2}{f_1} \tag{4.11}$$

Therefore, we can conclude that:

$$MRS_{x_1x_2} = \frac{f_1}{f_2} = \frac{1}{f_2/f_1} = \frac{1}{MRS_{x_2x_1}} \tag{4.12}$$

From the principle of diminishing marginal returns, MRS diminishes as more and more of one input is required to replace a single unit of the other with output constant.

4.3 Economic Characteristics of Production: The Output Perspective[24]

This section presents some economic aspects of production from the output side for production with two variable inputs. The discussion focuses on the problems faced by a producer to determine how much of a single output to produce to maximize profits.

4.3.1 Some Basic Economic Concepts

From an output-side perspective, the focus is on the cost function defined in terms of output. Variable cost, VC, is the cost of production that changes with the level of output produced and is the cost associated with the purchase of variable inputs. Fixed costs, FC, are costs incurred whether or not production occurs. Since the production of agricultural commodities normally involves more than one input, variable cost is usually expressed per unit of output, y, rather than per unit of input, x:

$$VC = \tilde{c}(y) \tag{4.13}$$

The variable cost function for more than one variable input can be derived by transforming the expansion path which is a specific isocline that connects all points on an isoquant map where the slopes of the isoquants are equal to the ratio r_1/r_2, where r_1 and r_2 are input prices (see Figure 4.2). For the production function, $y=f(x_1,x_2)$, we can derive the conditional input demand functions for x_1 and x_2 as:

[24] This section is drawn from Beattie and Taylor (1985, pp.143-171) and Debertin (1986, pp.62-79).

$$x_1 = x_1(r_1, r_2, y) \tag{4.14}$$

$$x_2 = x_2(r_1, r_2, y) \tag{4.15}$$

Since the input cost equation for x_1 and x_2 is:

$$c \equiv r_1 x_1 + r_2 x_2 \tag{4.16}$$

By substituting(4.14) and(4.15) into(4.16) , the variable cost function is:

$$VC = r_r x_1(r_1, r_2, y) + r_2 x_2(r_1, r_2, y) = \tilde{c}(r_1, r_2, y) \tag{4.17}$$

Fixed cost, b, does not change with output, so:

$$FC = b \tag{4.18}$$

Total cost, TC:

$$TC \quad = VC + FC \quad = \tilde{c}(y) + b \tag{4.19}$$

Average variable cost, AVC, is the variable cost per unit of output:

$$AVC = \frac{VC}{y} = \frac{\tilde{c}(y)}{y} \tag{4.20}$$

Average fixed cost is fixed cost per unit of output:

$$AFC = \frac{FC}{y} = \frac{b}{y} \tag{4.21}$$

Average total cost, ATC, is total cost, TC, divided by output, y:

$$ATC = \frac{TC}{y} = \frac{\tilde{c}(y) + b}{y} \tag{4.22}$$

Also:

$$ATC = AVC + AFC \tag{4.23}$$

or:

$$\frac{TC}{y} = \frac{VC}{y} + \frac{FC}{y} \tag{4.24}$$

Marginal cost is defined as the change in total cost (or total variable cost), resulting from an incremental change in output. It is the slope of the total cost function, that is:

$$MC = \frac{dTC}{dy} = \frac{dVC}{dy} = \frac{d[\tilde{c}(y) + b]}{dy} = \frac{d\tilde{c}(y)}{dy} \tag{4.25}$$

Total revenue, TR, is the total income received from the sale of the output. Since the output price, P, is given:

$$TR = Py \tag{4.26}$$

Determined by the demand function for the product, average revenue, AR, is:

$$AR = \frac{TR}{y} = \frac{Py}{y} = P \tag{4.27}$$

Marginal revenue, MR, is the value of the incremental revenue resulting from an additional unit of output produced. It is the slope of the TR function:

$$MR = \frac{d(Py)}{dy} = P \tag{4.28}$$

Equations (4.27) and (4.28) indicate that AR=MR.

4.3.2 Profit Maximisation

Consider profit-maximisation from the output side.[25] With cost-minimising input levels implicit in the total cost function, profit, Π, is:

$$\Pi = TR - TC = Py - [\tilde{c}(y) + b] \tag{4.29}$$

[25] In addition to profit maximisation from the output side, there is an alternative view of profit maximisation from the input side. Here, profit is equivalent to the total value product, TVP, minus the total factor cost, TFC. Maximum profit is reached where the slopes of TVP and TFC are equal; that is where marginal value of product is equal to marginal factor cost. This implies that the firm equates the marginal value product to the input price. To guarantee maximum profit, the profit function must be concave at that point.

that is, profit is equal to the total revenue minus the total cost, and maximum profit is achieved at the point where the difference between TR and TC is greatest. The first-order conditions for maximization of (4.29) require that:

$$\frac{d\Pi}{dy} = \frac{d[Py - \tilde{c}(y) - b]}{dy} = P - \frac{d\tilde{c}(y)}{dy} = 0 \tag{4.30}$$

From the definitions of MC and MR in (4.25) and (4.28), (4.30) can be rearranged:

$$MR = MC \tag{4.31}$$

Since MR=P, (4.31) becomes:

$$P = MC \tag{4.32}$$

Equation (4.31) is a necessary condition for selecting the output that maximises profit. However, this condition does not ensure maximum profits because profit might be a minimum. The second-order condition for maximum profit requires that the profit function be concave at the value of y that satisfies the first-order condition, (4.31):

$$\frac{d^2\Pi}{dy^2} = \frac{d^2\left(Py - \tilde{c}(r_1, r_2, y) - b\right)}{dy^2} = \frac{d\left(P - \frac{d\tilde{c}(y)}{dy}\right)}{dy} = -\frac{d^2\tilde{c}(y)}{dy^2} < 0 \tag{4.33}$$

This second-order condition implies that the rate of change of MR must be less than the rate of change of MC. Both first- and second-order conditions, together with the total condition that TR-VC>0 are sufficient to ensure maximum profit (Beattie and Taylor, 1985, pp.158-159).

4.3.3 Product Supply Function

The supply function shows output as a function of both output and input prices. We can derive a profit-maximising supply function from the first-order conditions for profit maximisation. It is the inverse of the marginal cost function when MC=P. Differentiating (4.29) to give the first-order condition and setting to zero gives:

$$\frac{d\Pi}{dy} = P - \frac{\partial\left(\tilde{c}(r_1, r_2, y) - b\right)}{\partial y} = P - MC = 0 \tag{4.34}$$

Here and in the remainder of this sub-section, $d\Pi/dy$ is used to stress that there is only one first-order condition to be considered, and the partial derivative of variable cost with respect to y is used to emphasise that input prices are treated as parameters or exogenous variables. Marginal cost is a function of y and we can derive the inverse function from (4.30) as:

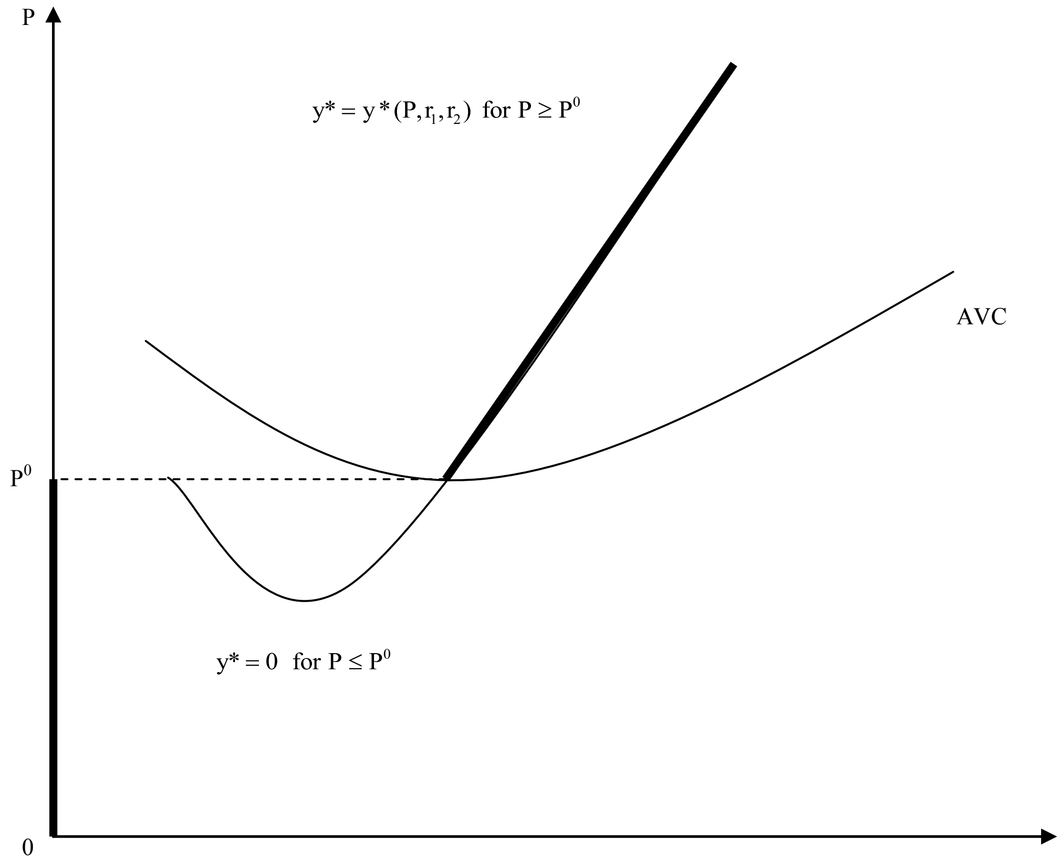
$$y^* = y^*(P, r_1, r_2) \tag{4.35}$$

Thus, supply is a function of output and input prices (and the given technology). However, the marginal cost function is not the supply function where MC<AVC; a firm's supply function is specified by the disjointed function:

$$y^* = \begin{cases} y^*(P, r_1, r_2) & \text{for } P \geq \text{minimum AVC} \\ 0 & \text{for } P \leq \text{minimum AVC} \end{cases} \tag{4.36}$$

This supply function in (4.35) is illustrated in Figure 4.3.

Figure 4.3 A Firm's Product Supply Function



Source: adapted from Beattie and Taylor (1985, p.164).

4.3.4 Some Comparative Static Relationships

The analysis of comparative static relationships from the supply-side involves the determination of qualitative information about the partial derivatives $\partial y^*/\partial r_i$ and $\partial y^*/\partial P$ which are associated with partial derivatives of the production function. One method of analysing supply-side comparative statics can be illustrated as follows. Consider the two-input production function, $y=f(x_1,x_2)$. By substituting the input demand functions, x_i^*, which are functions of output and input prices, into the production function, we obtain the supply function, $y^* = f(x_1^*, x_2^*)$. The total differential of the supply function is:

$$dy^* = (\partial f / \partial x_1) dx_1^* + (\partial f / \partial x_2) dx_2^* = f_1 dx_1^* + f_2 dx_2^* \tag{4.37}$$

For the profit maximisation model viewed from input perspectives:

$$dx_1^* = \frac{f_{22}(dr_1 - f_1 dP) - f_{12}(dr_2 - f_2 dP)}{P(f_{11} f_{22} - f_{12}^2)} \tag{4.38}$$

and

$$dx_2^* = \frac{f_{11}(dr_2 - f_2 dP) - f_{12}(dr_1 - f_1 dP)}{P(f_{11} f_{22} - f_{12}^2)} \tag{4.39}$$

Substituting (4.38) and (4.39) for dx_1^* and dx_2^*, respectively, in (4.37) , we obtain dy^*, as a function of dr_1, dr_2, dP, and partial derivatives of the production function:

$$dy^* = f_1\left(\frac{f_{22}(dr_1 - f_1 dP) - f_{12}(dr_2 - f_2 dP)}{P(f_{11}f_{22} - f_{12}^2)}\right)$$
$$+ f_2\left(\frac{f_{11}(dr_2 - f_2 dP) - f_{12}(dr_1 - f_1 dP)}{P(f_{11}f_{22} - f_{12}^2)}\right)$$

$$= \frac{(f_1 f_{22} - f_2 f_{12})dr_1 + (f_2 f_{11} - f_1 f_{12})dr_2 + (2f_1 f_2 f_{12} - f_1^2 f_{22} - f_2^2 f_{11})dP}{P(f_{11}f_{22} - f_{12}^2)} \tag{4.40}$$

From (4.40), comparative static relationships can be derived. With r_1 and r_2 constant, that is $dr_1=dr_2=0$:

$$\frac{dy^*}{dP} = \frac{2f_1 f_2 f_{12} - f_1^2 f_{22} - f_2^2 f_{11}}{P(f_{11}f_{22} - f_{12}^2)} > 0 \tag{4.41}$$

With P and r_2 constant, that is $dP=dr_2=0$:

$$\frac{dy^*}{dr_1} = \frac{f_1 f_{22} - f_2 f_{12}}{P(f_{11}f_{22} - f_{12}^2)} \quad \begin{cases} < 0 \\ = 0 \\ > 0 \end{cases} \tag{4.42}$$

With P and r_1 constant, that is $dP=dr_1=0$:

$$\frac{dy^*}{dr_2} = \frac{f_2 f_{11} - f_2 f_{12}}{P(f_{11}f_{22} - f_{12}^2)} \quad \begin{cases} < 0 \\ = 0 \\ > 0 \end{cases} \tag{4.43}$$

The (common) denominator in (4.41)-(4.43) is positive from the second-order condition for profit maximisation (a strictly concave production function). The numerator in (4.41) is positive if the production function is strictly quasi-concave and the sign of (4.41) is positive. The signs of the partial derivatives in (4.42) and (4.43) are indeterminate and depend on f_{12} which can take any value depending on the technical relationships between the inputs (Beattie and Taylor, 1985, pp.169-171). Equation (4.41) shows what happens to y^* when an output price changes. Since the partial derivative in (4.41) is positive, a product supply function always slopes upward. Equation (4.42) and (4.43) show how output changes in response to changes in factor prices. The signs of dy^*/dr_i can be negative, zero, or positive and the relationships between output and input prices are indeterminate.

4.4 Production of More Than One Product[26]

We now consider the theory of a multiple product firm which involves the combinations of alternative products which can be produced from a given set of inputs. Multiproduct production analysis depends on inputs which are either allocable or non-allocable. For an allocable input, x_i, we can distinguish between units used in producing product y_1 from the amount of x_i used in producing y_2 ($y_1 \neq y_2$), where x_{i1} is the amount of factor x_i used in producing y_1. If a allocable single factor, x_1, is used to produce two products, y_1 and y_2, then the total amount of x_1 used is $x_1=x_{11}+x_{12}$. By contrast, a non-allocable input is a factor which we cannot distinguish between units producing y_1 and those producing y_2. In this section, we introduce a two-product production with a single allocable factor.

[26] This section is drawn from Beattie and Taylor (1985, pp.179-221).

4.4.1 Two-product Production with a Single Allocable Factor

A production function for a two-product, single allocable input is denoted in implicit form as:

$$F(y_1, y_2, x_1) = 0 \tag{4.44}$$

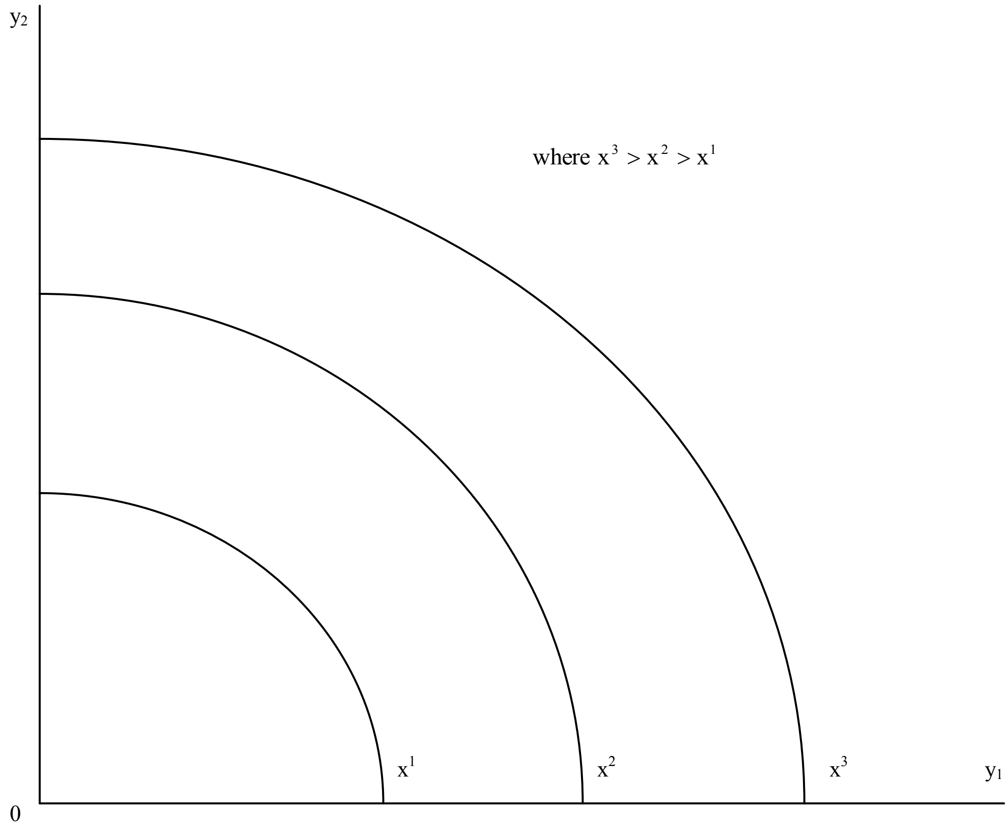
where y_1 and y_2 are outputs of the products and x_1 is the total amount of the single allocable input used in producing the two products (Beattie and Taylor, 1985, pp.179-180). We now omit the subscript from x for notational convenience. The production function can be expressed as:

$$x = w(y_1,y_2) \tag{4.45}$$

Thus, the amount of the input used is a function of the quantities of each product produced, y_1 and y_2. The production function in (4.44) or (4.45) can be illustrated in two-dimensional space by using the concept of a product transformation or production possibility curve which is defined as the locus of output combinations that can be produced for a given amount of the variable input. A family of product transformation curves, which shows the technical relationships between products in multiproduct production, is illustrated in Figure 4.4. In general, product transformation curves have negative slopes and are concave toward the origin. The point at which the curve reaches each axis is the maximum amount of each output which can be produced for the given input. The negative of the slope of a product transformation curve measures the rate of product transformation, RPT, and shows how one output can be substituted for the other with the given input:

$$RPT_{12} = -\frac{dy_2}{dy_1} \tag{4.46}$$

Figure 4.4 A Family of Product Transformation



Source: adapted from Beattie and Taylor (1985, p.185).

By taking the total differential of the explicit form of the production function in (4.45), we obtain the rate of product transformation as follows:

$$dx = \frac{\partial x}{\partial y_1} dy_1 + \frac{\partial x}{\partial y_2} dy_2 = w_1 dy_1 + w_2 dy_2 \tag{4.47}$$

Each partial derivative, w_1 and w_2, is the change in the use of the input, x, which is caused by a change in the production of one of the outputs, y_1 and y_2. Although w_1

and w_2 are similar to inverse marginal productivities for x in the production of y_1 and y_2, they are not so in the conventional sense since the arguments in w_1 and w_2 are y_1 and y_2,, while the usual inverse marginal productivities are a function of x and y. However, w_1 and w_2 in (4.47) may be regarded as inverse marginal productivities if we assume that the substitutions for the correct explanatory variable in w_1 and w_2 have been made(Beattie and Taylor, 1985, pp.187-188).

Since the use of the input along a given product transformation curve is unchanged, (4.47) becomes:

$$0= w_1 dy_1 + w_2 dy_2 \tag{4.48}$$

Therefore,

$$\frac{dy_2}{dy_1} = -\frac{w_1}{w_2} \tag{4.49}$$

and:

$$RPT_{12} = -\frac{dy_2}{dy_1} = \frac{w_1}{w_2} = \frac{\partial x/\partial y_1}{\partial x/\partial y_2} = \frac{\partial y_2/\partial x}{\partial y_1/\partial x} \tag{4.50}$$

Equation (4.50) indicates that the rate of product transformation is equal to the ratio of the marginal productivity of x in the production of y_2 to the marginal productivity of x in the production of y_1.

We now examine profit maximisation in the two-product, single allocable variable input model. The profit function, excluding fixed cost, is defined as:

$$\Pi = TR - c = P_1 y_1 + P_2 y_2 - rx = P_1 y_1 + P_2 y_2 - h(x)x \tag{4.51}$$

where r=h(x) is the factor supply function and P_1 and P_2 are the prices of product y_1 and y_2. Since there is no factor-factor relationship (because a single factor is used), $c=rx=h(x)x=h[w(y_1,y_2)]w(y_1,y_2)=VC$. To be exact, the VC function can be derived by substituting the explicit form of the production, (4.45), for x into the variable factor cost equation, c.

Consider the unconstrained profit-maximisation of (4.51) subject to the production function in (4.45). Substituting the production function, (4.45), for x in (4.51) is tantamount to substituting the VC function for c in (4.51):

$$\Pi = TR - VC = P_1 y_1 + P_2 y_2 - h[w(y_1, y_2)]w(y_1, y_2) \tag{4.52}$$

By taking the first-partial derivatives of the profit function (4.52) with respect to y_1 and y_2, and setting each equation to zero, the first-order conditions are:

$$\frac{\partial \Pi}{\partial y_1} = P_1 - h[w(\cdot)]w_1 - w(\cdot)h_1[w(\cdot)] = 0 \tag{4.53}$$

$$\frac{\partial \Pi}{\partial y_2} = P_2 - h[w(\cdot)]w_2 - w(\cdot)h_2[w(\cdot)] = 0 \tag{4.54}$$

where $w(\cdot)$ denotes $w(y_1,y_2)$. After rearranging, (4.53) and (4.54) become:

$$P_1 = h[w(\cdot)]w_1 + w(\cdot)h_1[w(\cdot)] \tag{4.55}$$

$$P_2 = h[w(\cdot)]w_2 + w(\cdot)h_2[w(\cdot)] \tag{4.56}$$

Alternatively, by substituting notation, (4.55) and (4.56) become:

$$MR_1 = MC_1 \tag{4.57}$$

$$MR_2 = MC_2 \tag{4.58}$$

Since MC_j is dependent on outputs, y_1 and y_2, we can solve (4.57) and (4.58) simultaneously to derive profit-maximizing values of y_1^* and y_2^*. In addition, by substituting y_1^* for y_j in the production function, (4.45), we can obtain the profit-maximizing input level, that is, $x^* = w(y_1^*, y_2^*)$.

The second–derivative condition for maximum profit requires that the principal minors of a Hessian determinant alternate in sign:

$$\frac{\partial^2 \Pi}{\partial y_1^2} = -rw_{11} < 0 \Rightarrow w_{11} > 0$$

$$\frac{\partial^2 \Pi}{\partial y_2^2} = rw_{22} < 0 \Rightarrow w_{22} > 0$$

$$\begin{vmatrix} \frac{\partial^2 \Pi}{\partial y_1^2} & \frac{\partial^2 \Pi}{\partial y_1 \partial y_2} \\ \frac{\partial^2 \Pi}{\partial y_2 \partial y_1} & \frac{\partial^2 \Pi}{\partial y_2^2} \end{vmatrix} = \begin{vmatrix} -rw_{11} & -r_{12} \\ -rw_{21} & -rw_{22} \end{vmatrix} = r^2(w_{11}w_{22} - w_{12}w_{21}) > 0$$

$$\Rightarrow (w_{11}w_{22} - w_{12}^2) > 0$$

(4.59)

Equation (4.59) implies that the production function in the input-dependent explicit form must be strictly convex.

Solving the equations (4.55) and (4.56) gives the product supply function:

$$y_j^* = y^*(P_1, P_2, r) \qquad \text{for j=1, 2}$$

(4.60)

This expression implies that the supply of each output is a function of own price, the prices of alternative products, input price, and the levels of fixed inputs.

4.4.2 Economic Interdependence of Products and Comparative Statics

The relationship between two products produced from an allocable factor is considered in a way that a change in the price of one product affects the amount supplied of other product. We can consider the economic interdependence of products by analysing the total differential of the first-order conditions for profit maximisation:

$$P_j - rw_j = 0 \quad \text{for j = 1,2}$$

(4.61)

Taking total differentials of (4.60) yields:

$$-rw_{11}dy_1^* - rw_{12}dy_2^* = dP_1 + w_1 dr$$
$$-rw_{21}dy_1^* - rw_{22}dy_2^* = dP_2 + w_2 dr$$
(4.62)

Since the w_i's are first-partial derivatives of $x=w(y_1, y_2)$, the differentials, dy_1 and dy_2, also exist in (4.62). However, to emphasise that the comparative statics must be analysed in terms of outputs optimal levels, dy_1 and dy_2 become dy_1^* and dy_2^*. Using Cramer's rule, we can solve the simultaneous equations in (4.62) for dy_1^* and dy_2^*:

$$dy_1^* = \frac{\begin{vmatrix} (-dP_1 + w_1 dr) & -rw_{12} \\ (-dP_2 + w_2 dr) & -rw_{22} \end{vmatrix}}{\begin{vmatrix} -rw_{11} & -rw_{12} \\ -rw_{21} & -rw_{22} \end{vmatrix}} = \frac{rw_{22}(dP_1 - w_1 dr) - rw_{12}(dP_2 - w_2 dr)}{r^2(w_{11}w_{22} - w_{12}w_{21})}$$
(4.63)

Likewise:

$$dy_2^* = \frac{rw_{11}(dP_2 - w_2 dr) - rw_{21}(dP_1 - w_1 dr)}{r^2(w_{11}w_{22} - w_{12}w_{21})}$$
(4.64)

Given that input and output prices in (4.63) and/or (4.64) are constant:

$$\frac{dy_j^*}{dP_k} \equiv \frac{\partial y_j^*}{\partial P_k} = \frac{-rw_{jk}}{r^2(w_{11}w_{22} - w_{12}^2)} \begin{cases} > \\ =0 \\ < \end{cases} \qquad \text{for } j \neq k \text{ and } j,k = 1,2$$
(4.65)

Since the denominator in (4.65) is positive if the second-order condition is satisfied, the economic interdependence of the products depends on the negative of the cross-partial derivative of the explicit form of the production function. We can define three types of interdependence between products. First, if $w_{jk}>0$, $\partial y_j^* / \partial P_k < 0$, and y_j and y_k are competing products. Second, if $w_{jk}<0$, $\partial y_j^* / \partial P_k > 0$, and y_j and y_k are complementary products. Finally, if $w_{jk}=0$, $\partial y_j^* / \partial P_k = 0$ and y_j and y_k are independent. This categorisation implies that if the increase in price of y_2 induces the producer to increase y_1 and y_2, the relationship is complementary. In contrast, if the price of y_2 is increased and the producer increases y_2 but decreases y_1, it is a competitive relationship. Some further comparative statics for the two-product, single allocable input profit-maximisation model can be examined through (4.63) and (4.64). Assuming constant output prices, that is $dP_1=dP_2=0$ in (4.63) and (4.64), we get:

$$\frac{dy_1^*}{dr} \equiv \frac{\partial y_1^*}{\partial r} = \frac{-w_1 w_{22} + w_2 w_{12}}{r(w_{11}w_{22} - w_{12}^2)} \begin{cases} > \\ =0 \\ < \end{cases}$$

$$\frac{dy_2^*}{dr} \equiv \frac{\partial y_2^*}{\partial r} = \frac{-w_2 w_{11} + w_1 w_{12}}{r(w_{11}w_{22} - w_{12}^2)} \begin{cases} > \\ =0 \\ < \end{cases} \tag{4.66}$$

Further, if the input price is constant, that is $dr=0$, and the appropriate alternative product price differentials equal zero in (4.63) and (4.64), we obtain:

$$\frac{dy_1^*}{dP_1} \equiv \frac{\partial y_1^*}{\partial P_1} = \frac{w_{22}}{r(w_{11}w_{22} - w_{12}^2)} \geq 0$$

$$\frac{dy_2^*}{dP_2} \equiv \frac{\partial y_2^*}{\partial P_2} = \frac{w_{11}}{r(w_{11}w_{22} - w_{12}^2)} \geq 0$$

(4.67)

The signs of the partial derivatives in (4.65)-(4.67) follow from the strict convexity of the production function. Equation (4.66) shows how outputs react to changes in factor price. Since the signs of dy_j^*/dr can be either negative, zero, or positive, the relationships between output and input price are indeterminate. The signs of the partial derivatives in (4.67) are positive and the product supply functions are upward sloping.

4.4.3 Multi-Output, Multi-input Supply Function

Most firms produce more than one product and use many inputs and we turn to examine the multi-product, multi-input firm. By combining the one-output, two input supply function, (4.35), with the two-output, single allocable variable input supply function, (4.60), we can develop the supply functions for the multiple-output, multiple input firm as:

$$y_j^* = y^*(P_1, P_2, ..., P_m, r_1, r_2, ..., r_n) \qquad \text{for } j=1,\dots,m$$

(4.68)

Equation (4.68) shows a complex multi-dimensional set of functional relationships between outputs and own price, the prices of other relevant products, input prices, and the levels of fixed inputs. Market supply is the total supply of every firm which is willing and able to sell the product and is derived by summing the individual supplies of each firm.

4.5 Agricultural Supply Response

There are three key aspects to note about agricultural supply response. First, it is concerned not only with the effects of price changes (Ghatak and Ingersent, 1984, p.72) but also with changes in supply shifters (Tomek and Robinson, 1981, p.86). Second, while the supply of agricultural products strictly means the amount of output supplied to the market, empirical studies typically concentrates on actual or potential farm output. Third, we can differentiate between short- and long-run supply response. The short run is characterised by fixed inputs - equipment, irrigation, and infrastructure and so on - and adjustment of output to changes in prices is limited. In the long run, producers fully adjust output since fixed short-run inputs can be varied through investment, although some non-price factors like environmental features are exogenous and cannot be controlled. Accordingly, long-run supply responses are higher than short-run responses (Sadoulet and de Janvry, 1995, p.72). By contrast, the traditional supply model is theoretically reversible: if output price rises and then falls, supply reverts to its original level so that an instantaneous and complete supply response is induced by a change in an explanatory variable in the same production period. In the real world, producers may not adjust instantaneously to a change in prices for three reasons. First, producers have a psychological resistance to change especially to adopting new techniques. Second, difficulties may be caused by the institutional setting, for example, production quotas, limitation on input exploitation, market infrastructure, accessibility to credit, and so on. Third, fixed inputs may limit adjustment in the short run. Biological constraints in both livestock and perennial crops production and rotation might also impede the response to changing product prices. Thus, complete adjustment of producers in response to varying conditions may be gradual, taking place over several production periods; agricultural supply response analysis is dynamic (Colman and Young, 1989, pp.35-38). The effect of this limited adjustment is that agricultural supply is often found to be inelastic.

In the following sections, the effects of some relevant factors which cause changes in output are examined. These include both price and other related non-price variables, and uncertainty and risk.

4.5.1 The Effects of Price Variables on Output

According to the supply function in (4.68), the response of producers to a change in output price is measured by the own-price elasticity of supply which is defined as the percentage change in the quantity of output supplied in response to a one percent change in output price, other factors held constant, that is:

$$E_j = \frac{\partial y_j / y_j}{\partial P_j / P_j} = \frac{\partial y_j}{\partial P_j} \cdot \frac{P_j}{y_j} \tag{4.69}$$

These elasticities are generally positive but in subsistence farming, farmers produce for themselves and not for the market. Thus, supply does not respond to market signals and E_j=0. The case of perverse supply response is where E_j<0 and producers decrease production when price increases and *vice versa*. This concept breaks the ‘law’ of supply. Peasant farmers in developing countries may react perversely to price incentives and an alternative theoretical framework is required

(Ozanne, 1999, pp.251-252). Four explanations have been developed to support the failure of the law of supply. The first, which highlights the total supply of agricultural products, relates to the "target income" or "fixity-of-wants" hypothesis, which is based on the assumption that farmers and labourers in peasant agriculture are backward, indolent and irrational, and have fixed wants, tastes and aspirations. The second focuses on marketed surplus as opposed to the total supply of food crops produced. Peasant farmers react to price incentives in the same way as 'economic man' in neoclassical theory. However, the assumption that production and consumption are distinguishable may be invalid since own-consumption is ignored. The third focuses on uncertainty and risk aversion, which is discussed in Section 4.5.3. Fourth is the development of more complicated farm-household models where production, consumption, and the labour-supply decision are analysed in a single model (Ozanne, 1999).

Supply also depends on the prices of alternative products including prices of competing crops, say P_k. That is, a change in the price of a competing product, *ceteris paribus*, shifts the supply curve of product j due to the changes in resource allocation between products j and k. The responsiveness of output to changes in the price of a competing crop - the cross-price elasticity of supply - is the proportionate change in quantity of such a product, y_j deriving from a proportionate change in the price of another product, P_k:

$$E_{jk} = \frac{\partial y_j / y_j}{\partial P_k / P_k} = \frac{\partial y_j}{\partial P_k} \cdot \frac{P_k}{y_j} \tag{4.70}$$

In general, agricultural products are competing, that is, if P_k increases, the supply of y_j falls and $E_{jk}<0$.

A change in input prices also shifts the supply curve. If the price of an input changes, *ceteris paribus*, marginal cost changes, and the supply curve shifts. A measure of responsiveness is the proportionate change in quantity of a product resulting from a proportionate change in the price of input i, r_i:

$$E_{jr_i} = \frac{\partial y_j / y_j}{\partial r_i / r_i} = \frac{\partial y_j}{\partial r_i} \cdot \frac{r_i}{y_j} \tag{4.71}$$

The sign of E_{jr_i} is indeterminate since the sign of $\partial y_j / \partial r_i$ is indeterminate. The sign of $\partial y_j / \partial r_i$ depends on the signs of the partial derivatives of the quantity of input used to produce profit-maximising output, x_i, with respect to the price of output, $\partial x_i / \partial P_j$.[27] These derivatives are linked via the symmetry conditions which postulate that $\partial y_j / \partial r_i = \partial x_i / \partial P_j$. Thus, if $\partial x_i / \partial P_j$ >0 and $\partial y_j / \partial r_i$ <0, then E_{jr_i}<0; on the other hand, if $\partial x_i / \partial P_j$ <0, and $\partial y_j / \partial r_i$ >0, then E_{jr_i}>0; alternatively, if $\partial X_i / \partial P_j$ =0, and $\partial Q_j / \partial r_i$ =0, and E_{jr_i}=0.

4.5.2 The Role of Non-price Variables in Supply Response

Agricultural supply is influenced by various non-price factors. Technological change is a key determinant of crop supply. Technology is defined as the stock of accessible techniques or the state of knowledge regarding the input-output relationship. Thus,

[27] See Beattie and Taylor (1985, pp.201-202).

technological change is an improvement in the state of knowledge where the possibilities of production are developed. If technology enhances, the production function shifts. This implies that farmers can produce more output with the same quantity of inputs or the equivalent output can be produced by using lesser amounts of inputs (Colman and Young, 1989, pp.53-54). Technological change may be integrated in advances in capital such as machinery, building, drainage and irrigation, or it may be as improvement of high-yielding varieties of crops, more effective fertilisers, pesticides and insecticides. Technological change also includes the improvement of disembodied cultivation techniques and farmers' managerial skills (Colman and Young, 1989, pp.57-58). Since there are a number of factors determining technological change, and definitional and measurement problems of technological change arise, it is difficult to incorporate this factor explicitly into supply response models. Further, similar problems occur from increased labour productivity. Several studies have utilised time trends to proxy technological change without identifying and measuring those factors that account for changing technology, and it is unclear what they actually measure. Time trends also imply that there is a smooth deterministic change in technology, which is doubtful. Nevertheless, the use of time trends is popular since they capture the effect of unobservable or omitted variables which are thought to affect supply over time. The inclusion of a time trend usually results in increased statistical significance and improved overall fit.

The weather or environmental conditions are major determinants of agricultural supply. These include rainfall, temperature, humidity, sunshine, wind, quality of soil, and so on. Many studies use rainfall as a proxy, but a limitation is that average annual rainfall does not represent rainfall distribution through time and space, nor does it represent temperature, humidity, daytime and so on. Alternative specifications include total rainfall lagged one year, past averages of rainfall, and recent standard deviations.

The government also determines agricultural supply response. The objective of policy intervention is to maximise social welfare by determining the allocation of resources through political process. Many policies have been adopted to manipulate the behaviour of farmers. Based on the level in the production or distribution system at which governmental intervention is used, we can classify them into three groups. The first are direct instruments at the farm level and include deficiency payments, production subsidies, input subsidies/credit, investment grants, and production or acreage quotas. The second are instruments at the domestic market level and include state trading or marketing boards, intervention buying, and public investment in infrastructure, education and research. Third, intervention at the national frontier includes import tariffs, levies or duties, export subsidies or taxes, import quotas, and non-tariff barriers (Colman and Young, 1989, pp.270-271). Other government policies include land arrangements, irrigation and infrastructure in rural areas, the public provision of credit, and extension services. Some government interventions may also influence product and input prices and the development of new technology. Importantly, some policies directly influence the supply of agricultural products, and these interventions should be included as explicit variables in the supply function. However, one of the major problems in supply analysis is that some policy instruments are used for a very short period of time, making the information gained through historical observation of these variables limited.

In the context of rubber production in Thailand, one of the most important production support measures is the subsidisation for replanting programme. These subsidies involve input subsidies and cash payments. Input subsidies usually mean subsidies per unit of a variable input used, and are wildly used in developing countries for inputs such as fertiliser, improved seeds and chemicals. Under partial equilibrium analysis, these subsidies reduce the costs of production and increase output. Cash payments aim to alleviate a temporary shortfall in income to smallholders after deforestation of old trees and is considered as an incentive to induce replanting. Another government measure is export taxes to protect the domestic farmers from world price fluctuations. The imposition of export taxes decreases domestic supply because their effect is to reduce domestic price.

4.5.3 Risk and Uncertainty

The theory presented in Section 4.2 assumes that a producer has perfect knowledge of all input-output relationships and prices. Agricultural production processes are generally a complex combination of decisions made under conditions of risk and uncertainty.[28] Agricultural production in developing countries is particularly characterised by uncertainty (Colman and Young, 1989, pp.64-65; Ellis, 1988, pp.80-82). In this section, we present a model of the competitive firm under uncertainty which arises when expected and actual outcomes diverge.

There are four major kinds of uncertainty. First, uncertainty about environmental factors or yield uncertainty from the weather, diseases, insects and pests, and other

[28] Uncertainty and risk are often used interchangeable but uncertainty refers situations where the probabilities of the outcomes of decision-making are unknown and subjective, whereas risk is where the probabilities are known and objective. Following the literature, we use these terms synonymously.

natural variables. Second, all prices are uncertain. With respect to output prices, this is the difference between the price at planting and that at harvest. Third, social uncertainty relates to insecurity attributed to the unbalanced power over resources, e.g., relationships between landlords and farmer. Finally, uncertainty surrounds government policies which may significantly change over time.

The neoclassical theory of the firm has been extended to include uncertainty. Several approaches have been developed to explain producer's behaviour under uncertainty (Ozanne, 1999, pp.258-259), One of the most important models is based on the expected utility maximization approach deriving from the work of von Neumann and Morgenstern (1944). Following Sandmo (1971), assume that the output price is unknown, and that the farmer is a risk-averse price-taker who maximises expected utility. The farmer's utility function is a concave, continuous and differentiable function of profits, Π, that is, $u'(\Pi) > 0$ and $u''(\Pi) < 0$ where u is utility.[29] The profit of the firm is:

$$\Pi(y) = Py - \tilde{c}(y) - b \tag{4.72}$$

where y is output, P is output price which is assumed to be a random variable, $\tilde{c}(y)$ is the variable cost function, where $\tilde{c}(0)=0$ and $\tilde{c}''(y)>0$, and b is fixed cost. The objective of the firm is to maximise the expected utility of profits:

[29] An economic agent is risk averse if the utility function is strictly concave. We can measure the degree of risk aversion by means of the Arrow-Pratt measure of absolute risk aversion, $R_A(\Pi) = -\frac{u''(\Pi)}{u'(\Pi)}$ (Arrow, 1965; Pratt, 1964). If $R_A(\Pi)$ is a decreasing function of Π, $R'_A(\Pi) < 0$, it follows that if an economic agent becomes wealthier, his risk premium for any risky prospect, defined as the maximum amount that the risk-averse individual is willing to pay to have the sure return rather than the expected return from the uncertain prospect, decreases (Takayama, 1994, pp.271-278).

$$\max_{y} E[u(Py - c(y)]$$
(4.73)

where E is the expectations operator. The expected utility of profits can be written as:

$$E[u(Py - \tilde{c}(y) - b)]$$
(4.74)

Differentiating (4.74**)** with respect to y and setting equal to zero gives the first-order condition for a maximum:

$$E[u'(\prod)(P - \tilde{c}'(y))] = 0$$
(4.75)

The second-order condition is:

$$D = E[u''(\prod)(P - \tilde{c}'(y))^2 - u'(\prod)c''(y)] < 0$$
(4.76)

To compare the optimal output under uncertainty with the familiar competitive result under certainty, (4.75**)** can be written as:

$$E[u'(\prod)P] = E[u'(\prod)\tilde{c}'(y)]$$
(4.77)

Subtracting $E[u'(\prod)\overline{P})]$, where E(P)= $\overline{P}$, from each side of (4.77) gives:

$$E[u'(\prod)(P - \overline{P})] = E[u'(\prod)(\tilde{c}'(y) - \overline{P})]$$
(4.78)

Since $E(\prod) = \bar{P}y - \tilde{c}(y) - b$, we have $\prod = E(\prod) + (P - \bar{P})y$, that is:

$$u'(\prod) \le u'[E(\prod)] \qquad \text{if } P \ge \bar{P} \tag{4.79}$$

Then, multiplying both sides of (4.79) by $(P - \bar{P})$ gives:

$$u'(\prod)(P - \bar{P}) \le u'(E(\prod))(P - \bar{P}) \qquad \text{if } P \ge \bar{P} \tag{4.80}$$

The inequality in (4.80) holds for all P: the inequality sign in (4.79) is reversed if $P \le \bar{P}$ and multiplication by $(P - \bar{P})$ does not change its sign. Note that $u'[E(\prod)]$ is a given number, and taking expectations on both sides of (4.80) yields:

$$E[u'(\prod)(P - \bar{P})] \le u'[E(\prod)]E(P - \bar{P}) \tag{4.81}$$

Since by definition the right-hand side is equal to zero, the left-hand side becomes negative. Further, the right-hand side of (4.78) is also negative:

$$E[u'(\prod)(\tilde{c}'(y) - \bar{P}) \le 0 \tag{4.82}$$

Since marginal utility is always positive, then:

$$\tilde{c}'(y) \le \bar{P} \tag{4.83}$$

Thus, the optimal output under price uncertainty is where marginal cost is less than the expected price. If marginal cost is increasing in output, then for the same expected price, output under price uncertainty is lower than the certainty output. Thus under uncertainty, risk averse farmers use resources at sub-optimal levels, while the reverse occurs for risk-lovers.

Now consider the firm's supply function. Since price is a random variable, it is inappropriate to enquire how output changes as price varies. Therefore, consider the related problem where there is a change in the distribution of the price parameter. Write price as $P+\theta$ where θ is a random variable with mean zero. Increasing θ is the same as moving the probability distribution to the right while its shape is unchanged. Differentiating (4.75) with respect to θ and evaluating the derivative at $\theta=0$ gives:

$$\frac{\partial y}{\partial \theta} = -y \cdot \frac{1}{D} E[u''(\Pi)(P - \tilde{c}'(y))] - \frac{1}{D} E[u'(\Pi)] \tag{4.84}$$

The second term is positive and is a substitution effect. The sign of the first term is subject to the degree of absolute risk aversion. Let $\overline{\Pi}$ be the level of profits when P= $\tilde{c}'(y)$. If absolute risk aversion is decreasing, then

$$R_A(\Pi) \le R_A(\overline{\Pi}) \qquad \text{for } P \ge \tilde{c}'(y)$$

$$R_A(\Pi) \ge R_A(\overline{\Pi}) \qquad \text{for } P \le \tilde{c}'(y) \tag{4.85}$$

From the definition of $R_A(\Pi)$, we obtain:

$$-\frac{u''(\Pi)}{u'(\Pi)} \le -\frac{u''(\overline{\Pi})}{u'(\overline{\Pi})} \quad \text{for } P \ge \tilde{c}'(y)$$

$$-\frac{u''(\Pi)}{u'(\Pi)} \ge -\frac{u''(\overline{\Pi})}{u'(\overline{\Pi})} \quad \text{for } P \le \tilde{c}'(y)$$

(4.86)

Multiplying both sides by $-u'(\Pi)(P-\tilde{c}'(y))$, we have:

$$u''(\Pi)(P-\tilde{c}'(y)) \ge R_A(\overline{\Pi})u'(\Pi))(P-\tilde{c}'(y)) \text{ for all P} \tag{4.87}$$

Taking expectations of (4.87):

$$E[u''(\Pi)(P-\tilde{c}''(y))] \ge R_A(\overline{\Pi})E[u'(\Pi))(P-\tilde{c}'(y))] \tag{4.88}$$

The first-order condition (4.75) implies that the right-hand side of (4.88) is zero. Thus, the left-hand side is positive, and the first term of (4.84) is positive. As a result, the derivative in (4.84) is positive, and decreasing absolute risk aversion is sufficient for $\partial y/\partial\theta > 0$, namely, for an upward-sloping supply curve.

According to Ozanne (1999, pp.258-260), the literature suggests that there is a theoretical possibility of perverse supply response under uncertainty. These studies, such as Baron (1970) and MacLaren (1983), suggest the existence of the possibility of a downward sloping supply curve in the single-output models under uncertainty.

Nowshirvani (1968) and Just and Zilberman (1986) show that perverse supply response is a theoretical possibility for multiple-output technologies.

In empirical studies of agricultural supply response in risky environments, a problem exists in defining risk variables. Various formulations have been proposed and used to create proxies for risk and uncertainty. These variables vary from simple evaluation of variability to complicated measures involving complex estimation procedures. For example, Behrman (1968) uses three-year moving average standard deviations of yield and price to measure both yield and price variability and the latter is relative to the standard deviation of competing crop prices over the same production period. Just (1974) considers producers' subjective evaluation of the variance of price and yields on the assumption that they formulate expectations from geometrically weighting past observations on price and yield expectations. Lin (1977) uses a three-year moving average standard deviation of past actual returns per acre. Adesina and Brorsen (1987) measure risk in terms of a weighted three-year average of squared percentage deviation of expected and actual price. Chavas and Holt (1990) determine risk as the variance and covariance of product prices, where the variance is a weighted sum of the squared deviations of past prices from their expected values. Kraus *et al* (1995) and Lin and Dismukes (2007) also incorporate risk variables similar to the model of Chavas and Holt (1990).

By comparing various different risk variables, Traill (1978) and Brennan (1980) find that the more complex variables have greater theoretical attraction, but they do not provide any superior explanatory power. Thus, Brennan (1982) suggests that even though using the simpler approach may cause a loss in terms of accuracy, we can gain benefits through the simplicity and easiness of the approach. This implies the acceptance of using a simple measure, the moving range, to represent risk in response models.

The neoclassical framework of a profit-maximizing firm provides a set of supply functions where each output is a function of own price, the prices of all alternative output, all input prices, and the levels of all fixed inputs. Supply is also a function of non-price and risk variables. The supply function might be:

$$y_j^* = y^*(P_1, P_2, ..., P_m, r_1, r_2, ..., r_n, T, W, G, R) \qquad \text{for } j=1,\dots,m \tag{4.89}$$

where y_j is output of product j, P_j is own price and the prices of alternative products, r_i are prices of inputs i, T is technology, W is weather, G represents the role of government, and R is risk. A qualitative summary of the effects on supply of changes in these variables is shown in Table 4.1.

Table 4.1 A Summary of Factors Affecting on Output

Factors	Effect on output
Own-price	+
Complementary crop price	+
Competing crop price	-
Input prices	?
Technology	+
Role of government	?
Weather	?
Risk	-

4.6 Modelling Natural Rubber Supply Response in Thailand

In general, there are two alternative models that have been considered in the literature, an output model, and an acreage/yield model. We consider both.

4.6.1 Output Model

Using (4.89), the factors affecting the output of natural rubber production in Thailand are the natural rubber price, alternative crop prices, input prices, and other relevant factors. Two major possible alternative crops - rice and oil palm - compete with natural rubber especially in terms of labour and land requirements. Both their prices are introduced separately and jointly. Only important inputs - labour, fertilisers, and land - are included due to data constraints. Even though most of the labour used in Thai rubber production is family labour, hired labourers are normally employed and they are paid through a product-sharing system. The wage rate is a proxy for labour costs and reflects the opportunity cost of labour. The fertiliser price is also included but land prices are not available and are excluded.

Other relevant factors affecting natural rubber production include technology, government's subsidies, and weather. A time trend is used to reflect technological improvements such as the growth in the use of high-yielding varieties, and new cultivation practices. This specification does not represent the effects of age distribution and improvement of varieties of rubber trees directly. Net government subsidies are incorporated to capture the effects of the replanting programme and the export tax. Weather is also included and is proxied by rainfall. Price risk has two proxies, the coefficient of variation of rubber price, and the standard deviation of rubber price. The output function is initially specified as:

$QNT_t = f(PNR_t, PPAD_t, PPALM_t, PFER_t, WAGE_t, TIME_t, SUB_t, RAIN_t, CVP_t/SDP_t)$

(4.90)

where QNT_t is the output of natural rubber, PNR_t is the price of natural rubber, $PPAD_t$ and $PPALM_t$ are the prices of alternative crops, paddy and oil palm, $PFER_t$ is the price of fertiliser, $WAGE_t$ is the wage rate, $TIME_t$ is a time trend, SUB_t is the net subsidy to farmers, $RAIN_t$ is annual rainfall, CVP_t is the coefficient of variation of the rubber price, and SDP_t is the standard deviation of the rubber price. To illustrate the dynamic specification of output response, an error correction model (ECM) is used following Hallam and Zanoli (1993, pp.157-158):

$$\Delta \ln QNT_t = \alpha_0 + \alpha_1 \Delta \ln QNT_t^* + \alpha_2 (\ln QNT_{t-1}^* - \ln QNT_{t-1}) \tag{4.91}$$

where ln is the natural logarithm. As Hallam and Zanoli (1993, pp.157-158) note, the model in (4.91) coincides with a wide variety of possible processes that explain the adjustment of output towards the desired level. The natural logarithm of desired output, $\ln QNT_t^*$, is a linear function of expectations of the set of explanatory variables in (4.90), that is,

$$\begin{aligned} \ln QNT_t^* = {} & \beta_0 + \beta_1 \ln PNR_t + \beta_2 \ln PPAD_t + \beta_3 \ln PPALM_t + \beta_4 \ln PFER_t \\ & + \beta_5 \ln WAGE_t + \beta_6 TIME_t + \beta_7 \ln SUB_t + \beta_8 \ln RAIN_t \\ & + \beta_9 (\ln CVP_t \text{ or } \ln SDP_t) + \varepsilon_t \end{aligned} \tag{4.92}$$

Price expectations are assumed to be rational, that is, expected future values of price variables are reflected in their generation process. The ECM that evaluates short-run supply response in (4.92) is:

$$\begin{aligned}\Delta \ln QNT_t^* &= \delta_0 + \sum_{i=1}^{k_1} \delta_{1i} \Delta \ln QNT_{t-i} + \sum_{i=0}^{k_2} \delta_{2i} \Delta \ln PNR_{t-i} + \sum_{i=0}^{k_3} \delta_{3i} \Delta \ln PPAD_{t-i} \\ &+ \sum_{i=0}^{k_4} \delta_{4i} \Delta \ln PPALM_{t-i} + \sum_{i=0}^{k_5} \delta_{5i} \Delta \ln PFER_{t-i} + \sum_{i=0}^{k_6} \delta_{6i} \Delta \ln WAGE_{t-i} \\ &+ \sum_{i=0}^{k_7} \delta_{7i} \Delta \ln SUB_{t-i} + \sum_{i=0}^{k_8} \delta_{8i} \Delta \ln RAIN_{t-i} + \sum_{i=0}^{k_9} \delta_{9i} (\Delta \ln CVP_{t-i} \text{ or } \Delta \ln SDP_{t-i}) \\ &+ \lambda \varepsilon_{t-1} + \omega_t \end{aligned} \qquad (4.93)$$

where k_j (j=1 to 9) is lags of each variables. If cointegration exists in (4.92), there is a long-run relationship between the variables, and the ECM in (4.93) is valid. The error correction coefficient, λ, is generally negative and measures the speed of adjustment towards long-run equilibrium.

4.6.2 Acreage-Yield Model

The total production of natural rubber is the product of the rubber acreage tapped and average yield:

$$QNT_t = TAPA_t \times YLD_t \qquad (4.94)$$

where $TAPA_t$ is the mature acreage that is being tapped, YLD_t is the actual average yield. Thus, farmers respond to various stimuli not only by adjusting area, but also by adjusting other inputs. We therefore develop an alternative model by separating yield from area and estimate these components separately. This approach is sometimes used because output is affected by some exogenous factors such as weather, diseases and insects which are out of the control of farmers, while acreage is more directly associated with factors that the farmer can control.

i) The Acreage Model

Natural rubber is different from other perennial crops in that its production can be halted anytime, so the mature acreage that is being tapped could be less or equal to the mature acreage, MA_t, that is, $TAPA_t \leq MA_t$. MA_t is a proxy for the existing stock of mature trees and hence productive capacity. The mature acreage of rubber trees in any period is a result of producer's expectations and decisions which have been made in the past. The mature acreage in the current period is the mature acreage in the previous period plus the new mature acreage from plantings made k periods previously, where k is the number of period of gestation period, minus removals of trees during the current period, that is:

$$MA_t = MA_{t-1} + NPL_{t-k} - RML_t \qquad (4.95)$$

where NPL_t is new plantings, RML_t is removals. The mature acreage in (4.95) assumes that all removals take place on mature tree acreage but some may be from non-bearing trees due to disease, and the mature acreage relationship becomes:

$$MA_t = MA_{t-1} + NPL_{t-k} - RML_t - NPLR_{tk} \qquad (4.96)$$

where $NPLR_{tk}$ is the number of acres of new planting in year t-k removed before year t. This can be expressed in more convenient form as:

$$MA_t = MA_{t-1} + \rho NPL_{t-k} - RML_t \tag{4.97}$$

where ρ is a proportion of the amount of removals from young trees and $\rho < 1$. Due to a lack of data on removals by age, most empirical work assumes $\rho = 1$. Moreover while MA_t is an important variable, the modelling of separate new planting and removal equations to examine investment and disinvestment decisions is prohibited due to data limitations. Thus, a rubber acreage model where acreage is being tapped or planted rubber acreage, $PLTA_t$, is estimated.

Using (4.89), the amount of rubber acreage being tapped or planted rubber acreage is a function of rubber prices, alternative crop prices, and input prices. Alternative crop prices are the prices of paddy and palm oil which are included individually and jointly, while input prices consist only of the wage rate due to data limitations. We also include net government subsidies to capture the effects of the replanting programme and the export tax. A time trend is used to proxy technological improvement. Two price risk variables are separately included. The acreage model becomes:

$$PLTA_t/TAPA_t = f(PNR_t, PPAD_t, PPALM_t, WAGE_t, TIME_t, SUB_t, CVP_t/SDP_t) \tag{4.98}$$

Following Hallam and Zanoli (1993, pp.157-158), we can illustrate a dynamically unrestricted form of the ECM for the acreage being tapped and acreage planted of natural rubber as:

$$\Delta \ln PLTA_t = \beta_0 + \beta_1 \Delta \ln PLTA_t^* + \beta_2 (\ln PLTA_{t-1}^* - \ln PLTA_{t-1}) \qquad (4.99)$$

and

$$\Delta \ln TAPA_t = \alpha_0 + \alpha_1 \Delta \ln TAPA_t^* + \alpha_2 (\ln TAPA_{t-1}^* - \ln TAPA_{t-1}) \qquad (4.100)$$

Again, the models in (4.99) and (4.100) are consistent with a variety of possible processes describing the adjustment of acreage tapped and planted to their desired levels. Both the natural logarithm of desired acreages, $\ln PLTA_t^*$ and $\ln TAPA_t^*$, are assumed to be a linear function of the expectations of the explanatory variables in (4.101) and (4.102), that is,

$$\begin{aligned} \ln PLTA_t^* = {} & \pi_0 + \pi_1 \ln PNR_t + \pi_2 \ln PPAD_t + \pi_3 \ln PPALM_t + \pi_4 \ln WAGE_t \\ & + \pi_5 TIME_t + \pi_6 \ln SUB_t + \pi_7 (\ln CVP_t \text{ or } \ln SDP_t) + \nu_t \end{aligned} \qquad (4.101)$$

$$\begin{aligned} \ln TAPA_t^* = {} & \gamma_0 + \gamma_1 \ln PNR_t + \gamma_2 \ln PPAD_t + \gamma_3 \ln PPALM_t + \gamma_4 \ln WAGE_t \\ & + \gamma_5 TIME_t + \gamma_6 \ln SUB_t + \gamma_7 (\ln CVP_t \text{ or } \ln SDP_t) + \varepsilon_t \end{aligned} \qquad (4.102)$$

Again, we assume rational price expectations which implies that expected future values of price variables are reflected in their data generation process. Equations (4.101) and (4.102) are written in the general ECM as:

$$\begin{aligned}\Delta \ln PLTA_t^* &= \theta_0 + \sum_{i=1}^{k_1} \delta_{1i} \Delta \ln PLTA_{t-i} + \sum_{i=0}^{k_2} \theta_{2i} \Delta \ln PNR_{t-i} + \sum_{i=0}^{k_3} \theta_{3i} \Delta \ln PPAD_{t-i} \\ &+ \sum_{i=0}^{k_4} \theta_{4i} \Delta \ln PPALM_{t-i} + \sum_{i=0}^{k_5} \theta_{5i} \Delta \ln WAGE_{t-i} + \sum_{i=0}^{k_6} \theta_{6i} \Delta \ln SUB_{t-i} \\ &+ \sum_{i=0}^{k_7} \theta_{7i} (\Delta \ln CVP_{t-i} \text{ or } \Delta \ln SDP_{t-i}) + \lambda_2 \nu_{t-1} + \zeta_t\end{aligned} \tag{4.103}$$

$$\begin{aligned}\Delta \ln TAPA_t^* &= \delta_0 + \sum_{i=1}^{k_1} \delta_{1i} \Delta \ln TAPA_{t-i} + \sum_{i=0}^{k_2} \delta_{2i} \Delta \ln PNR_{t-i} + \sum_{i=0}^{k_3} \delta_{3i} \Delta \ln PPAD_{t-i} \\ &+ \sum_{i=0}^{k_4} \delta_{4i} \Delta \ln PPALM_{t-i} + \sum_{i=0}^{k_5} \delta_{5i} \Delta \ln WAGE_{t-i} + \sum_{i=0}^{k_6} \delta_{6i} \Delta \ln SUB_{t-i} \\ &+ \sum_{i=0}^{k_7} \delta_{7i} \Delta \ln CVP_{t-i} \text{ or } \Delta \ln SDP_{t-i} + \lambda_1 \varepsilon_{t-1} + \psi_t\end{aligned} \tag{4.104}$$

where k_j (j=1 to 7) is lags of each variable.

ii) The Yield Model

The yield response model has a similar specification to the acreage model except that the fertiliser price is included while the planting subsidy is excluded. Thus:

$$YLD_t = f(PNR_t, PPAD_t, PPALM_t, PFER_t, WAGE_t, TIME_t, RAIN_t, CVP_t/SDP_t) \tag{4.105}$$

The dynamically unrestricted form of the ECM for yield is:

$$\Delta \ln YLD_t = \sigma_0 + \sigma_1 \Delta \ln YLD_t^* + \sigma_2 (\ln YLD_{t-1}^* - \ln YLD_{t-1}) \tag{4.106}$$

The natural logarithm of desired or long-run rubber yield, $\ln YLD_t^*$, is a linear function of the expectations of the explanatory variables in (4.105), that is,

$$\begin{aligned} \ln YLD_t^* = {} & \kappa_0 + \kappa_1 \ln PNR_t + \kappa_2 \ln PPAD_t + \kappa_3 \ln PPALM_t + \kappa_4 \ln PFER_t \\ & + \kappa_5 \ln WAGE_t + \kappa_6 TIME_t + \kappa_7 \ln RAIN_t + \kappa_8 (\ln CVP_t \text{ or } \ln SDP_t) + \eta_t \end{aligned} \tag{4.107}$$

Rational price expectations are assumed and (4.107) is written in the general ECM as:

$$\begin{aligned} \Delta \ln YLD_t^* = {} & \tau_0 + \sum_{i=1}^{k_1} \tau_{1i} \Delta \ln YLD_{t-i} + \sum_{i=0}^{k_2} \tau_{2i} \Delta \ln PNR_{t-i} + \sum_{i=0}^{k_3} \tau_{3i} \Delta \ln PPAD_{t-i} \\ & + \sum_{i=0}^{k_4} \tau_{4i} \Delta \ln PPALM_{t-i} + \sum_{i=0}^{k_5} \tau_{5i} \Delta \ln PFER_{t-i} + \sum_{i=0}^{k_6} \tau_{6i} \Delta \ln WAGE_{t-i} \\ & + \sum_{i=0}^{k_7} \tau_{7i} \Delta \ln RAIN_{t-i} + \sum_{i=0}^{k_8} \tau_{8i} (\Delta \ln CVP_{t-i} \text{ or } \Delta \ln SDP_{t-i}) \\ & + \lambda \eta_{t-1} + \xi_t \end{aligned} \tag{4.108}$$

where k_j (j=1 to 8) is lags of each variable.

4.7 Summary

The theoretical framework used for describing and interpreting the behaviour of producers in this study is based on the economic theory of production. The major objective of the chapter is to elucidate the hypothesis development of the study. Agricultural supply response is influenced by both price and non-price variables. The prices include own price, the prices of competing crops, and the price of inputs while non-price variables contain technology, weather conditions, and institutional settings such as government policies. Furthermore, we should include risk and uncertainty into consideration. This study presents models of natural rubber supply which show the response of Thai rubber production to determinants. We consider two alternative models, an output model, and an acreage/yield model. To illustrate the dynamic specification of agricultural production response, an error correction model (ECM) is used. The econometric methodology for the study will be represented in the next chapter.

Chapter 5 The Econometric Methodology

5.1 Introduction

In this study, we employ econometric methodology to model the dynamic long-run relationships of rubber production. We address one of challenges of time series analysis, namely the problem of spurious regression whereby the results of the regression model indicate that the variables are significantly related in the long run with a high coefficient of determination, R^2, but in reality the relationship is not a meaningful causal relation (Granger and Newbold, 1974).

When we examine long-run relationships, it is necessary to examine the underlying properties of the statistical or stochastic mechanism, or data-generating processes (d.g.p.) of the time series variables employed to distinguish between stationary and non-stationary variables and how many times the variables have to be differenced to become a stationary series, otherwise it may lead to the spurious regression problem. In general, traditional time series studies implicitly assume that the underlying processes generating the data are stationary. By contrast, most economic time series are non-stationary and conventional statistical approaches developed for stationary processes are generally invalid. Detrending the data is not appropriate to resolve this problem. Transforming the data by differencing may overcome the problem, but it also removes any information about the long-run relationships. Importantly in time series analysis, it is necessary to confirm that long-run information reveals co-movement of the data due to underlying equilibrating tendencies of economic forces rather than general time trends (Harris and Sollis, 2005, p. 1).

Since the mid-1980s, modelling the long run with the non-stationary variables has led to major developments of econometrics and in particular to the concept of cointegration (Engle and Granger, 1987; Granger, 1981). Several alternative cointegration methodologies have been developed. In general, the concept of cointegration proposes that if two (or more) series are associated to create an equilibrium relationship in the long run, then these series even if non-stationary tend to move closely together over time and the variation between them is unchanged, i.e., their difference is stationary. In this situation, the dynamic model of these integrated series can be converted into an error correction model (ECM) which contains information on both the short- and long-run properties of the model. Disequilibrium in the short run leads to a process of adjustment to restore long-run equilibrium.

The cointegration approach is discussed in this chapter which is organised as follows. Section 5.2 introduces some important concepts of modern time series analysis. Section 5.3 describes unit root tests to examine whether a time series is stationary. The Dickey-Fuller (Said and Dickey, 1984; Dickey and Fuller, 1981; 1979) and the KPSS (Kwiatkowski *et al*., 1992) tests are discussed. Section 5.4 presents the Engle and Granger (1987) single-equation cointegration test. Section 5.5 presents Johansen's (1988) full information maximum likelihood cointegration test in multivariate systems. Section 5.6 discusses the modelling of short-run dynamics. Section 5.7 discusses impulse response analysis, and Section 5.8 summarises.

5.2 Some Concepts in Modern Time Series Analysis

5.2.1 Stationary and Non-stationary Processes

In considering long-run relationships between variables, we need to examine their underlying properties to distinguish between stationary and non-stationary variables because models having non-stationary variables often lead to spurious regressions. A time series can be regarded as being generated by a d.g.p. or a stochastic or random process, and a specific set of data can be considered as a particular realization, i.e. a sample of the underlying d.g.p. In general, a stochastic process is (weakly) stationary when it has a constant mean and variance over time and a constant covariance between two time periods that is independent of time and which is determined only by the distance or lag between the two time periods (Gujarati and Porter, 2009, p.740). A variable, y_t, is (weakly) stationary if the following conditions for all values of time, t, are satisfied:

Mean: $E(y_t) = \mu$ (5.1)

Variance: $var(y_t) = E[(y_t - \mu)^2] = \sigma_Y^2$ (5.2)

Covariance: $cov(y_t, y_{t+k}) = E[(y_t - \mu)(y_{t+k} - \mu)] = \gamma_k$ (5.3)

Equations (5.1) and (5.2) imply that the mean and variance are constant over time and (5.3) implies that the covariance (or autocovariance) between two values of y_t is constant and depends only on the distance in time between two values, i.e., the time period k and t. Briefly, a time series is stationary if its mean, variance and covariance at various lags are unchanged over time. By contrast, if the series does not satisfy any component of these conditions, it is non-stationary (Gujarati and Porter, 2009, p.740;

Greene, 2008, pp.718-719; Harris and Sollis, 2005, p.27). Figure 5.1 shows a stationary series which fluctuates around its means and has a finite variance.

Figure 5.1 An Example of Stationary Series

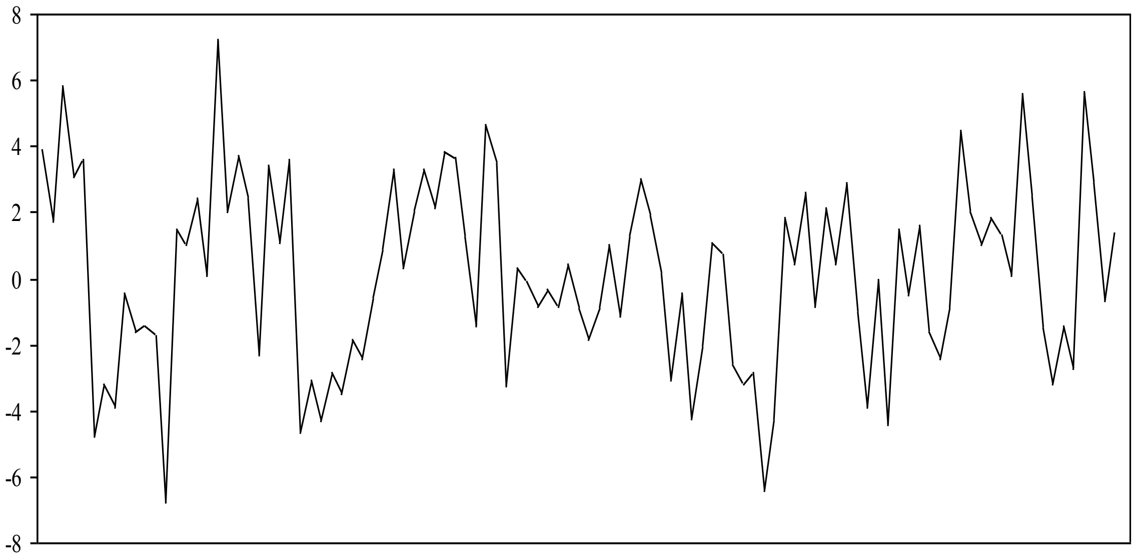
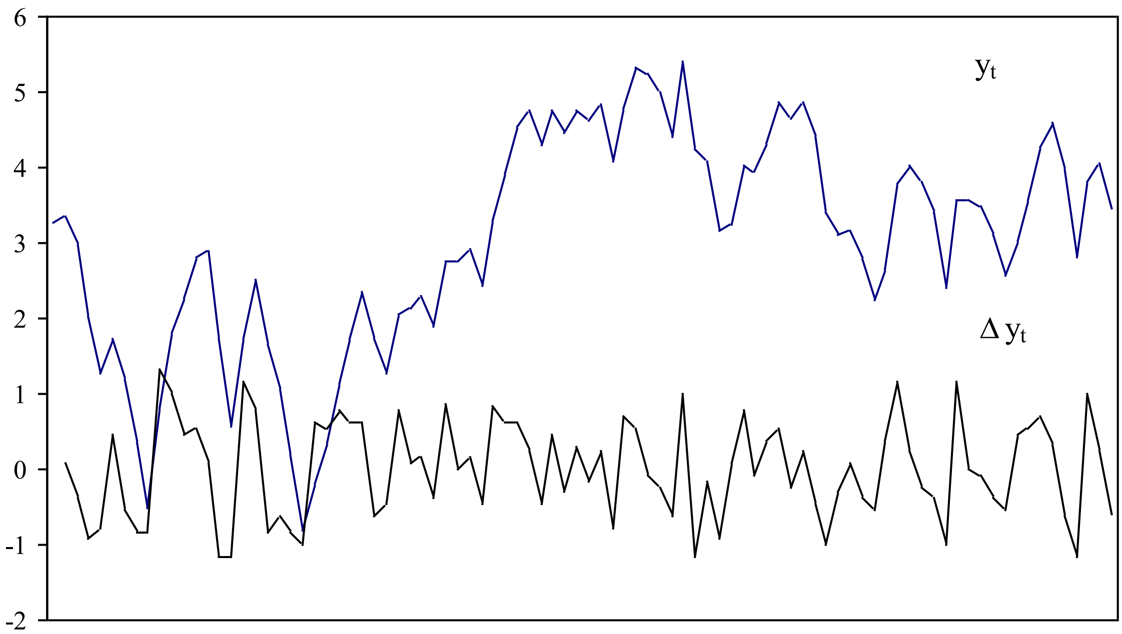


Figure 5.2 An Example of Non-stationary Series



By contrast, Figure 5.2 is an example of a non-stationary series, y_t, where the mean, variance, and covariance are time-variant. However, a non-stationary variable can be converted to be stationary after it is differenced. Therefore, the first difference of y_t, Δy_t, is stationary since Δy_t has a constant mean and constant variance. How many times a variable needs to be differenced to become stationary series depends on the number of unit roots it contains.

Alternatively, consider a stochastic time series, y_t, that is generated by a first-order autoregressive (AR) process:

$$y_t = \rho y_{t-1} + u_t \tag{5.4}$$

In (5.4), the current value of y_t is determined by the lagged value y_{t-1} and a disturbance term u_t, which has zero mean, constant variance, and is non-autocorrelated, following classical assumptions. Such an error term is known as a white noise error term.[30] The series y_t is stationary if $\rho<1$, and if $\rho=1$, it becomes non-stationary and has a unit root.[31] A stationary series reverts to its mean value and varies around it within a relatively constant range. By contrast, a non-stationary series

---

[30] The error term stands for the impact of all other variables excluded from the model that are presumed to be random; hence, u_t has a zero mean, $E(u_t) = 0$, a constant variance, $E(u_t^2) = 0$, and it is serially uncorrelated process, $E(u_t u_{t-i}) = 0$. These statistical properties imply that u_t is a white noise process. If we assume that the explanatory variable(s), x_t, in the model are stochastic and are independent of the error term, $E(x_t u_t) = 0$, then we can obtain unbiased estimates of the parameters from estimators like ordinary least squares (OLS). However, this condition does not exist in (5.4), since the predetermined explanatory variable is y_{t-1} and $E(y_t u_{t-i}) \neq 0$ for $i \geq 1$. Furthermore, if we assume that u_t is drawn from the multivariate normal distribution, i.e., $u_t \sim IN(0, \sigma_u^2)$ which means that u_t is an independently distributed random white noise process drawn from the normal distribution, it is sufficient to create inference procedures for testing hypotheses relating to the parameters (Harris and Sollis, 2005, p.9).

[31] The terms non-stationary and unit root can be considered synonymously with the terms random walk and stochastic trend (Gujarati and Porter, 2009, p.744).

contains various means at different points in time and its variance changes with the sample size (Harris and Sollis, 2005, pp.28-29). If a time series is non-stationary but after differencing once is stationary, the original series is integrated of order 1, I(1). In general, if the original series must be differenced d times before it becomes stationary, the original series is integrated of order d, or I(d). Thus an integrated time series of order 1 or greater is a non-stationary time series. By contrast, if d = 0, the I(0) process is stationary.

5.2.2 Trend and Difference Stationarity[32]

The difference between a stationary and non-stationary stochastic processes can be ascertained on whether the time trend in the time series is deterministic or stochastic (Gujarati and Porter, 2009, p.745).[33] If we allow (5.4) to have a non-zero constant, then it can be written as:

$$y_t = \phi + \rho y_{t-1} + u_t \tag{5.5}$$

where u_t is a white noise error term. If $\rho = 1$, then y_t is non-stationary and by rearranging and accumulating y_t for different periods, starting with an initial value of y_0, the series y_t can be rewritten as:

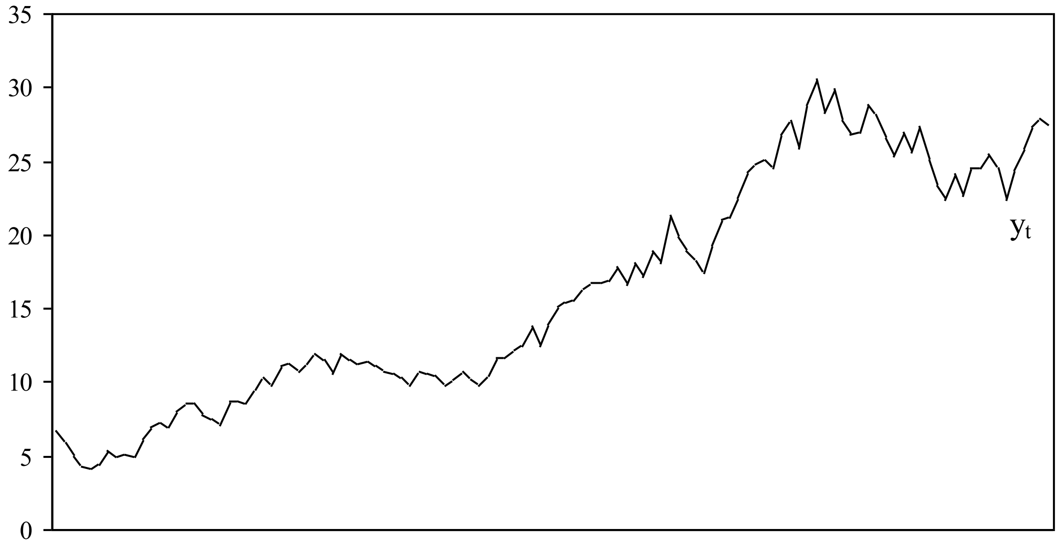
$$y_t = y_0 + \phi t + \sum_{j=1}^{t} u_j \tag{5.6}$$

[32] This section draws on Harris and Sollis (2005, pp.30-32).

[33] If the trend is a deterministic function of time, it is deterministic. Alternatively, if the trend is unpredictable, it is stochastic.

where t is a time trend. In (5.6), y_t consists of a deterministic trend component, ϕt, and the component $y_0 + \sum_{j=1}^{t} u_j$ which can be considered as a stochastic intercept term. Each random error term, u_j, signifies a shift and causes a permanent effect in the intercept. Due to the sum of these error terms, y_t does not converge to a fixed deterministic trend, $y_0 + \phi t$, and it is said to have a stochastic trend. That is, if $\rho = 1$, y_t follows a stochastic trend and it moves upward or downward determined by the sign of ϕ. Figure 5.3 presents an example of a series which follows a stochastic trend.

Figure 5.3 An Example of Non-stationary Series with a Stochastic Trend



By taking the first differences of y_t, we obtain:

$$\Delta y_t = \phi + u_t \tag{5.7}$$

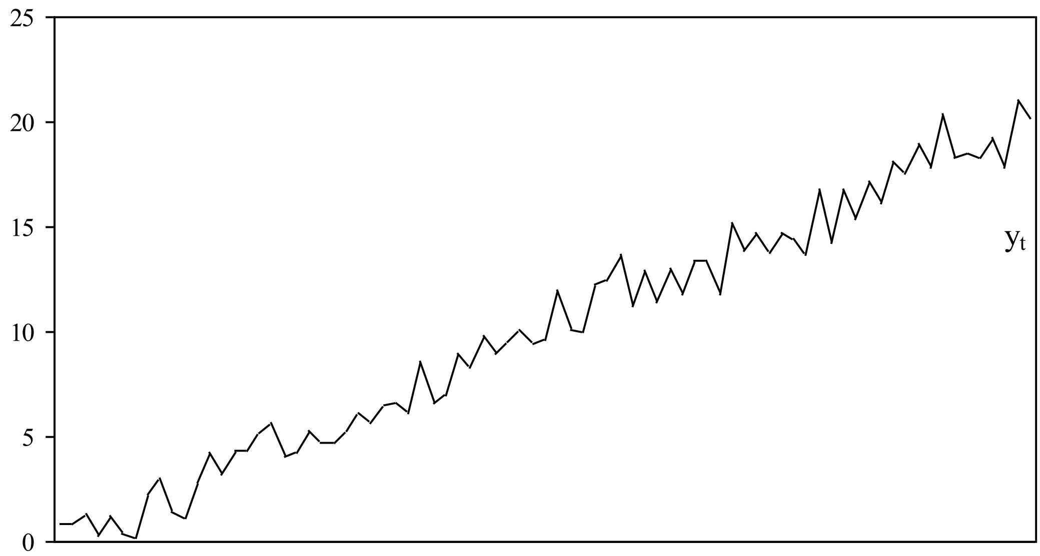
and the value of Δy_t fluctuates around its mean of ϕ and has a finite variance. Thus, the first difference of y_t is stationary and y_t is difference-stationary because it is stationary after differencing. By contrast, consider the d.g.p.:

$$x_t = \alpha + \phi t + u_t \tag{5.8}$$

where $\alpha + \phi t$ is a trend and the disturbance u_t is the non-trend or stochastic part. Where u_t is stationary, x_t is a trend-stationary series which means that it may have a trend, but deviations from the deterministic trend are stationary, as shown in Figure 5.4. That is, it may exhibit a trend but variations from the deterministic trend are stationary. Equations (5.6) and (5.8) are similar in that they both present a linear trend, but the disturbance term in (5.6) is non-stationary.

An economic time series can be a trend-stationary or difference stationary process. A trend-stationary time series has a deterministic trend, which is stationary, while a difference-stationary time series has a variable or stochastic trend, which is non-stationary. We can test whether the trend in a series is deterministic or stochastic by applying a unit root test. If the given time series has a unit root, i.e., is non-stationary, such a time series has a stochastic trend whereas if the time series does not have a unit root, it has a deterministic trend.

Figure 5.4 An Example of a Trend-stationary Series



5.2.3 Spurious Regression

Since most economic time series data are non-stationary, conventional statistical regression approaches are generally invalid because they do not permit meaningful statistical inferences. If two or more time series data are uncorrelated I(1) variables and exhibit stochastic trends, regressions between these series using standard statistical techniques developed for stationary processes may give statistically significant results with high R^2. In fact, the relationship is insignificant and R^2 should tend towards zero. Thus the results are spurious and may not reflect meaningful relationships between the series, and this problem generally increases with the sample size. Such a relationship, which is caused by a common trend among the variables, does not entail the sort of causal relationship that might be deduced from stationary series (Harris and Sollis, 2005, p.32).

A common practice to avoid spurious association is detrending. In general, detrending involves either regressing the variable on time and then obtaining a new stationary variable without trend from its residuals or including the trend variable as one of the regressors. The direct introduction of the trend in the regression is reasonable since time series data are likely to drift in the same direction due to a common time trend embodied in all variables. However, these procedures are valid only if the trend variable is deterministic and not stochastic (Harris and Sollis, 2005, p.32) and most economic time series do not posses deterministic trends. An alternative way to eliminate a trend is to transform a non-stationary series by differencing following Box and Jenkins (1976; 1970). However, a problem with this method is that any information about the long run is also removed. That long-run information is necessary to reveal co-movement of the data due to underlying equilibrating tendencies of economic forces rather than general time trends.

In summary, the problem of spurious regression due to non-stationary data cannot be solved by simple methods. This leads to the necessity of a test for the presence of unit roots which determines whether a time series is stationary or not. If a variable has a unit root, then it is non-stationary, and it could combine with other non-stationary series to form a stationary cointegration relationship. In this case, regressions involving these series indicate meaningful economic relationships. However, the absence of cointegration causes the spurious regression problem.

5.2.4 Cointegration

When variables in a relationship are non-stationary, the appropriate way to estimate this relationship is to adopt the cointegration approach. This method was developed to treat non-stationary variables within an error correction model (ECM) which can provide information on both the short- and long-run properties of the dynamic model, with disequilibrium as a process of adjustment to long-run equilibrium.

Following the definition of cointegration of Engle and Granger (1987), two time series, y_t and x_t, that are both I(d), or contain d unit roots, are said to be cointegrated of order (d, b) if there exists a linear combination of these two vectors that is integrated of order I(d-b), where b>0. Thus, the vector of the coefficients that comprise the linear combination of the two series, or the cointegrating vector, is integrated of lower order than the process itself.[34] Consider the relation:

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \tag{5.9}$$

The system is in long-run equilibrium, and y_t and x_t are cointegrated, if the equilibrium error, ε_t, or the deviation from the long-run equilibrium, fluctuates around zero i.e.:

$$\varepsilon_t = y_t - \beta_0 - \beta_1 x_t = 0 \tag{5.10}$$

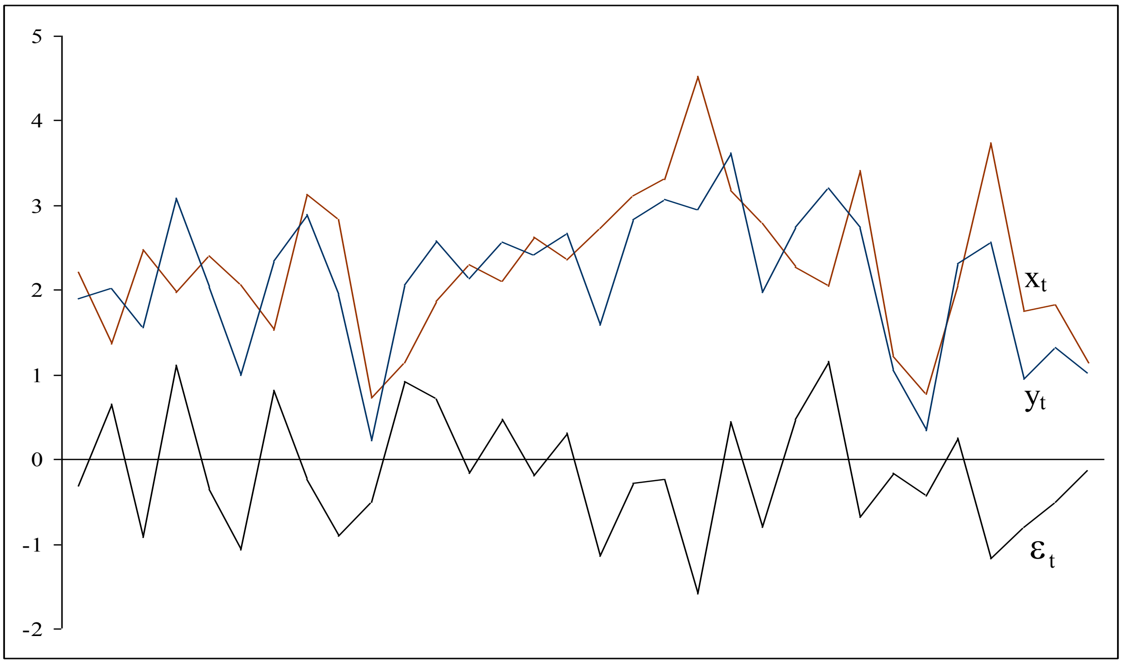
In other words, the long-run equilibrium is meaningful only if the equilibrium error is stationary, or I(0), with E(ε_t)=0. Cointegration between variables is a statistical property of the data that we can interpret as an economic equilibrium relationship (Juselius, 2006, p.80).[35] Nevertheless, if two or more series are linked together to

[34] Cointegration normally refers to a linear combination of non-stationary variables. However, theoretically, there is possibly an existence of a non-linear long-run relationship among variables, but the study of non-linear cointegrating relationships is in the early stages of econometric practice (Enders, 2010, p.359).

[35] The term ‘equilibrium’ is unfortunate because, in economic theory, it usually stands for equivalence between desired and actual transactions, but econometricians refer the term to any long-run relationship among non-stationary series. Nevertheless, in cointegration framework, the long-run relationship is not necessary generated by market powers or by individual behaviour. Based on Engle and Granger (1987),

generate an equilibrium relationship in the long run, the series themselves move concurrently over time and the discrepancy among them is constant, i.e., is stationary, even though they may contain stochastic trends. The concept of cointegration, therefore, implies the presence of a long-run equilibrium to which an economic system moves over time, and ε_t is the disequilibrium error which accounts for the extent to which the system diverges from equilibrium (Harris and Sollis, 2005, p.34). In the two variable case, a cointegrating vector is unique. The cointegration relationship between two series can be illustrated in Figure 5.5. In the upper part of Figure 5.5, both y_t and x_t series seem to be visually non-stationary. They also appear to move together over time, implying that there exists an equilibrium relationship among them. The equilibrium error term, ε_t, obtained from regressing y_t on x_t shown in the lower part of Figure 5.5 is possibly stationary. If this is the case, then y_t and x_t are cointegrated.

Figure 5.5 An Example of Cointegration



---

the equilibrium relationship is possibly causal, behavioural, or a reduced-form relationship among variables concerned (Enders, 2010, p.359).

To illustrate the concept of cointegration in the multivariate case, we commence with a set of economic variables in long-run equilibrium as:

$$\beta_1 z_{1t} + \beta_2 z_{2t} + \ldots + \beta_n z_{nt} = 0 \tag{5.11}$$

where $\boldsymbol{\beta}$ = $(\beta_1, \beta_2, \ldots, \beta_n)$ and $\mathbf{z}_t$ = $(z_{1t}, z_{2t}, \ldots, z_{nt})'$. If $\boldsymbol{\beta}\mathbf{z}_t = \mathbf{0}$, the system is in long-run equilibrium. The equilibrium error, or the deviation from long-run equilibrium, is $\boldsymbol{\varepsilon}_t$, and $\boldsymbol{\varepsilon}_t = \boldsymbol{\beta}\mathbf{z}_t$. As in the two variable case, long-run equilibrium has meaning when the equilibrium error is stationary or I(0) (Enders, 2010, p.359). From the definition of cointegration, the components of the vector $\mathbf{z}_t$ are cointegrated of order (d, b), or $\mathbf{z}_t \sim CI(d, b)$, on the condition that, first, all components of $\mathbf{z}_t$ are integrated of order d, i.e., they must be differenced d times before they are stationary, and, second, a vector $\boldsymbol{\beta}$, such as a linear combination $\boldsymbol{\beta}\mathbf{z}_t = \beta_1 z_{1t} + \beta_2 z_{2t} + \ldots + \beta_n z_{nt}$, exists and is integrated of order (d-b), where b > 0. The vector $\boldsymbol{\beta}$ is the cointegrating vector (Enders, 2010, p.359). In this case, $\boldsymbol{\beta}$ is not unique since there may be up to n-1 linearly independent cointegrating vectors. The number of cointegrating vectors is called the cointegrating rank of $\mathbf{z}_t$, which may range from 1 to n-1.

5.2.5 Cointegration and the Error Correction Model

It is possible that the system is in disequilibrium for some time since the economic agents confront limitations, especially adjustment costs, to instantly change in response to new information. To form the dynamic model, the current value of the dependent variable, y_t, is influenced by the current and lagged value of some explanatory variable, z_t, and lagged values of the dependent variable itself. The ECM of Sargan (1964) is suggested because its characteristic feature is that it comprises both differences and levels of the variables in the same model, and is able to capture both short- and long-run relationships of the variables. The Granger representation theorem (Granger, 1986; Engle and Granger, 1987) suggests that if two or more series are co-integrated, an ECM explaining that relationship exists, i.e. if two or more variables are cointegrated, there is a long-run relationship between them. In the short run, these variables may be in disequilibrium with the disturbances being the equilibrating error. The dynamics of this short-run disequilibrium relationship can always be described by the ECM, which incorporates both the short- and the long-run effects of the two variables. For the two variable case in (5.9), the ECM is:

$$\Delta y_t = \gamma_0 \Delta x_t - (1-\alpha_1)[y_{t-1} - \beta_0 - \beta_1 x_{t-1}] + u_t \qquad u_t \sim IN(0, \sigma_u^2) \tag{5.12}$$

where u_t is a white noise disturbance, γ_0 reflects the short-run effect of the changes in x_t on y_t, and β represents the long-run equilibrium relationship between the variables. The term $[y_{t-1} - \beta_0 - \beta_1 x_{t-1}]$ = ε_i is the deviation from the long-run equilibrium, indicating how much the system is from equilibrium at any time. This term is non-zero during disequilibrium, and is zero when the system reaches the long-run equilibrium. The term $(1-\alpha_1)$ is the speed of adjustment toward the long-run equilibrium representing how y_t reacts to disequilibrium. The ECM reincorporates the variables in levels and differences and provides a model comprising both short- and long-run relationships among the integrated series. Furthermore, since all the terms in the ECM are stationary, it is appropriate to use standard estimation methods based on classical OLS assumptions. Also, the ECM implies that differencing the variables is not a suitable method to avoid the spurious regression results since it causes loss of long-run information and misspecification error.

We can generalise a single equation ECM into a multivariate model by defining the vector $\mathbf{z}_t = (z_{1t}, z_{2t}, ..., z_{nt})'$. This allows n potentially endogenous variables and it is possible to specify the following d.g.p. and model $\mathbf{z}_t$ as an unrestricted vector autoregression (VAR) involving up to k lags of $\mathbf{z}_t$:

$$\mathbf{z}_t = \mathbf{A}_1\mathbf{z}_{t-1} + ... + \mathbf{A}_k\mathbf{z}_{t-k} + \boldsymbol{\varepsilon}_t \qquad \varepsilon_t \sim IN(0, \Sigma) \tag{5.13}$$

where $\mathbf{z}_t$ is an $(n \times 1)$ vector of I(1) variables, $\mathbf{A}_i$ is an $(n \times n)$ matrix of parameters, and $\boldsymbol{\varepsilon}_t$ is $(n \times 1)$ vector of white noise errors. The VAR model developed by Sims (1980) is used to estimate the dynamic relationships among jointly endogenous variables with no strong *a priori* restrictions. This (reduced form) system shows that each variable in $\mathbf{z}_t$ is a function of lagged values of itself and all other variables in the system and OLS is appropriate for estimating each equation.

Equation (5.13) can be reformulated into an vector error correction model (VECM):

$$\Delta\mathbf{z}_t = \boldsymbol{\Pi}\mathbf{z}_{t-1} + \boldsymbol{\Gamma}_1\Delta\mathbf{z}_{t-1} + \boldsymbol{\Gamma}_2\Delta\mathbf{z}_{t-2} + ... + \boldsymbol{\Gamma}_{k-1}\Delta\mathbf{z}_{t-k+1} + \boldsymbol{\varepsilon}_t \tag{5.14}$$

where $\boldsymbol{\Gamma}_i = -(\mathbf{I} - \mathbf{A}_1 - ... - \mathbf{A}_i)$, i = 1,…,k-1, and $\boldsymbol{\Pi} = -(\mathbf{I} - \mathbf{A}_1 - ... - \mathbf{A}_k)$. $\boldsymbol{\Pi}$ has $(n \times n)$ dimension. This specification is useful to capture both short- and long-run information through estimates of $\hat{\boldsymbol{\Gamma}}_i$ and $\hat{\boldsymbol{\Pi}}$, respectively. The key feature in (5.14) is the presence of $\boldsymbol{\Pi}$ where $\boldsymbol{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$, where α is the speed of adjustment toward equilibrium and $\boldsymbol{\beta}$ is a matrix of long-run coefficients. Both $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ have $(n \times r)$ dimension where r is the rank of $\boldsymbol{\Pi}$. The term $\boldsymbol{\beta}'\mathbf{z}_{t-k}$ implies cointegration relationships in the system. Since $\mathbf{z}_t$ is a vector of I(1) variables, all terms in (5.14) involving $\Delta \mathbf{z}_{t-i}$ are I(0), and $\boldsymbol{\varepsilon}_t$~I(0) are white noise errors, and $\boldsymbol{\Pi}\mathbf{z}_{t-k}$ is stationary. This VECM is essential for the cointegration test in a multivariate system and is discussed further in Section 5.5.

5.3 Unit Root Tests[36]

The first step in the cointegration approach is testing the order of integration in each series or testing for unit roots. There are several approaches but the most common are the Dickey-Fuller (DF) test (Dickey and Fuller, 1981; 1979), and the augmented Dickey-Fuller (ADF) test (Said and Dickey, 1984). In both, the null hypothesis is that a series contains a unit root, or is non-stationary, and the alternative is of stationarity.[37] Other tests test the null hypothesis that a series is stationary against the alternative of non-stationarity. These include the KPSS-test (Kwiatkowski *et al.*, 1992). Using both alternatives of the null is sometimes useful because each can be used to support the other. In this section we discuss both DF/ADF and KPSS tests.

5.3.1 The Dickey-Fuller Test

We start to examine unit root tests with the simplest form, that of the DF-test which necessitates estimation of:

$$y_t = \rho_a y_{t-1} + u_t \tag{5.15a}$$

or more conveniently as:

---

[36] This section is based on Harris and Sollis (2005, pp.41-63).

[37] With a similar null hypothesis, there are other unit root tests such as the Sargan-Bhargava (1983) cointegration regression Durbin-Watson (CRDW) test, based on the Durbin-Watson statistic, and the non-parametric Phillips and Perron Z-test (Phillips, (1987).

$$(1\text{-}L)y_t = \Delta y_t = (\rho_a - 1)y_{t-1} + u_t \tag{5.15b}$$

where u_t is a stochastic error term, assumed to be IID(0, σ^2),[38] and L is the lag operator. In (5.15a) and (5.15b), y_t is stationary if ρ_a <1, and is non-stationary or has a unit root if ρ_a =1. We test the null hypothesis of a unit root, H_0: ρ_a =1, against the alternative of stationary, H_1: ρ_a <1. If H_0 is rejected, y_t is stationary. However, (5.15b) is more advantageous for testing whether the series has a unit root, H_0: (ρ_a - 1)= ρ_a^* =0, against the alternative of stationary, H_1: ρ_a^* <0. This form is more convenient when the test involves a more complicated AR process. Under a standard approach, such a hypothesis is tested by using a t-test; however under non-stationarity, the statistic does not follow a standard t-distribution but rather a DF-distribution computed on the basis of Monte Carlo simulations with (5.15) as the underlying d.g.p.[39] Thus, critical values are obtained from the DF-distribution relating to τ - (tau) statistic (see Table 5.1).

Using (5.15), the unit root test involves the assumption that the d.g.p. for y_t is a simple first-order AR process with zero mean and no trend component, i.e., no deterministic variables. Furthermore, it assumes that at time t=0, y_t=0 because in a model without deterministic components the mean of the series is governed by the initial observation under the non-stationary hypothesis. Thus, (5.15) is valid if the overall mean of the series is zero. If we know the true mean of the d.g.p., we can subtract it from each

[38]An independently and identically distributed (IID) process (with a finite variance) is technically a white noise process. In (5.15), the errors u_t are drawn from the DF-distribution, rather than a normal distribution (Harris and Sollis, 2005, p.42).
[39] Inappropriate use of standard t-values may lead to under-rejection of the null hypothesis, and this problem is more severe if more deterministic components are included in the regression model.

observation and use (5.9) to test for a unit root. In general, we do not know whether y_0=0 and it is more appropriate to include a drift or constant term, α_b, in the model:

$$\Delta y_t = \alpha_b + (\rho_b - 1)y_{t-1} + u_t \tag{5.16}$$

In this case, the critical values to test the null of a unit root, H_0: (ρ_b -1)=0, are derived from the DF-distribution relating to τ_μ (see Table 5.1). The hypothesis of a unit root is accepted if the calculated τ_μ -value is greater than the critical τ_μ -value, and y_t is non-stationary. On the other hand, y_t is stationary if the unit root hypothesis is rejected. However, the unit root test is not valid using (5.16) when the underlying d.g.p. is derived from (5.16) as well. That is, if the null of a unit root is true, y_t follows a stochastic trend and drifts upward or downward depending on the sign of α_b. Under the alternative hypothesis, H_1: (ρ_b -1)<0, y_t is stationary with constant mean and no trend. Therefore, using (5.16) to test for a unit root is inappropriate since it does not nest both the null and alternative hypotheses. In practice, to find the most common form of the null hypothesis with the d.g.p. holding a stochastic trend against the alternative of trend stationary, we have to include deterministic regressors corresponding with the deterministic components in the d.g.p. Thus, we have to add a time trend, t, into the regression model and (5.16) becomes:

$$\Delta y_t = \alpha_c + \gamma_c t + (\rho_c - 1)y_{t-1} + u_t \tag{5.17}$$

Thus, y_t has both a stochastic and deterministic trend. The critical values for testing the unit root hypothesis, H_0: (ρ_c -1)=0, are derived from the DF-distribution relating to τ_τ (see Table 5.1). If the calculated τ_τ-value is greater than the critical τ_τ-value, then the unit root hypothesis is accepted and y_t is non-stationary. Further, $\tau_\tau < \tau_\mu < \tau$.

When (5.17) is used to test for a unit root, it is useful to examine the joint hypothesis of unit root and no trend H_0: (ρ_c-1)= γ_c=0 against the alternative hypothesis of trend stationary H_1: (ρ_c-1)= $\gamma_c \neq 0$, by using the non-standard F-statistic, Φ_3, with critical values from Dickey and Fuller (1981) (see Table 5.1). If the DF t-test in (5.17) indicates that the null H_0: ρ_c=1 is accepted, but the joint hypothesis H_0: (ρ_c-1)= γ_c=0 is rejected, then the trend is significant under the null of a unit root and asymptotic normality of the t-statistic [(ρ_c-1)/SE(ρ_c)] follows. The standard t-statistic (for n= ∞) therefore should be adopted to test H_0: (ρ_c-1)=0, instead of using the critical values from the DF-distribution. This situation occurs when a stochastic trend in the regression is dominated by a deterministic trend.

In the same way, when the joint hypothesis, H_0: (ρ_b-1)= α_2=0, is tested by using (5.16) and the F-statistic, Φ_1 (see Table 5.1), the similar situation arises. That is, if the null H_0: ρ_b=1 is not rejected, but the joint hypothesis H_0: (ρ_b-1)= α_2=0 is rejected, it implies that the constant is significant under the null of a unit root and asymptotic normality of the t-statistic [(ρ_c-1)/SE(ρ_c)] follows. Thus, the standard t-distribution should be adopted to test H_0: (ρ_b-1)=0. The complete set of test statistics and the source of their critical values for the DF-test is summarised in Table 5.1.

Table 5.1 Summary of the Dicky-Fuller Tests

Model	Null hypothesis	Test statistic	Critical values
$\Delta y_t = \alpha_c + \gamma_c t + (\rho_c - 1)y_{t-1} + u_t$	$(\rho_c - 1) = 0$	τ_τ	Fuller (table 8.5.2, block 3)
	$(\rho_c - 1) = \gamma_c = 0$	Φ_3	Dickey and Fuller (table VI)
	$(\rho_c - 1) = 0$	t	Standard normal
$\Delta y_t = \alpha_b + (\rho_b - 1)y_{t-1} + u_t$	$(\rho_b - 1) = 0$	τ_μ	Fuller (table 8.5.2, block 2)
	$(\rho_b - 1) = \alpha_b = 0$	Φ_1	Dickey and Fuller (table IV)
	$(\rho_b - 1) = 0$	t	Standard normal
$\Delta y_t = (\rho_a - 1)y_{t-1} + u_t$	$(\rho_a - 1) = 0$	τ	Fuller (table 8.5.2, block I)

Notes: 1. Critical values are derived from Fuller (1976) and Dickey and Fuller (1981).

2. This table is adapted from Harris and Sollis (2005, p.47).

5.3.2 The Augmented Dickey-Fuller Test

The principal assumption of the DF-statistic is that the error term u_t is white noise so the problem of autocorrelation in the residuals of the regression arises when the error term is not white noise. This problem may happen due to misspecification of the dynamic structure of the series y_t. That is, if a simple AR(1) DF-model is employed when the series y_t is actually an AR(p) process, then the error term is autocorrelated, and these nullify the use of the DF-distributions.

To overcome this problem, the augmented Dickey-Fuller (ADF) test is developed by generalising (5.15)-(5.17). The models are expanded to permit the d.g.p. containing deterministic components (i.e., constant and trend) as before, but now including lagged values of the dependent variable on the right hand side of the equation. Thus, the model used to test the null hypothesis of non-stationary (i.e. stochastic trend) against the alternative of stationary (i.e. deterministic trend) is:

$$\Delta y_t = \alpha + \gamma t + \varphi^* y_{t-1} + \sum_{i=1}^{p-1} \varphi_i \Delta y_{t-i} + u_t \qquad u_t \sim IID(0, \sigma^2) \tag{5.18}$$

where $\varphi^* = (\varphi_1 + \varphi_2 + ... + \varphi_p) - 1$. In (5.18), we test the null hypothesis of a stochastic trend (non-stationary) against the alternative of a deterministic trend (stationary). Since the ADF-test statistic has the same asymptotic distribution as the DF-statistic, the critical values of the DF-test can be used. However, this situation is only strictly valid in large samples (Banerjee, 1993, p.106). Thus, the ADF-test is similar to the DF-test except we add an unknown number of lagged first differences of the dependent variable as representatives of omitted autocorrelated variables, which may otherwise go into the error term u_t.[40] Thus, we can test for a unit root when the underlying d.g.p. is quite general.

A further issue is the appropriate number of lagged difference terms to include because too few lags may cause over-rejection of the null when it is true while too many may decrease the power of the test because unnecessary nuisance parameters reduce the effective number of observations (Harris and Sollis, 2005, pp.48-49). Several criteria have been suggested for allowing the data to determine the lag length (or the choice of p in (5.18)). The most commonly used are the Akaike Information Criterion (AIC) (Akaike, 1973) and the Schwarz Information Criterion (SC or SIC) (Schwarz, 1978), which is also known as the Schwarz Bayesian Criterion (SBC) or

[40] An alternative method for improving the DF-test by adding lagged first differences of the dependent variable is the Phillips and Perron approach which applies a non-parametric correction to take account of any autocorrelation (Harris and Sollis, 2005, p.49).

Bayesian Information Criterion (BIC). These criteria contain a procedure that search for a model that has a good fit with few parameters. These criteria are based on the maximal value of the likelihood function and a penalty that is an increasing function of the number of estimated parameters. The penalty is included to prevent overfitting of the model because increasing the estimated parameters enhances the goodness of fit, notwithstanding the number of estimated parameters, in the data-generating process. In general, the BIC penalises the number of parameters more strongly than does the AIC. The preferred model is the one with minimum AIC or BIC value based on the AIC and BIC, respectively. Both criteria are available in RATS.

5.3.3 The Sequential Procedure for Unit Root Test

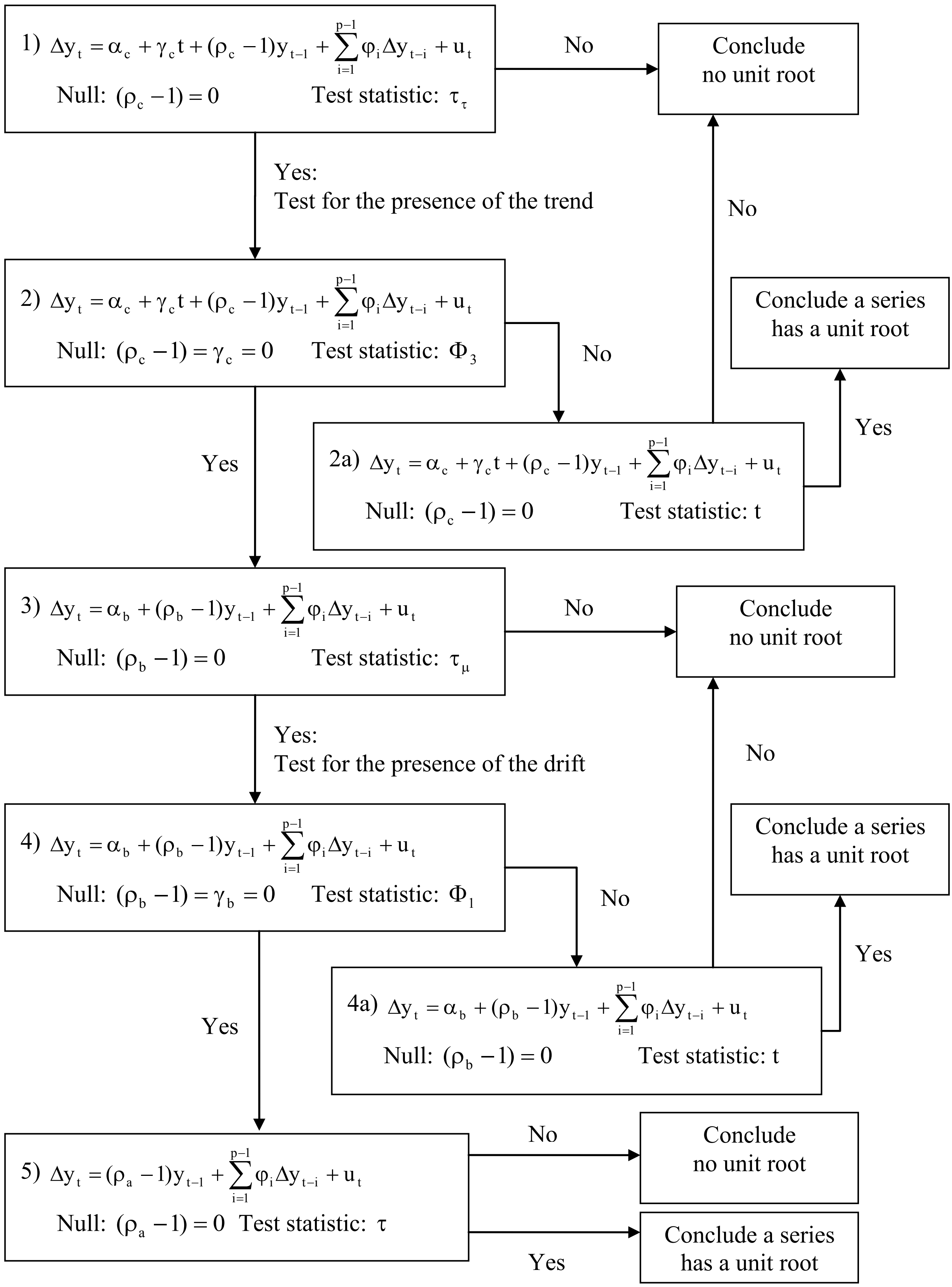
DF/ADF-tests do not nest both the null and alternative hypotheses if the deterministic components in the regression model are less than those in the hypothesized d.g.p. Since we do not know the underlying d.g.p., we use the most general of the models in (5.17). However, the presence of additional nuisance parameters, i.e., constant and trend terms, decreases both degrees of freedom and the power of the test against the alternative hypothesis of stationary. Reduced power implies that we may not be able to reject the null of a unit root when a series is stationary. Another problem is that the appropriate statistic for testing for a unit root is determined by the number of regressors in the model. These problems indicate the importance of model selection which reflects the actual d.g.p.

Following Perron's (1988) procedure based on the DF-test to test for a unit root, a sequential testing procedure based on the ADF-test is shown in Figure 5.6 The first step is to consider the least restrictive model in (5.18) which includes a trend and constant term, and the τ_τ-statistic is used to test the null $(\rho_c - 1) = 0$. If the null is rejected, the procedure does not continue and we conclude that the underlying series contains no unit root. By contrast, if we cannot reject the null, possibly due to the low power of the test, we should continue to test down to more restricted specifications since too many deterministic regressors are included and this reduces the power of the test. The significance of the trend term is preceded by testing the hypothesis $(\rho_c - 1) = \gamma_c = 0$ in Table 5.1 - Step 2 using the Φ_3-statistic. If the trend is significant, we test for the presence of a unit root again by using the standard normal test in Table 5.1 - Step 2a. If the null of a unit root is rejected, there is no need to proceed and we conclude that the series does not contain a unit root. Otherwise, we conclude that the series contains a unit root. If the trend is not significant, we proceed to test the model without the trend, (5.16), in Table 5.1 - Step 3. The null hypothesis $(\rho_b - 1) = 0$ is tested using the τ_μ-statistic. If the null is rejected, we conclude that the series does not contain a unit root. However, if we cannot reject the null hypothesis of a unit root, we continue the test for the significance of the constant by testing the hypothesis $(\rho_b - 1) = \gamma_b = 0$, using the Φ_1-statistic in Table 5.1 - Step 4. If the constant is significant, the null hypothesis $(\rho_b - 1) = 0$ is tested for the presence of a unit root using the standardized normal test in Table 5.1 - Step 4a. If the null hypothesis is rejected, we conclude that the series does not contain a unit root. Otherwise, we conclude that the series contains a unit root. If the constant is not significant, we have to test the model without the trend or constant, (5.15), in Table 5.1 - Step 5. The hypothesis of a unit root $(\rho_a - 1) = 0$ is tested using the τ-statistic. If the null is rejected, we conclude that the series does not contain a unit root. Otherwise, we conclude that the series contains a unit root.

In this procedure, we continue to test down to more restricted specifications until we can reject the null of a unit root when testing stops. In addition, we test Steps 2a and 4a only if we can reject the joint hypotheses in Steps 2 and 4. However, on some occasions, the statistic relating to the DF-distributions may be selected instead, so we must use the test results carefully (Harris and Sollis, 2005, p.47). Critical Dickey-Fuller tables have been further developed by MacKinnon (1991) through Monte Carlo simulations and these are widely adopted by most econometric packages including RATS (Estima, 2004; Doornik, 1998), which is used in this study.

In the standard sequence of testing for unit root, if the hypothesis of the presence of a unit root in the level of the series, y_t, is not rejected, we would then test the first differences for the presence of a second unit root and so on. If y_t must be differenced d times before it becomes stationary, it is integrated of order d, I(d), and the series has d unit roots. The testing procedure from lower to higher orders of integration is carried on until the null hypothesis of a unit root is rejected.

Figure 5.6 Unit Root Testing Procedures Using the ADF-test (Unknown d.g.p.).



5.3.4 The KPSS Test[41]

The DF/ADF tests is used to examine whether a series is stationary or non-stationary and employs the unit root as the null against the alternative of stationary or I(0). However, the use of a single statistic to provide a test of the null may not provide a powerful test of the alternative and *vice versa*, because in classical hypothesis testing theory, the null hypothesis is rejected only if there is clear evidence against it (Maddala, 2001, p.552). Hence, it is useful to test the null hypothesis that a series is stationary against the alternative of non-stationarity to ensure that each supports the other (Harris and Sollis, 2005, p.42). Several tests have been developed by Tanaka (1990), Park (1990), Kwiatkowski *et al* (1992), Saikkonen and Luukkonen (1993), Choi (1994), Leybourne and McCabe (1994), and Arellano and Pantula (1995). The most commonly-used of these is the KPSS test (Kwiatkowski *et al.*, 1992). The test considers a components representation of an underlying series as the sum of deterministic trend, random walk, and stationary error with the linear regression model:

$$y_t = \lambda t + \xi_t + \varepsilon_t \qquad (5.19)$$

where t is a deterministic trend, $\xi_t = \xi_{t-1} + u_t$ is a random walk where u_t~IID(0, σ_u^2) and ε_t is a stationary error. To test if y_t is a trend stationary process, that is, the series is stationary around a deterministic trend, the null is formulated as H_0: $\sigma_u^2 = 0$, which means that the intercept is a fixed element, or ξ_t is constant, against the alternative that H_0: $\sigma_u^2 > 0$ and the Lagrange multiplier (LM) statistic is applied (Nabeya and Tanaka, 1988). For testing the null of level stationarity where the series is stationary

[41] This section is based on Maddala and Kim (1998, pp.120-128).

around a fixed level, the test is developed in a similar way except that the residuals used in the calculation of the statistic are derived from the regression of the series on an intercept only.

We use the KPSS test to complement the DF/ADF-tests. If the one rejects the null but the other does not, or *vice versa*, we have confirmation. However, there is a problem when both reject their nulls. Nevertheless, applying both tests provides more useful information than using each test alone.

5.3.5 Limitations of Unit Root Tests

The major weakness of using DF/ADF tests is poor size and power (Diebold and Senhadji, 1996; Rudebusch, 1993; Blough, 1992; Rudebusch, 1992; Cochrane, 1991; Schwert, 1989; West, 1988; Schwert, 1987). Respectively, this implies that the null is inclined to be under-rejected when it is inclined false, and over-reject when true. Selection of the accurate form of the ADF-model and applying different lag lengths have been found to cause the unit root tests to be sensitive, that is, different forms and lag lengths produce different outcomes to rejecting the null of a unit root. Another problem associated with size and power of the test is the issue of the properties of the tests in small samples (Harris and Sollis, 2005, p.54). Notwithstanding alternative unit root tests which use trend-stationary as the null against the alternative of non-stationary, it is unclear that alternative tests like the KPSS test are better than the standard DF/ADF-test. Moreover, Caner and Kilian (2001) demonstrate by using a Monte Carlo simulation that the KPSS test tends to have enormous size distortions if the null approaches the alternative of a unit root.

5.4 Single-Equation Cointegration Test: The Engle-Granger Approach[42]

One of the major approaches to test for cointegration is the Engle-Granger method or the residual-based ADF-test for cointegration. Consider a simple model comprising two non-stationary variables, y_t and x_t, both which are I(1). As noted in Section 5.2.4, the concept of cointegration implies that the variables have a propensity to converge in the long run, though they may move away from each other in the short run. The Engle-Granger cointegration test is applied to examine whether the equilibrium error, ε_t, from the estimated long-run relationship between the variables is stationary. If so, the variables are cointegrated. Thus, the null hypothesis that $\varepsilon_t \sim I(1)$ is tested against the alternative that $\varepsilon_t \sim I(0)$; and if these deviations are found to be stationary, the two series are cointegrated of order (1,1). Even though several tests can be used, Engle and Granger (1987) indicate that the ADF-test is more favourable than other tests because of its power. Consider the relation:

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \tag{5.20}$$

The ADF-test is in the form:

$$\Delta\hat{\varepsilon}_t = \psi^* \hat{\varepsilon}_{t-1} + \sum_{i=1}^{p-1} \psi \Delta\hat{\varepsilon}_{t-i} + \mu + \delta t + \omega_t \tag{5.21}$$

where $\hat{\varepsilon}_t$ are obtained following from estimating the cointegrating regression (5.20) and $\omega_t \sim IID(0, \sigma^2)$. If we reject the null that $\psi^* = 0$, we conclude that the

---

[42] This section is based on Harris and Sollis (2005, pp.79-83).

disturbance term is stationary and the variables are cointegrated. The deterministic components, i.e., a trend and/or a constant term, can be included in either the long-run regression (5.20) or the test regression (5.21) but not in both. A constant term and a trend should be included if the alternative hypothesis of cointegration allows a non-zero mean and a non-zero deterministic trend for $\hat{\varepsilon}_t$ respectively (Harris and Sollis, 2005, p.80). However, using a Monte Carlo simulation, Hansen (1992) shows that the inclusion of a time trend in(5.21), irrespective of whether the trend appears in $\hat{\varepsilon}_t$ or not, causes a loss of power, that is, it leads to under-rejection of the null of no cointegration when false and over-rejection when true. The critical values for the ADF-statistics used to test for cointegration in the Engle-Granger procedure are different from those used to test for a unit root in each variable. Two main reasons are provided. First, since the standard DF/ADF tables of critical values are derived from the OLS estimation, the estimated residuals obtained from (5.20) are as stationary as possible. Consequently, the standard DF distribution tends to over-reject the null. Second, since the number of regressors included in (5.20) influences the distribution of the test statistic under the null, different critical values are required when the number of regressors changes. Further, the critical values are affected by the existence of a constant and/or trend in (5.21) and the sample size; thus, various set of critical values are needed for testing the null hypothesis in each case (Harris and Sollis, 2005, p.81). Adjusted critical values are provided by MacKinnon (1991) and Banerjee *et al.* (1993). Similar to the ADF test, the value of p was set by both the Akaike Information Criterion (AIC) and by the Baysian Information Criterion (BIC).

If the null hypothesis of no cointegration is rejected, the variables are cointegrated and the residuals from the equilibrium regression can be used to estimate the ECM to capture both short-and long-run information. This is (5.12) which is rewritten for convenience:

$$\Delta y_t = \gamma_0 \Delta x_t - (1-\alpha_1)[y_{t-1} - \beta_0 - \beta_1 x_{t-1}] + u_t \tag{5.22}$$

This Engle-Granger two-step estimation procedure has several limitations. First, the test has lower power against alternative tests. Second, it is possible to obtain biased estimates of the long-run relationship from finite samples. Third, the standard t-statistics cannot be used in inferences involving the significance of the long-run parameters in the static model (Harris and Sollis, 2005, p.83). Fourth, the results of cointegration test may vary depending on the choice of the variable selected to be the dependent variable especially in small samples. Fifth, in the case of three or more variables, there may be more than one cointegrating vector and there is no systematic method for separate estimation of multiple vectors. Sixth, the coefficient tested in the cointegration test in Step 2 is obtained by estimating a regression using the errors in the long-run model in Step 1, and it is possible that any error in Step 1 is transferred to Step 2 (Enders, 2010, pp.385-386). To circumvent these problems, several methods have been developed. Among them, Johansen's (1995; 1988) full information maximum likelihood approach is widely used for estimating and testing in multiple cointegration frameworks.

5.5 Cointegration Test in Multivariate Systems: The Johansen Approach[43]

The Johansen's full information maximum likelihood approach can be used to estimate and test for the presence of multiple cointegrating vectors. This method is based on the VAR model suggested in (5.13). However, the system can be reformulated into a VECM in (5.14), which is rewritten here for convenience:

$$\Delta \mathbf{z}_t = \mathbf{\Pi z}_{t-k} + \mathbf{\Gamma}_1 \Delta \mathbf{z}_{t-1} + \mathbf{\Gamma}_2 \Delta \mathbf{z}_{t-2} + \ldots + \mathbf{\Gamma}_{k-1} \Delta \mathbf{z}_{t-k+1} + \boldsymbol{\varepsilon}_t \qquad \boldsymbol{\varepsilon}_t \sim \mathrm{IN}(0, \Sigma) \tag{5.23}$$

A key feature in (5.23) is $\mathbf{\Pi} = \boldsymbol{\alpha\beta}'$ where $\boldsymbol{\alpha}$ is the speed of adjustment to equilibrium and $\boldsymbol{\beta}$ is a matrix of long-run coefficients. Both $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ have $(n \times r)$ dimension where r is the rank of $\mathbf{\Pi}$.[44] The term $\boldsymbol{\beta}'\mathbf{z}_{t-k}$ represents the cointegration relationships in the system. The term $\mathbf{\Pi z}_{t-k}$ must be stationary so that $\mathbf{z}_t$ is a vector of I(1) variables since all terms in (5.23) involving $\Delta \mathbf{z}_{t-i}$ are I(0), and $\boldsymbol{\varepsilon}_t$~I(0) are white noise errors.

Even though $\mathbf{\Pi z}_{t-k}$ can be I(0), and the most important interest is when there is up to (n-1) cointegration relationships where the term $\boldsymbol{\beta}'\mathbf{z}_{t-k}$ ~I(0). In this case, $\boldsymbol{\beta}$ comprises of both r≤(n-1) cointegration vectors and (n-r) non-stationary vectors. However, only the cointegration vectors in $\boldsymbol{\beta}$ are included in (5.23) to make $\mathbf{\Pi z}_{t-k}$ ~I(0) while the last (n-r) columns of $\boldsymbol{\alpha}$ are insignificantly small. The Johansen

---

[43] This section is based on Harris and Sollis (2005, pp.110-142).

[44] The rank of a square (n x n) matrix **A** is the number of linearly independence rows (or columns) in the matrix. The notation rank(**A**)=r indicates that the rank of **A** is equal to r. If rank(**A**)=n, the matrix **A** is of full rank (Enders, 2010, p.422).

approach determines how many $r \leq (n-1)$ cointegrating vectors are in $\boldsymbol{\beta}$ (or which columns of $\boldsymbol{\alpha}$ are zero). Therefore, testing for cointegration is equivalent to testing the rank of $\boldsymbol{\Pi}$, i.e., finding the number of r linearly independent columns in $\boldsymbol{\Pi}$, or testing that the last (n-r) columns of $\boldsymbol{\alpha}$ are insignificantly small. If rank($\boldsymbol{\Pi}$)=0, all elements of $\boldsymbol{\Pi}$ are zero and (5.23) becomes a VAR in first differences. By contrast, if $\boldsymbol{\Pi}$ has full rank, the vector process is stationary and traditional statistical methods can be applied. Intermediate cases are of key interest when rank($\boldsymbol{\Pi}$)=1 where there is a unique cointegrating vector and $\boldsymbol{\Pi}\,\mathbf{z}_{t-k}$ can be illustrated in error-correction terms, or when 1<rank($\boldsymbol{\Pi}$)<n where multiple cointegration vectors occur (Enders, 2010, p.390).

Estimates of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ as well as characteristic roots or eigenvalues of $\boldsymbol{\Pi}$ can be obtained by using the reduced rank regression procedure which is based on maximum likelihood estimation. Two test statistics can be used to determine cointegration rank, r, by examining the significance of the characteristic roots. The trace statistic is:

$$\lambda_{trace} = -T\sum_{i=r+1}^{n}\log(1-\hat{\lambda}_i) \qquad r=0, 1, 2,\ldots, (n-1) \tag{5.24}$$

where $\hat{\lambda}_i$ are the estimated values of the characteristic roots derived from the estimated $\boldsymbol{\Pi}$ and T is the number of utilisable observations. The trace statistic examines the null that the number of distinct cointegrating vectors is at most r, against the alternative that it is greater than r. The second test is the maximal eigenvalue or $\lambda-\max$ statistic:

$$\lambda_{max} = -T\log(1-\hat{\lambda}_{r+1}) \qquad\qquad r=0, 1, 2,\ldots, (n-1) \qquad (5.25)$$

which tests the null that the number of cointegrating vectors is r, against the alternative that r+1 cointegrating vectors exist. Due to the sequence of trace tests $(\lambda_0, \lambda_1, ..., \lambda_{n-1})$, a consistency test procedure is conducted, but it is not available for the $\lambda - \max$ test. In general, only the trace statistic is used to test for cointegration rank (Harris and Sollis, 2005, p.123). Further, Cheung and Lai (1993) show that the trace test has superior robustness to both skewness and excess kurtosis in the residuals. Therefore, the trace test may give more accurate results than the $\lambda - \max$ test.

Asymptotic critical values for trace and maximal eigenvalue statistics have been derived from Monte Carlo simulations (Pesaran *et al.*, 2000; Doornik, 1999; Osterwald-Lenum, 1992). These values vary depending on the deterministic components of the number of dummy variables, weakly exogenous variables, and possible structural breaks in the model (Dennis *et al.*, 2006, p.8). In small samples, these tests are likely to have power and size problems when using asymptotic critical values (Harris and Sollis, 2005, pp.123-124). That is, the trace statistic sometimes has poorer size properties while the maximal eigenvalue statistic often lacks power (Lutkepohl *et al.*, 2001). Consequently, the Johansen approach over-rejects when the null is true (Reimers, 1992). To correct the cointegration rank test in small samples, Johansen (2002a; 2002b) considers a Bartlett-type correction to calculate appropriate critical values that is determined by the parameters of the VECM (Harris and Sollis, 2005, p.124). The small sample correction of the trace test derived in Johansen (2002b; 2000) is available in CATS in RATS for simulating the asymptotic distribution (Dennis *et al.*, 2006, p.14). Even though the application of the small sample Bartlett corrections to the trace test statistic can give a more accurate size, it does not necessarily improve the power problem. That is, the probability of rejecting a correct null hypothesis ($r=r^*$, where r^* is the true value) is high and the probability of accepting a correct alternative ($r \neq r^*$) is small for relevant hypotheses in the 'near unit root' region. Consequently, the trace test might not determine the correct value of r (Juselius, 2006, p.141).

The reduced rank regression procedure suggests how many cointegrating vectors span the cointegration space. If r=1, there is a single cointegrating vector. However, if there are multiple cointegrating vectors, it is important to examine whether they are unique, and then determine the structural economic relationships of each cointegrating vector. Estimates of cointegrating vector(s) obtained from the Johansen procedure are presented in normalized form, which is achieved by simply dividing each cointegrating vector by a selected element so that the dependent variable has a unit coefficient. The estimated coefficients in the normalised cointegrating vector are *ceteris paribus* long-run elasticities when the variables are defined in logarithms (Johansen, 2005).

In reduced rank tests, we need to consider testing the order of integration, formulating the dynamic model, the deterministic components, and testing of restrictions on cointegrating vectors. The analysis of the Johansen approach presented here follows the Hendry procedure of general-to-specific modelling. It begins with a general unrestricted model which is then reduced to various particular models by imposing restrictions on parameters, and model selection is based on restriction tests consistent with economic theory and diagnostic statistics.

5.5.1 Testing the Order of Integration of the Variables

Before performing reduced rank tests, we need to test for the order of integration of each variable, using unit root tests presented in Section 5.3. These tests often have poor size and power properties which suggest that multivariate cointegration tests should still be applied even if unit root tests show that the variables are unbalanced where the variables cannot cointegrate down to a common lower order of integration.[45] The Johansen approach provides an alternative test for unit roots with the null of stationarity against the alternative of non-stationarity but it is not known whether this test has better power and size properties than standard tests (Dennis *et al.*, 2006, pp.11-12).

5.5.2 Specification of the Dynamic Model

To specify the dynamic model, selecting the appropriate lag length of the VAR, k, or the lag length of the $\mathbf{\Delta z}_{t-k+1}$ in the VECM, is essential since appropriate lag length leads to Gaussian residuals.[46] The Johansen procedure may be affected by the lag length of the VAR and Cheung and Lai (1993) show that cointegration rank tests are robust to over-parameterisation but there are size distortions in the case of too small lag lengths. Lutkepohl and Saikkonen (1999) also indicate that if the lag length is too

[45] We could obtain a model comprising of series with different integration orders when there are three or more series in the model. Wickens and Pagan (1989) show that cointegration exists when a subset of the higher order series cointegrate to the order of the lower order series. For example, if $y_t \sim I(1)$, $x_t \sim I(2)$ and $z_t \sim I(2)$, then if there is a cointegration relationship between x_t and z_t such that $v_t(=x_t-\delta z_t)\sim I(1)$, then v_t can potentially cointegrate with y_t to obtain $w_t\ (=v_t-\gamma\ y_t)\sim I(0)$ (Harris and Sollis, 2005, p.35).

[46] That is, the model does not have problems of autocorrelation, non-normality, etc.

short, severe size distortions regularly happen, and if the lag length is too large, it causes a loss of power. Lag length can be chosen from information criteria, such as the Akaike information criterion (Akaike, 1973) and Schwarz Baysian information criterion (Schwarz, 1978), the Hannan-Quinn criterion (HQ) (Hannan and Quinn, 1979), or a likelihood ratio (LR) test (Greene, 2008). Similar to the AIC and BIC criteria which are suggested in Section 5.3.2, the HQ criterion is an information criterion based on the maximal value of the likelihood function with an additional penalty associated with the number of estimated parameters, but the strength of the penalty is different, namely that the preferred lag length is the one with minimum value. If information criteria suggest different lags, it is usual to use the HQ criterion (Johansen *et al.*, 2000, p.233). Without a penalising factor, the LR test is used to test for reducing the number of lags of the VAR model. Based on the χ^2 distribution, the LR test procedure begins with testing the null hypothesis that the model has k lags against the alternative hypothesis that the model has k+1 lags. From the longest to shortest lag, the first null hypothesis is expected to be accepted and the last is expected to be rejected. The change from acceptance to rejection indicates the minimum number of lags. These test procedures are available in CATS in RATS.

Stationary variables can be included in the model to establish the long-run relationship among non-stationary variables particularly if supported by economic theory. These I(0) variables do not enter the long-run cointegration space, but only influence the short-run model. To illustrate and assuming that k=2, (5.23) becomes:

$$\Delta \mathbf{z}_t = \mathbf{\Pi} \mathbf{z}_{t-2} + \mathbf{\Gamma}_1 \Delta \mathbf{z}_{t-1} + \psi \mathbf{D}_t + \mathbf{u}_t \tag{5.26}$$

where $\mathbf{D}_t$ contains short-run shocks to the system such as policy interventions. These I(0) variables are often dummy variables and their number influences the underlying distribution of test statistics and critical values for the cointegration rank tests.

5.5.3 Deterministic Components in the Cointegration Model

Consider the deterministic components in the cointegration model, i.e., the constant and trend. To illustrate, and assuming k=2 and excluding $\mathbf{D}_t$ for simplicity, we can develop the VECM in (5.23) to incorporate various choices to be considered:

$$\Delta \mathbf{z}_t = \mathbf{\Gamma}_1 \Delta \mathbf{z}_{t-1} + \boldsymbol{\alpha} \begin{bmatrix} \boldsymbol{\beta} \\ \mu_1 \\ \delta_1 \end{bmatrix} \tilde{\mathbf{z}}_{t-k} + \boldsymbol{\alpha}_{\perp} \mu_2 + \boldsymbol{\alpha}_{\perp} \delta_2 t + \mathbf{u}_t \tag{5.27}$$

where $\tilde{z}_{t-k} = (z'_{t-k}, 1, t)$, μ_1 and μ_2 are constant terms, and t is the time trend. Three possible models – commonly referred to as Models 2-4 - are nested in (5.27) by imposing restrictions (Harris and Sollis, 2005, p.133-134).[47] In Model 2, the data have no linear trends in levels so there is a zero mean in the first difference form, and $\delta_1 = \delta_2 = \mu_2 = 0$. Here the constant is restricted to the long run or to the cointegration space. Osterwald-Lenum (1992) develops critical values for this model and these have been extended for including weakly exogenous I(1) variables by Persaran *et al*. (2000). Critical values using the Gamma distribution are available in Doornik (1999). When the data have linear trends in level form, Model 3 is specified

[47] Model 1, where $\delta_1 = \delta_2 = \mu_1 = \mu_2 = 0$, is the model without constant deterministic trend in the cointegrating space. This is excluded from consideration since is improbable to happen in practice. Another omitted model is Model 5 which is derived from Model 4. The data in this model have quadratic trends in level form and linear trends exist in the short-run model. Model 5 is economically difficult to rationalise if the variables are in logs because it entails improbable ever-increasing or decreasing rates of change.

with $\delta_1 = \delta_2 = 0$ and the relationships among I(1) variables can drift. However, Model 3 only has a constant in the short run since the constant in the cointegration vector(s) is cancelled out by the constant in the short-run model. Critical values for Model 3 are available in Pesaran *et al*. (2000). Model 4 represents the situation where the data have no quadratic trends in level form and there is no trend in the short-run model. We can include a linear trend in the cointegration vector(s) to account for unknown exogenous growth, e.g., technological progress. The restriction in this model is that $\delta_2 = 0$. Critical values for Model 4 are in Pesaran *et al*. (2000).

The choice of appropriate model when testing for the cointegration rank is important. Johansen (1992) proposes a test of the joint hypothesis of both rank order and deterministic components based on the Pantula principle. First, all three models are estimated and the test results are then tabulated in order from the most restrictive Model 2, where r=0, to the least restrictive Model 4, where r=n-1. The next step compares the trace statistic with critical values at each stage starting with the least restrictive alternative to the most restrictive. The procedure stops when the null hypothesis is not rejected for the first time (Harris and Sollis, 2005, p.134).

5.5.4 Testing of Restrictions on Cointegrating Vector

The Johansen procedure allows for testing of restrictions in the cointegrating vector(s) through $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. Recall that $\boldsymbol{\beta}$ is the matrix of cointegrating parameters and $\boldsymbol{\alpha}$ is the matrix of the speed of adjustment parameters in (5.23). The existence of $r \leq (n-1)$ cointegrating vectors in $\boldsymbol{\beta}$ implies that the last (n-r) columns of $\boldsymbol{\alpha}$ are zero. In general, each of the r non-zero columns of $\boldsymbol{\alpha}$ represents how each cointegrating vector combines with the corresponding short-run equation, and measures the speed of short-run adjustment towards equilibrium. Given the number of cointegrating vector(s), restrictions on the cointegration space can be tested using log-likelihood ratios (LR). In this study, three hypothesis tests are tested, for exogeneity, stationarity, and variable exclusion.

Consider testing for weak exogeneity. All variables in a cointegrated system generally respond to a discrepancy from long-run equilibrium. However, if one of the adjustment parameters in the matrix $\boldsymbol{\alpha}$ is zero, the variable in question does not respond to the deviation from the long-run equilibrium and this variable is weakly exogenous (Enders, 2010, p.407). For notational simplicity, assume that $\mathbf{z}_t = [z_{1t} \quad z_{2t} \quad z_{3t}]'$ and r=1, so that $\boldsymbol{\alpha}' = [\alpha_1 \quad \alpha_2 \quad \alpha_3]$ and $\boldsymbol{\beta}' = [\beta_1 \quad \beta_2 \quad \beta_3]$. If α_3 =0, the partial VECM model is:

$$\begin{bmatrix} \Delta z_{1t} \\ \Delta z_{2t} \end{bmatrix} = a_0 \Delta z_{3t} + \Gamma_1 \begin{bmatrix} z_{1t-1} \\ z_{2t-1} \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} [\beta_1 \quad \beta_2 \quad \beta_3] \begin{bmatrix} \Delta z_{1t-1} \\ \Delta z_{2t-1} \\ \Delta z_{3t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{5.28}$$

Thus, information about the long run in $\boldsymbol{\beta}$ does not enter the equation governing $\Delta \mathbf{z}_{3t}$ and this variable is weakly exogenous to the system. This implies that Δz_{1t} does not react to disequilibrium errors, but might still respond to lagged of Δz_{1t} and Δz_{2t} (Johansen, 1992, p.322). The weakly exogenous variable remains in the cointegrating vector but its short-run behaviour cannot be modelled because it disappears from the vector on the left-hand side of the VECM, entering on the right-hand side instead. To examine whether each variable is weakly exogenous, the null hypothesis for z_{3t} for example is:

$$H_1: \alpha' = [* \quad * \quad 0] \qquad \text{or} \quad \alpha_3 = 0 \tag{5.29}$$

where asterisks indicate unrestricted parameters, and LR~ χ^2_1. Estimating the multivariate model having conditioned on the weakly exogenous variables or the partial model provides advantages. In particular, if the weakly exogenous variables are problematical, conditioning on them usually improves the stochastic properties of the rest of the system, and we may obtain a partial system with more stable parameters than the full system. This advantage is obvious in the short-run model because the number of short-run variables in the VECM is decreased. (Juselius, 2006, p.198; Harris and Sollis, 2005, pp.137-138). In general, we need to estimate the full system and then examine weak exogeneity. Thus, a partial model conditional on a weakly exogenous variable is typically estimated after determining restrictions on $\boldsymbol{\alpha}$. The cointegration rank is still based on the full system and is not re-estimated (Juselius, 2006, p.198). However, testing for weak exogeneity may not always be necessary if weak exogeneity is provided by economic theory, and we can estimate a partial system with a conditional weakly exogenous variable from the outset. In that case, we need to determine the cointegration rank from the partial system (Juselius, 2006, p.198; Harris and Sollis, 2005, p.138). The asymptotic distribution of the cointegration rank test statistics for estimating a partial model allowing for weakly exogenous regressors in the long run is reported in Pesaran *et al*. (2000, table 6), Harbo *et al* (1998), and Doornik (1998), which is available in CATS (Dennis *et al.*, 2006).

The Johansen procedure also provides an alternative means of testing for unit roots where the null is stationarity. To test whether each series is stationary, the hypothesis of stationarity of z_{3t}, for example, is:

$$H_2:\ \beta' = [0 \quad 0 \quad *] \qquad \text{or} \quad \beta_1 = \beta_2 = 0 \tag{5.30}$$

and LR~ χ^2_2. In testing for variable exclusion, we test if each series is part of the equilibrium relationship (with the other variables). The null of individual exclusion of z_{3t} from the long run is:

$$H_3:\ \beta' = [* \quad * \quad 0] \qquad \text{or} \quad \beta_3 = 0 \tag{5.31}$$

and LR~ χ^2_1.

5.5.5 Misspecification Tests

The multivariate normality assumption of the VAR model implies that the residuals or the discrepancy between the mean and the actual realisation is a white noise process, $\boldsymbol{\varepsilon}_t \sim N(0, \Sigma)$. Misspecification tests of the residuals can be used to assess the adequacy of a given model. In particular, checking the white noise requirement of the residuals is important for statistical interference. The existence of white noise residuals also supports the economic interpretation for explaining the behaviour of rational agents who avoid making systematic errors caused by their decisions at time t with the available information at time t-1 (Juselius, 2006, pp.46, 55). If the residuals are not white noise, the estimates may not have optimal properties and lack meaning. Also, we cannot claim that the results are based on full information maximum likelihood inference if $\boldsymbol{\varepsilon}_t$ is non-normal. Valid statistical inference is susceptible to infringement of some assumptions, such as autocorrelated residuals and skewed residuals, but quite robust to others, such as excess kurtosis and moderate residual heteroscedasticity (Juselius, 2006, p.47).

Since the cointegrating rank tests should be performed on a well-specified model, we should adopt the residuals obtained from the unrestricted model to examine whether the model is accepted or not. That is, after the unrestricted model has been estimated, the multivariate normality assumption underlying the VAR model should be tested against the data using the residuals, $\hat{\varepsilon}_t$ (Juselius, 2006, p.55). For multivariate tests, the trace correlation is used to measure an overall goodness of fit, which is similar to the conventional R^2 in a linear regression model (Juselius, 2006, p.73). Tests of residual autocorrelation include the Ljung-Box test of residual autocorrelation and the LM-test of j^{th} order autocorrelation. The test for normality is the Doornik-Hansen test while the test of residual autoregressive conditional heteroscedasticity is the ARCH test (Dennis *et al.*, 2006).

In many empirical economic applications, the assumption of multivariate normality is not satisfied for the VAR in its simplest form, and this causes serious problems for statistical inference. It is often possible to modify the VAR model to obtain a statistically well-behaved model. Methods include the use of intervention dummies representing important or institutional incident, conditioning on weakly or strongly exogenous variables, checking the measurements of the selected variable, which might not be precisely measured, and changing the sample period in order to avoid essential scheme shift (Juselius, 2006, pp.46-47).

5.6 Modelling the Short-run Multivariate System

After obtaining long-run estimates of the cointegration relationships using the Johansen approach, we can estimate the short-run structure of the model expressing information on the short-run adjustment of economic variables through the VECM with the error correction terms explicitly included. Following the Hendry approach of general-to-specific modelling, we then obtain a parsimonious representation of the system, which is the parsimonious VAR (PVAR), or a parsimonious VECM (PVECM). To illustrate, consider the long-run cointegration relations obtained from the Johansen approach. We reformulate and estimate the VECM including the error correction terms explicitly:

$$\mathbf{\Delta z}_t = \mathbf{\Gamma}_1 \mathbf{\Delta z}_{t-1} + \mathbf{\Gamma}_2 \mathbf{\Delta z}_{t-2} + \ldots + \mathbf{\Gamma}_{k-1} \mathbf{\Delta z}_{t-k+1} + \boldsymbol{\alpha}\widehat{\boldsymbol{\beta}}' \tilde{\mathbf{z}}_{t-k} + \omega \mathbf{D}_t + \mathbf{u}_t \tag{5.32}$$

By estimating the multivariate system in (5.32), we can test whether the lagged Δz_{t-k+1} are significant in each equation. A parsimonious model can be obtained by eliminating the insignificant regressors, and the validity of the reduction in the model can be examined by an F-test. However, Dennis *et al*. (2006, p.85) argue that several short-run parameters are often insignificant, but they still provide information of possible short-run effects in the reduced form of the model. By contrast, we should check for significance of dummies.

5.7 Analysis of Impulse Response Functions

Cointegration implies the existence of a stationary long-run relationship among variables in the cointegrated system, so the variables are not independent and there are systematic and joint movements among them. Any deviation from long-run equilibrium also affects the time paths of the cointegrated variables. To obtain greater understanding about the interaction between the variables in the system, it is useful to investigate the response of one variable to an impulse or shock in another (Lutkepohl, 2005, p.51). That is, if there is any shock to a particular variable, it can generate variations both in itself and in other variables which eventually return the system to a new equilibrium provided no further shocks occur. We investigate time paths of the variables to provide insights into short-run and long-run relations between the variables using impulse response function analysis.

A benefit of impulse response analysis is that its coefficients, based on total derivatives, do not suffer from the *ceteris paribus* assumption that can restrict the interpretation of the VECM (Lutkepohl and Reimers, 1992). That is, if there is a shock to one variable, this shock may cause a chain reaction effects among other variables. Thus the partial derivatives of the VECM, whose formation disregards interactions among variables, may have restricted use and generate an ambiguous understanding of the short- and long-run effect of such shocks. Impulse response analysis examines the net effect of direct and indirect effects of a shock through all periods after the shock occurs.

To illustrate, consider the simple first-order, two-variable VAR in standard form:[48]

$$\begin{bmatrix} z_{1t} \\ z_{2t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} z_{1t-1} \\ z_{2t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \tag{5.33}$$

[48] This is based on Enders (2010, p.307).

where $\mathbf{z}_t$ is an vector containing two variables included in the VAR, $\mathbf{c}_0$ is an vector of constant terms, $\mathbf{A}_i$ is an matrix of coefficients, $\mathbf{e}_i$ is an vector of error terms. We can rewrite a vector autoregression as a vector moving average which allows us to trace out the time path of the various shocks on the variables included in the VAR system. Equation (5.33) becomes:

$$\begin{bmatrix} z_{1t} \\ z_{2t} \end{bmatrix} = \begin{bmatrix} \bar{z}_1 \\ \bar{z}_2 \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^i \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \tag{5.34}$$

Further understanding is gained if we express $\mathbf{e}_t$ in terms of $\boldsymbol{\varepsilon}_{z_t}$ which are the disturbance terms in the structural VAR. The vector of error terms can be written as:

$$\begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} = \frac{1}{1-b_{12}b_{21}} \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{z_{1t}} \\ \varepsilon_{z_{2t}} \end{bmatrix} \tag{5.35}$$

where b_{12} and b_{21} are the contemporaneous effect of a unit change of z_{2t} on z_{1t} and z_{1t} on z_{2t} respectively. Combining (5.34) and (5.35) gives:

$$\begin{bmatrix} z_{1t} \\ z_{2t} \end{bmatrix} = \begin{bmatrix} \bar{z}_1 \\ \bar{z}_2 \end{bmatrix} + \frac{1}{1-b_{12}b_{21}} \sum_{i=0}^{\infty} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^i \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{z_{1t}} \\ \varepsilon_{z_{2t}} \end{bmatrix} \tag{5.36}$$

For simplicity, (5.36) can be rewritten as:

$$\begin{bmatrix} z_{1t} \\ z_{2t} \end{bmatrix} = \begin{bmatrix} \bar{z}_1 \\ \bar{z}_2 \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} \phi_{11}(i) & \phi_{12}(i) \\ \phi_{21}(i) & \phi_{22}(i) \end{bmatrix} \begin{bmatrix} \varepsilon_{z_{1t-i}} \\ \varepsilon_{z_{2t-i}} \end{bmatrix} \tag{5.37}$$

where $\phi_i = \frac{A_1^i}{1-b_{12}b_{21}} \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix}$.

The coefficients $\phi_{jk}(i)$ are the impulse response functions. If we know the parameters of the structural system, it is possible to trace out the time paths of the effects of pure $\boldsymbol{\varepsilon}_{zt}$ shocks. However, since an estimated VAR is under-identified and we do not know all of the parameters of the structural system, we require an extra restriction on the VAR system to identify impulse responses. One common tool is the application of the Choleski decomposition. In this two-variable VAR system, if we impose the restriction that z_{1t} does not have a contemporaneous effect on z_{2t} by setting $b_{21}=0$ in the structural system, the error terms in (5.35) can be decomposed as:

$$e_{1t} = \varepsilon_{z1t} - b_{12}\varepsilon_{z_{2t}} \tag{5.38}$$

$$e_{2t} = \varepsilon_{z_{2t}} \tag{5.39}$$

and estimates of all parameters in the system can be obtained. Even though the Choleski decomposition restricts the system by imposing that an $\varepsilon_{z_{1t}}$ shock has no direct influence on z_{2t}, lagged values of z_{1t} still affect indirectly the contemporaneous value of z_{2t}. We can see the asymmetry of the decomposition on the system since an $\varepsilon_{z_{2t}}$ shock has contemporaneous effects on $\mathbf{z}_t$. Thus, (5.38) and (5.39) are said to be an ordering of the variables, that is, z_{2t} is causally prior to z_{1t}. We plot the impulse responses graphically to illustrate the time path of the variables in response to the various shocks. However, if the variables have different scales, it sometimes provides a better representation of the dynamic relationships to consider shocks of one standard deviation rather than unit shocks (Lutkepohl, 2005, p.53).

5.8 Summary

In this chapter, we have introduced the major concepts in modern time series analysis and have presented an empirical methodology for testing unit roots and cointegration. To avoid the spurious regression problem, testing for the presence of unit roots among the variables is required. The most commonly-used unit root test is the augmented Dickey-Fuller test which examines the null hypothesis of non-stationarity against the alternative of stationarity. The appropriate testing strategy follows the sequential testing procedure proposed by Perron (1988). The Dickey-Fuller test might suffer from the poor size and power properties and the KPSS test, which tests the null of stationarity against the alternative of non-stationarity, is also applied.

In studying a system containing non-stationary variables, the cointegration approach suggests the concept of long-run or equilibrium relationship(s) among the variables. Two major cointegration approaches are considered. The first is the Engle-Granger approach in single equation models. This method adopts the augmented Dickey-Fuller for testing the order of integration of the residuals in the estimated relationship. However, a major limitation of this approach is the implication of a single cointegrating vector. In the case of three or more variables, there may be more than one cointegrating vector, but the Engle-Granger procedure does not provide a systematic method for the separate estimation of them. The Johansen approach is a cointegration test in multivariate systems. It is based on a VAR model which allows the estimation of all possible cointegrating vectors among the variables. Founded on the Granger representation theorem, cointegration implies the existence of a VECM model which is used to estimate the short-run structure of the model. Impulse response analysis is introduced to examine the response of one variable to an impulse or shock in another and it provides insights into short- and long-run relations between the variables.

Chapter 6 Data, Definitions and Their Time Series Properties

6.1 Introduction

Most economic time series data are trended over time and are non-stationary, and estimation with traditional regression methods may give meaningless results. To avoid spurious regression, modern time series analysis, that is, cointegration, is applied. However, the first step of cointegration approach is to test for the presence of unit roots, and to examine the order of integration of each variable in the model. The most common approach for testing unit roots is the augmented Dickey-Fuller (ADF) test which tests the null of non-stationarity against the alternative of stationarity. To confirm the results of these tests, we also perform KPSS-tests which test the null of stationarity against the alternative of non-stationarity. Unit root tests discussed in Chapter 5 are performed in RATS 6.35. However, before we test for unit roots formally, it is usual to examine each time series graphically to identify the existence of a trend and/or structural breaks.

This chapter examines the time series properties of the data relating to modelling natural rubber response in Thailand of section 4.6 of Chapter 4. The chapter is organised as follows. Section 6.2 describes the data and variables used. Section 6.3 presents a graphical analysis of the data to visually examine whether each series is stationary and to discover any evidence of a trend and/or structural breaks. Section 6.4 presents the test results of the unit root tests. The final section provides a summary and conclusion.

6.2 Data and Variables

The analysis of supply response of rubber production in Thailand is dependent on data availability. Annual time series data at the national level for 1962-2008 are used in this study. These data are obtained from different domestic public and international institutions. Data on rubber output, acreage planted, acreage being tapped, yield and the farmer's rubber price are collected from the Office of Agricultural Economics (OAE), Ministry of Agriculture and Co-operative. The coefficient of variation and standard deviation of rubber prices over the past three years are used to reflect risk.

There are two possible competing crops to rubber production, paddy and oil palm. Farm gate paddy prices for 1962-2005 are obtained from the International Rice Research Institution (IRRI) while those for 2006-2008 are obtained from OAE. Thai palm oil prices received by farmers for 1969-2007 are obtained from FAOSTAT and that for 2008 is obtained from OAE. Since the Thai palm oil price is unavailable for 1962-1968, we use the Malaysian palm oil price which is collected from the International Financial Statistics (IFS). However, since the original Malaysian data are export prices, we obtain the farmer's price level by adjusting the series by multiplying by 0.7 which is the typical ratio of the export value which farmers received from, based on the world price formation (DEFRA, 2009, p.16).

Fertiliser prices for Thailand are unavailable. Since the majority of fertiliser in Thailand is imported, we calculate an average price as the ratio of the total value of imports and the physical amount of imports. Data on fertiliser imports for 1962-2000 are collected from the Agricultural Statistics of Thailand while those for 2001-2008 are obtained from OAE. Even though the government supports rubber farmers by either providing fertilisers to them or making a payment directly to them for purchasing fertilisers, only rubber farmers registered in the replanting programme can access to these support. Further, data on value and amount of fertilisers supported to farmers are unavailable. Therefore, it is not possible to adjust the overall fertiliser price to the net fertiliser price.

Even though family-labour is mainly used in Thai rubber production, hired labourers are normally paid through a product-sharing system and a proxy for labour costs is the manufacturing wage to reflect the opportunity cost of labour. Data for 1962-1971 are calculated from the hourly wage rate reported in the UN Statistics Yearbook. Data on wages for 1972-1974 and 1976-1977 are obtained from interpolation while data for 1980-2007 are calculated from the monthly wage rate obtained from the International Labour Office (ILO) Statistics. Wage rates for 1975, 1978, and 2008 are calculated from the Labour Force Survey by the National Statistics Organisation.

One of the key variables of interest in this study is the net government's subsidy. The major subsidy concerned is the replanting subsidies supported from the Office of Rubber Replanting Aid Fund (ORRAF). Based on the work of Sectoral Economics Programmes (2001), average net subsidy is the difference between average replanting subsidy and an average tax on rubber exports including export duty and cess[49]. However, keep in mind that the average replanting subsidy is subject to the acreage supported while the average tax on exports is based on total rubber acreage. Data on replanting subsidy and cess are obtained from ORRAF while data on export tax are obtained from Department of Customs, Ministry of Finance.

---

[49]Apart from export duty, natural rubber exporters are required to pay a special tax, namely cess, to the government. Revenue from cess is mainly used as a fund for replanting programme (see more details in Chapter 2).

Since there are some very small rubber planted acreages in new rubber tree growing regions (or provinces) where the amount of rainfall is somewhat low in relation to that of traditional regions, average rainfall calculated based on every rubber region may be biased. Thus, average rainfall data used in this study are calculated from the amount of annual rainfall in major provinces[50] where rubber tree planted acreages are more than 8,000 hectares each year. Rainfall data are collected from the Agricultural Statistics of Thailand.

All nominal prices are deflated by the GDP deflator for Thailand (2005=100), which is obtained from the IFS, to obtain real prices. Natural logarithms of all series are used throughout. The variable definitions and data sources are summarised in Table 6.1.

[50] In 2009, Thailand comprises of 76 provinces, but the rainfall data of major rubber growing provinces are included in this study.

Table 6.1 Definition of Variables and Data Sources

Variables	Definition	Source
lnPLTA	Natural logarithms of planted rubber acreage (hectare)	OAE
lnTAPA	Natural logarithms of rubber acreage being tapped (hectare)	OAE
lnYLD	Natural logarithms of rubber yield (kilogramme/hectare)	OAE
lnQNT	Natural logarithms of rubber output (tonnes/hectare)	OAE
lnPNR	Natural logarithms of real price of rubber (baht/tonne)	OAE
lnPPAD	Natural logarithms of real price of paddy (baht/tonne)	IRRI and OAE
lnPPALM	Natural logarithms of real price of palm oil (baht/tonne)	FAOSTAT, OAE, and some parts calculated from data in IFS
lnPFER	Natural logarithms of real price of fertiliser (baht/tonne)	Calculated from data in the Agricultural Statistics of Thailand
lnWAGE	Natural logarithms of real wage rate (baht/year)	Calculated from data in the UN Statistics Yearbook, ILO database, and LFS
lnSUB	Natural logarithms of real net replanting subsidy per acreage (baht/hectare)	Calculated from data received from ORRAF, and Department of Customs
lnRAIN	Natural logarithms of average annual rainfall (millilitres)	Calculated from data in the Agricultural Statistics of Thailand
lnCVP	Natural logarithms of coefficient of variation of real rubber price (percentage)	Calculated from data received from OAE
lnSDP	Natural logarithms of standard deviation real rubber price (baht/tonne)	Calculated from data received from OAE

6.3 Graphical Analysis of the Data

Before we formally test for unit roots, it is useful to examine the time series graphically to identify whether trends and/or structural breaks exist. Graphs of the series (in logarithms) in levels and in first differences are illustrated in Figure 6.1–Figure 6.13 There are trends in the rubber planted acreage, lnPLTA, the rubber acreage being tapped, lnTAPA, the rubber yield, lnYLD, the rubber production, lnQNT. By contrast, it is not clear whether there is a trend in the real rubber price, lnPNR, the real paddy price, lnPPAD, the real Thai palm oil price, lnPPALM, the real fertiliser price, lnPFER, the real wage, lnWAGE, and the real net subsidy for replantings, lnSUB. However, it is clear that there is no trend in the rainfall, lnRAIN, the coefficient of variation of real rubber price, lnCVP, and the standard deviation of real rubber price, lnSDP. In the trended series, since their means and variances have changed over time, they are non-stationary in the level form. In first differences, all series do not show considerable changes in means and variances, and they appear stationary. It appears that there is no structural break in any series.

Figure 6.1 Rubber Planted Acreage

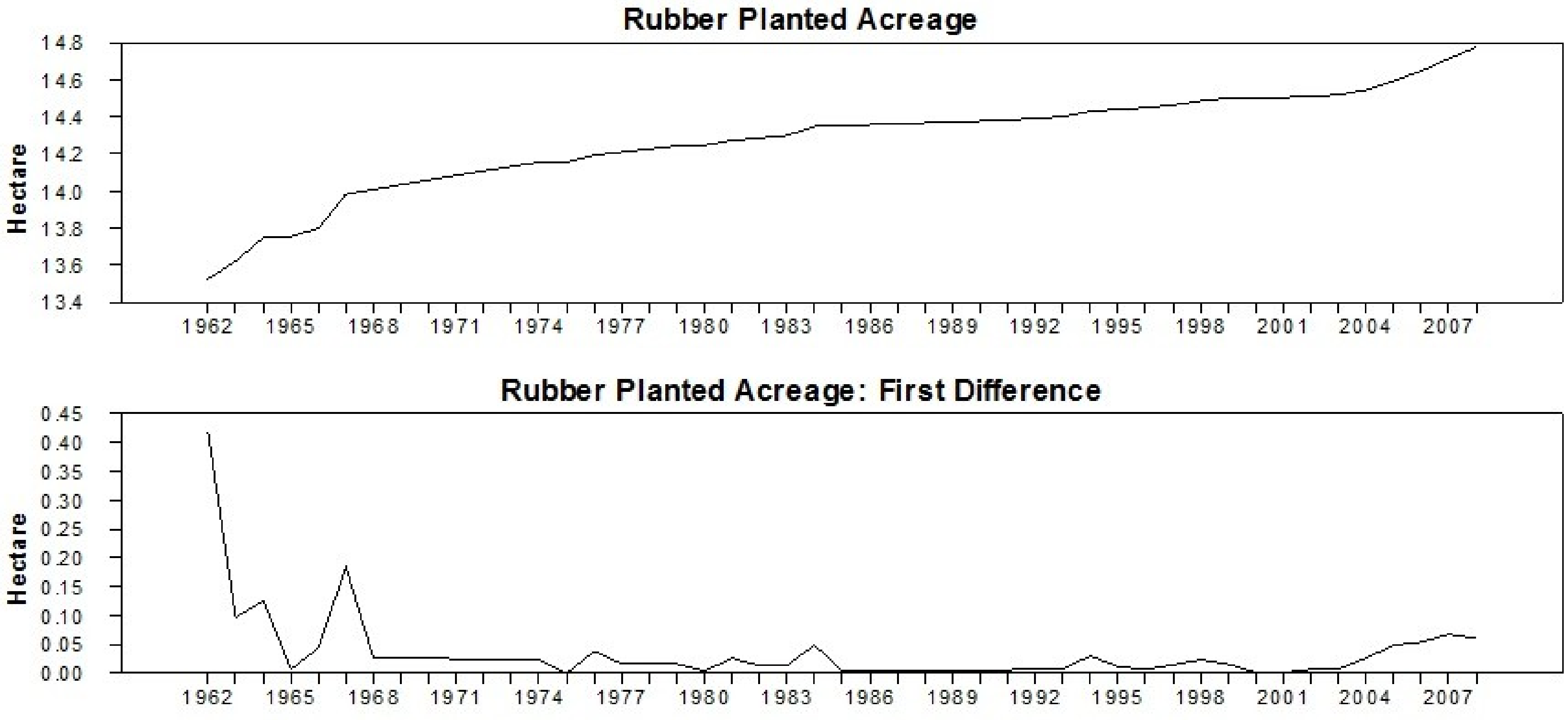


Figure 6.2 Rubber Acreage Being Tapped

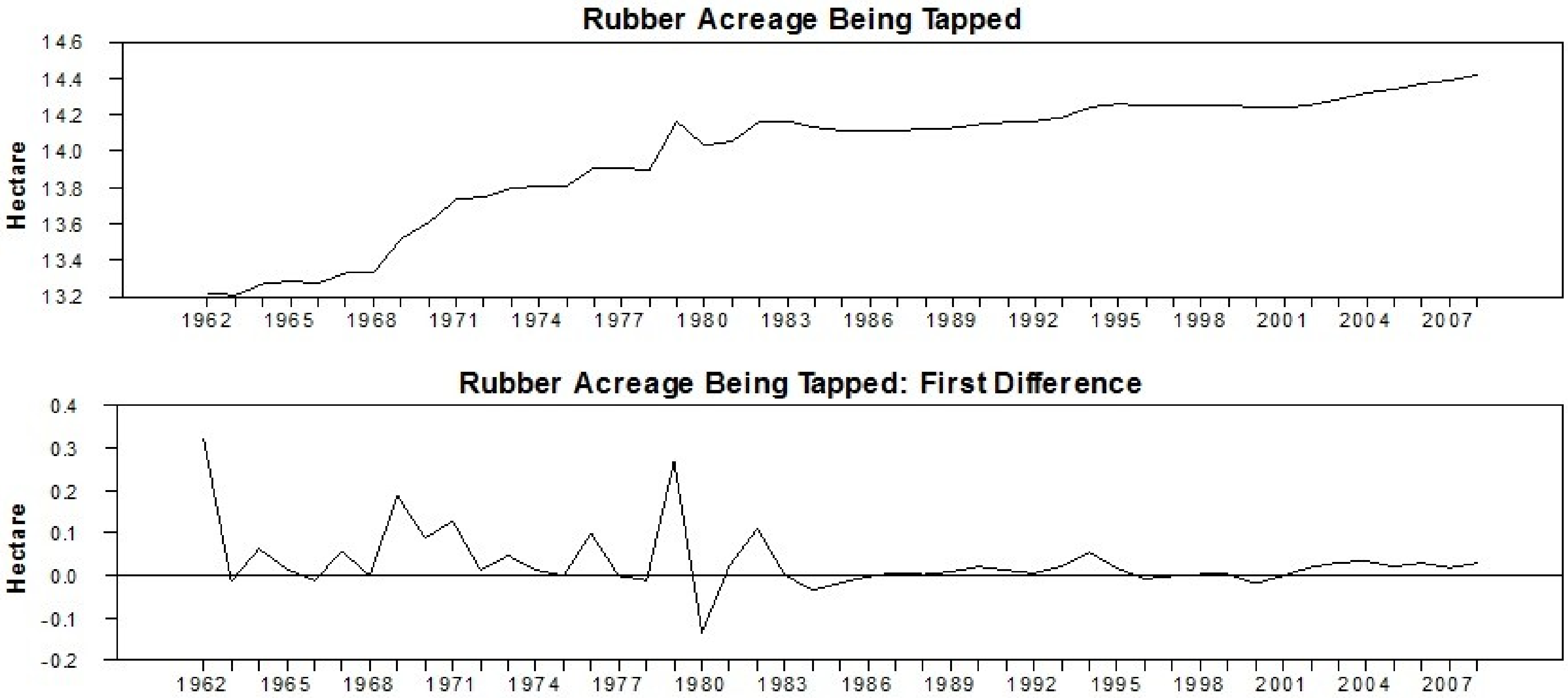


Figure 6.3 Rubber Yield

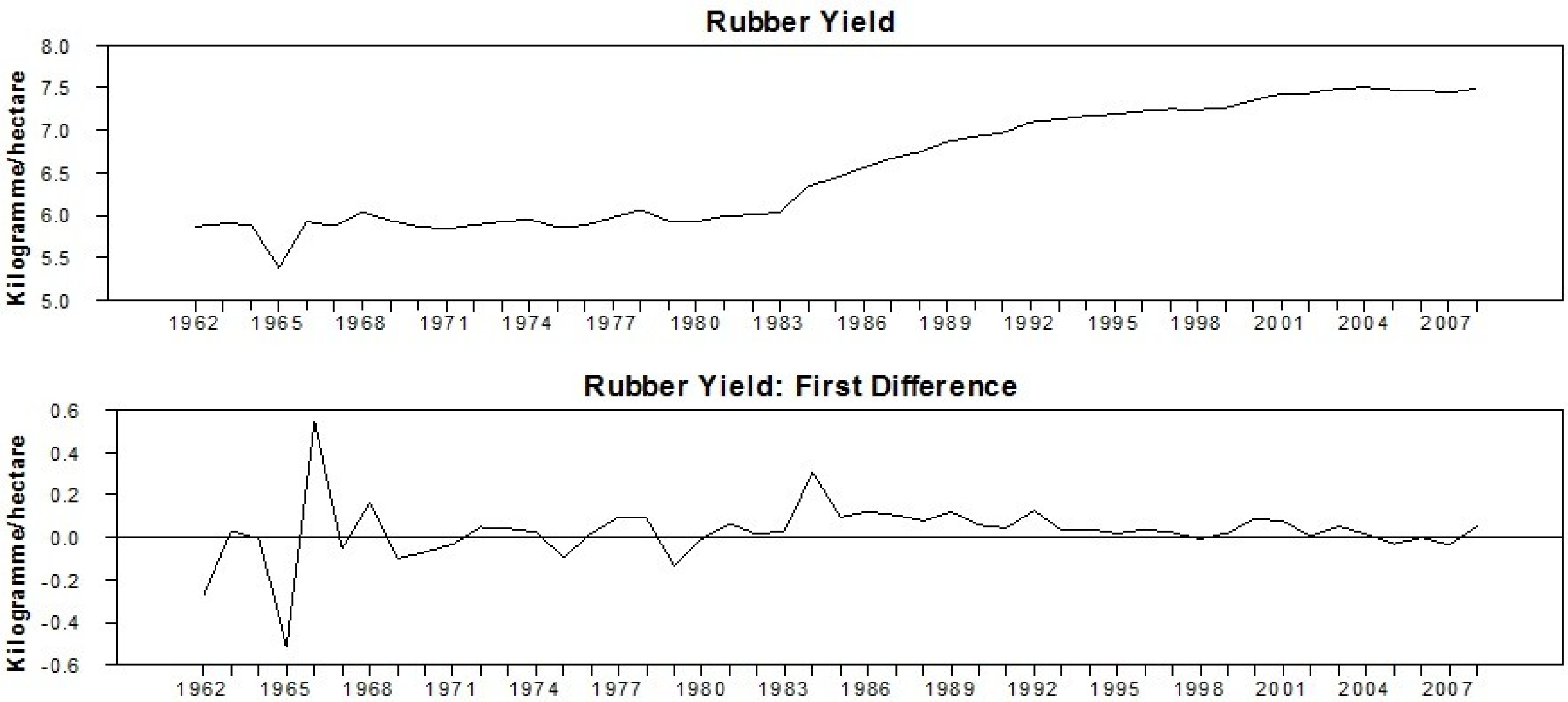


Figure 6.4 Rubber Production

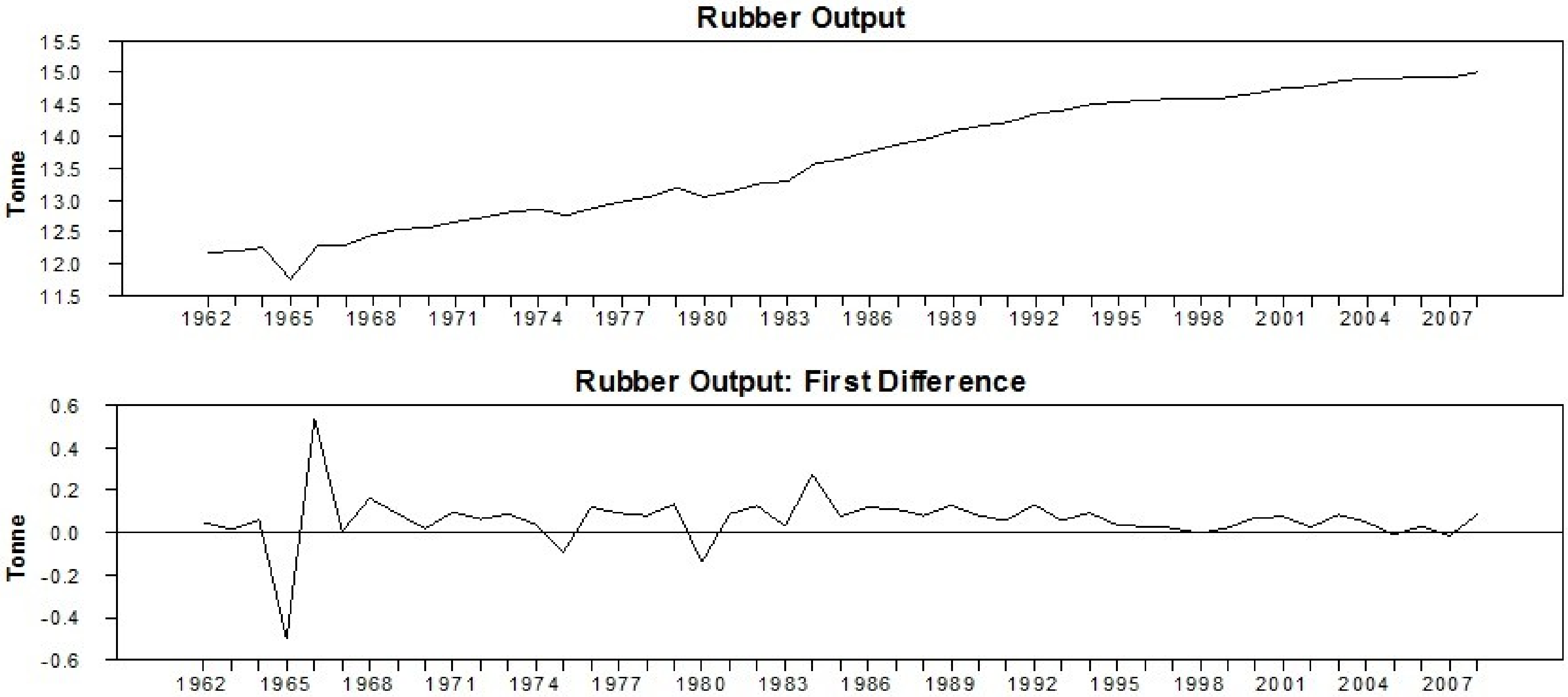


Figure 6.5 Real Rubber Price

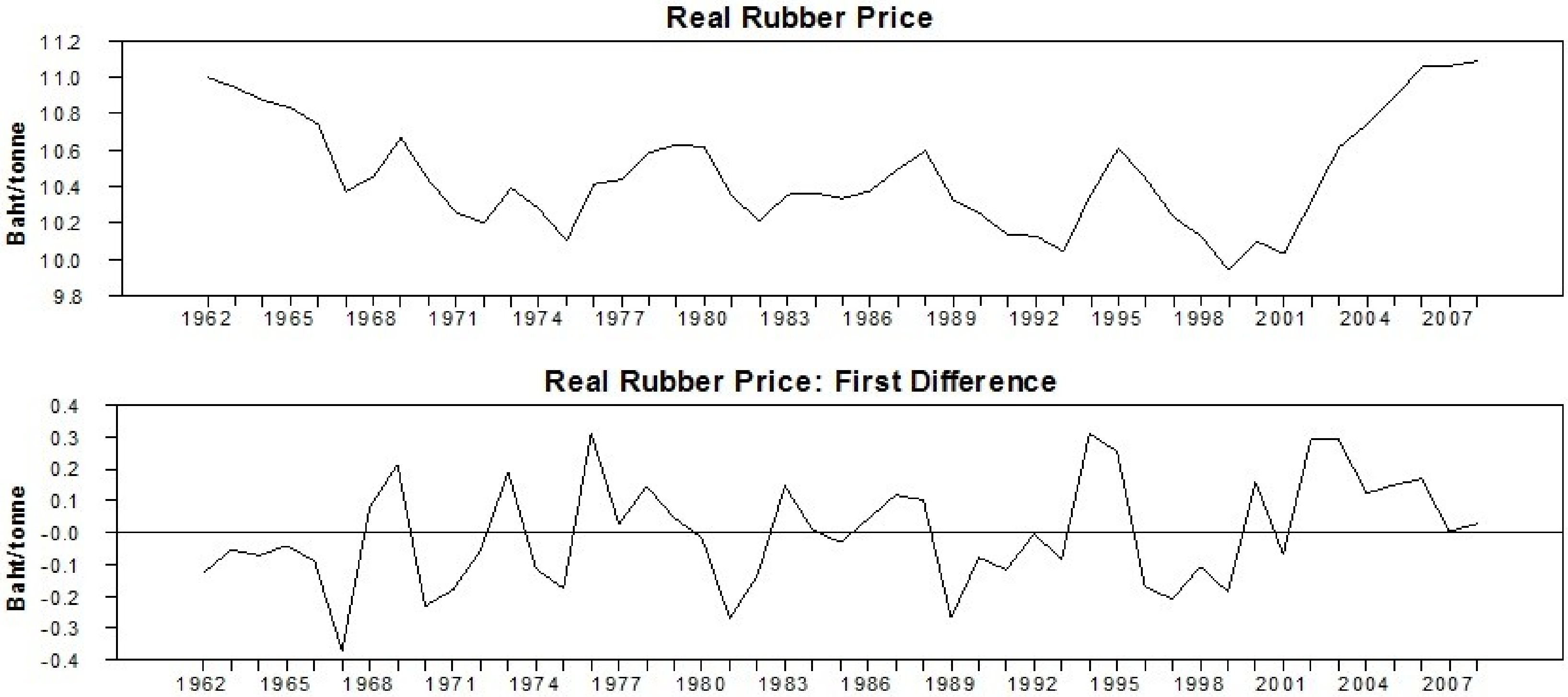


Figure 6.6 Real Paddy Price

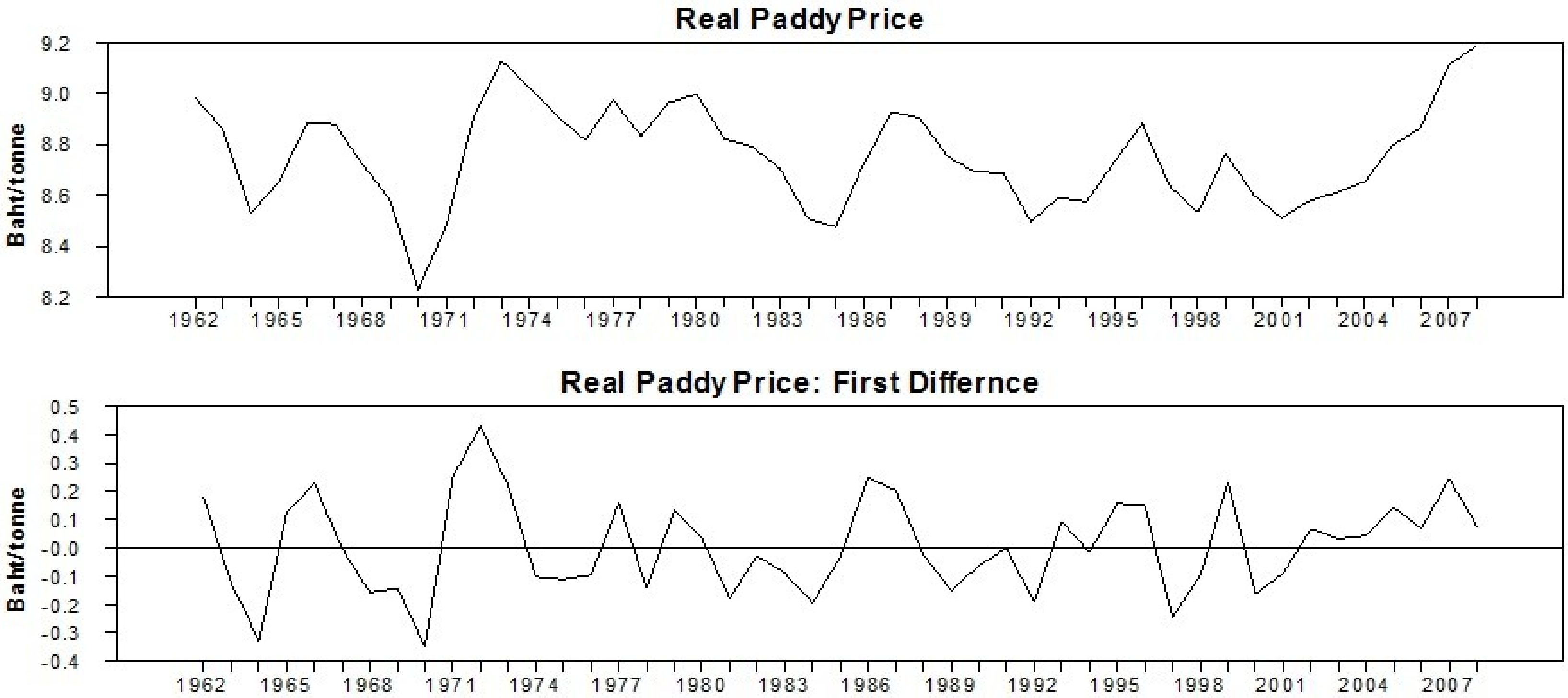


Figure 6.7 Real Palm Oil Price

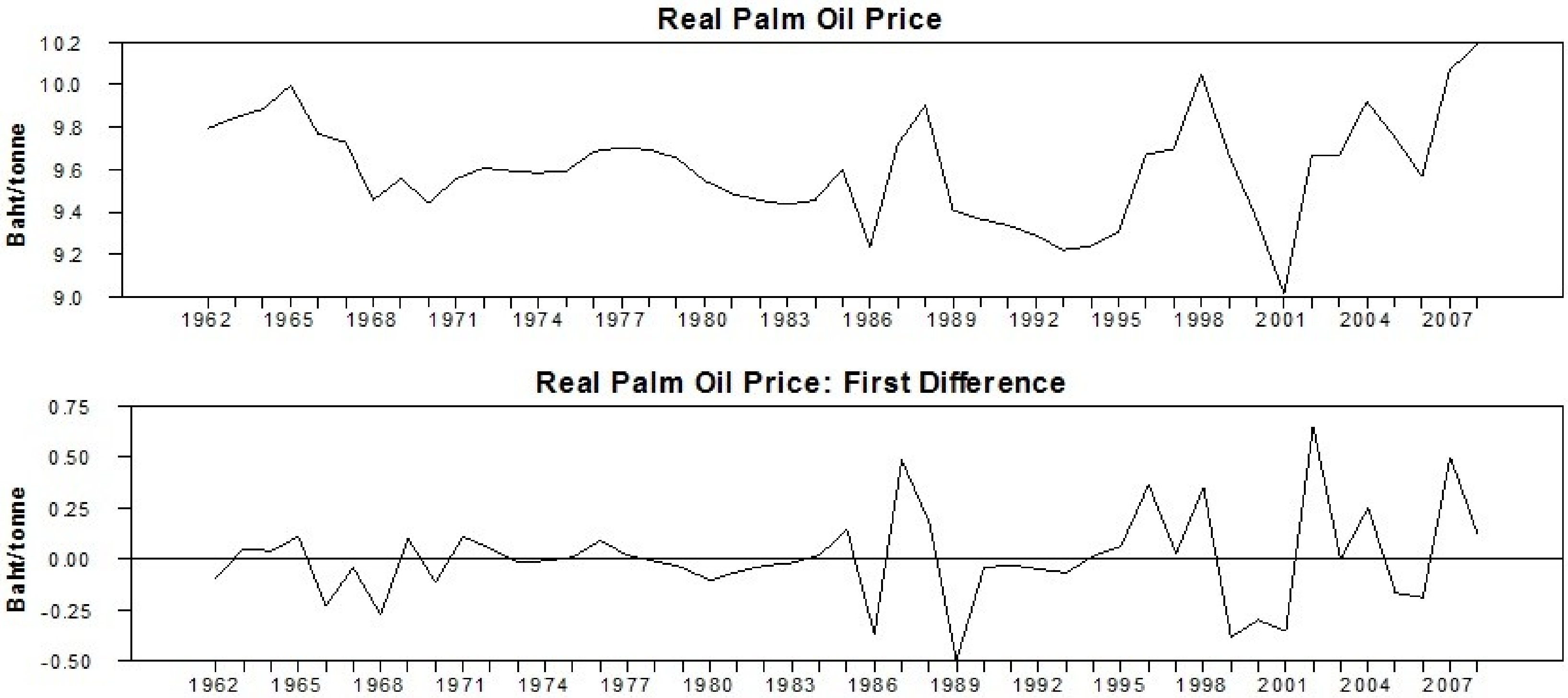


Figure 6.8 Real Fertiliser Price

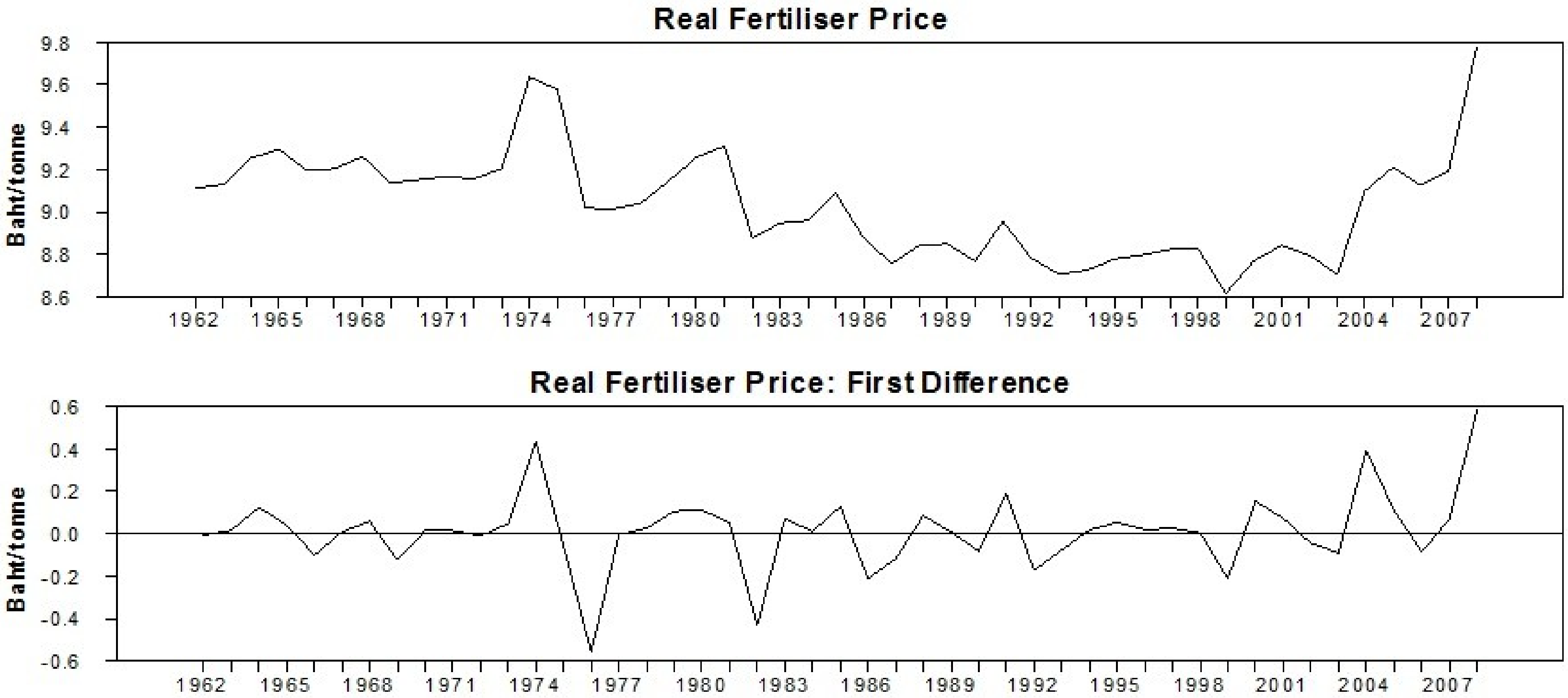


Figure 6.9 Real Wage Rate

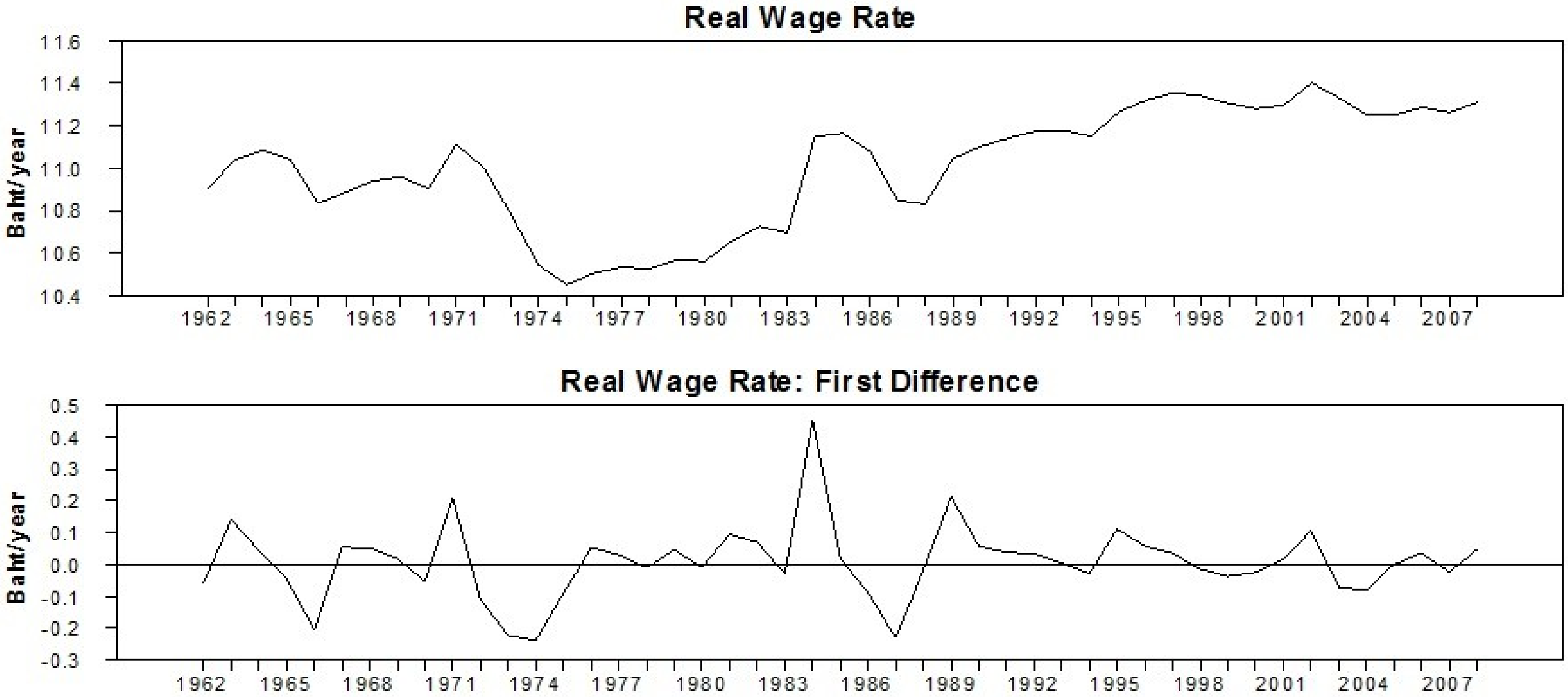


Figure 6.10 Real Net Subsidy for Replantings

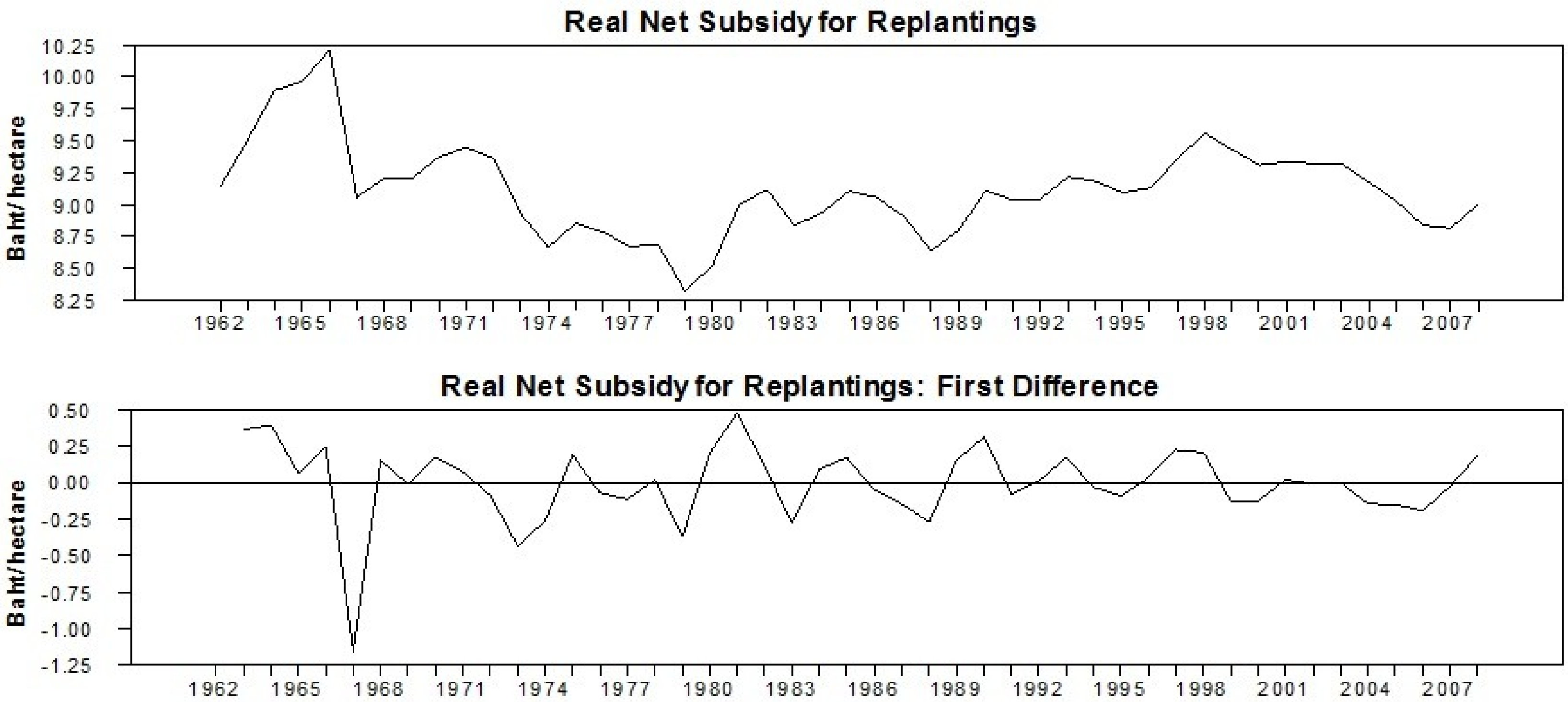


Figure 6.11 Rainfall

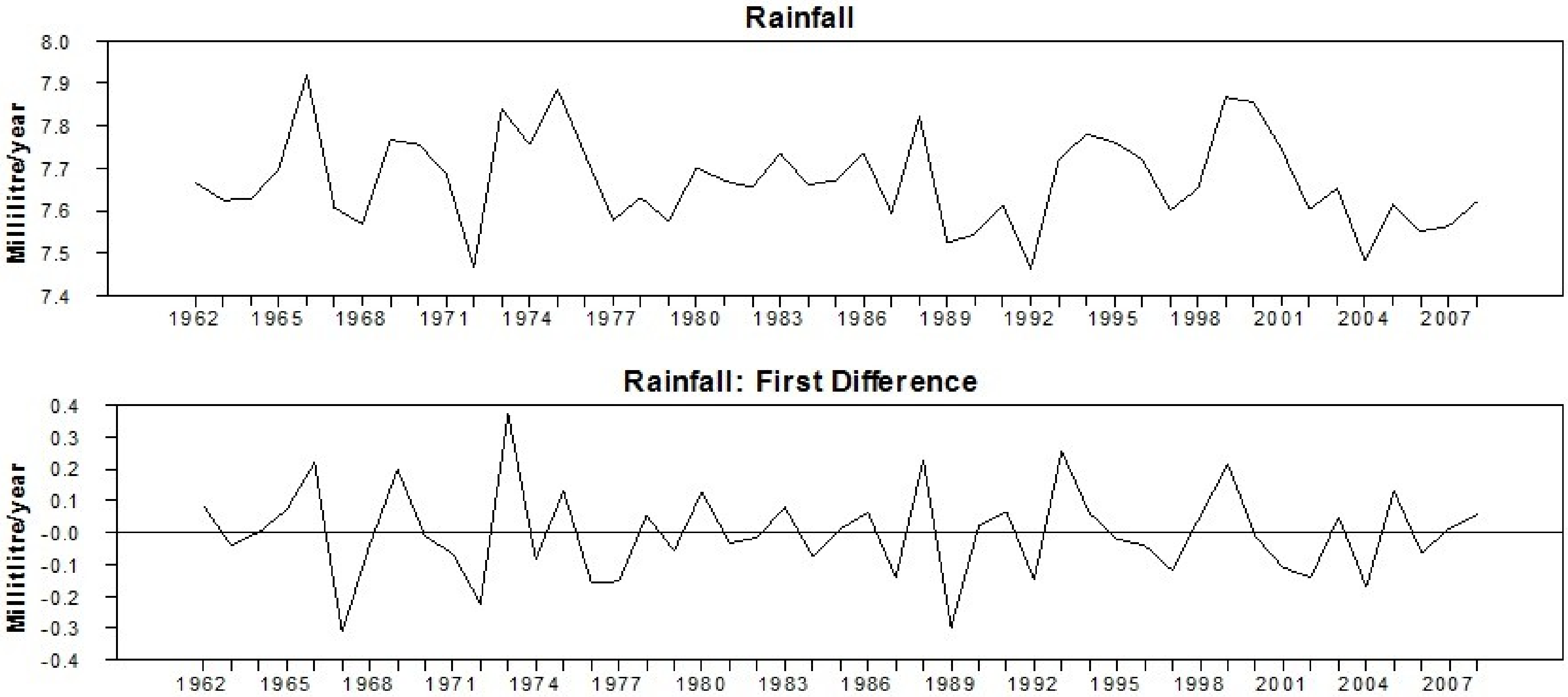


Figure 6.12 Coefficient of Variation of Real Rubber Price

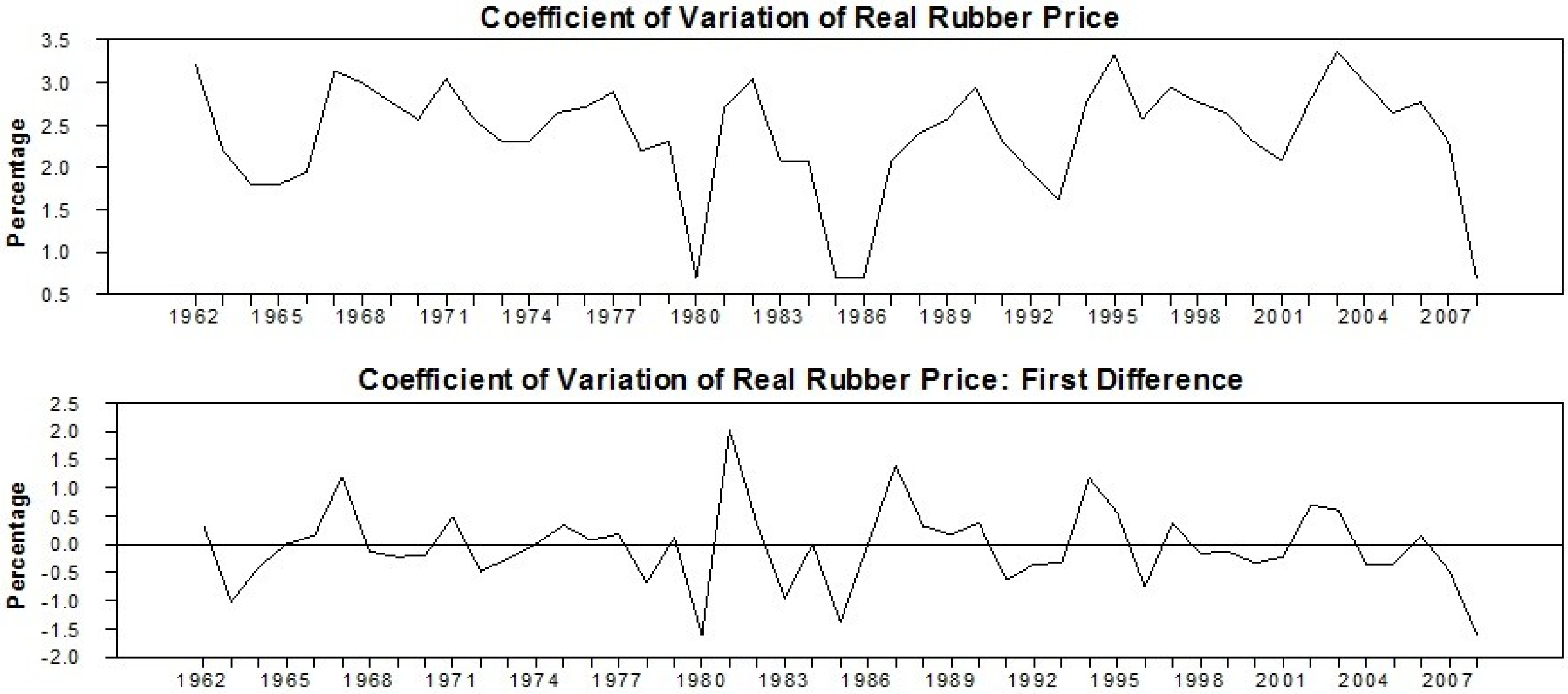
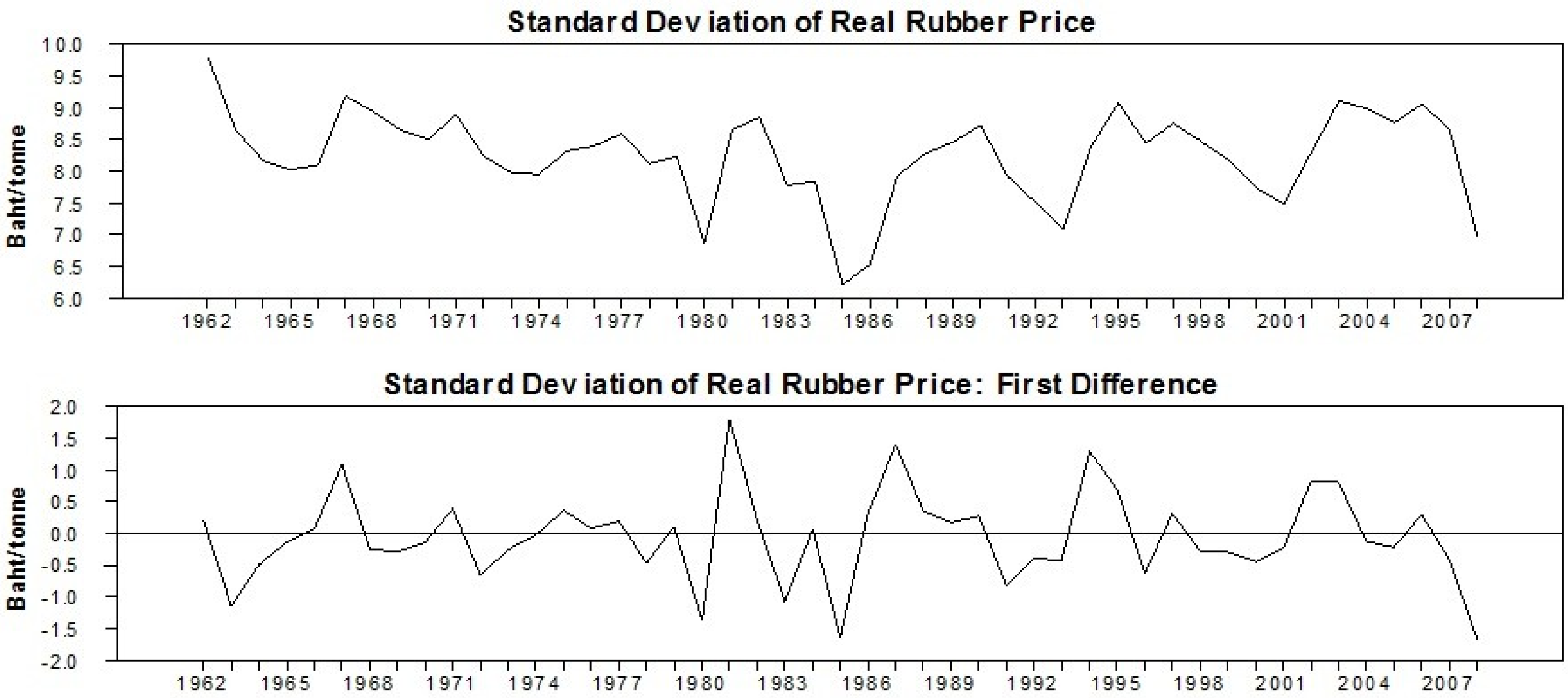


Figure 6.13 Standard Deviation of Real Rubber Price



6.4 Unit Root Tests

To test for the presence of unit roots, we perform augmented Dickey-Fuller (ADF) tests (Said and Dickey, 1984; Dickey and Fuller, 1981) following the sequential testing procedure outlined in Chapter 5. We first perform an ADF-test on each series in levels; the deterministic time trend is included in the test equation, and the null is of a unit root. The model used is that in Figure 5.6, which is rewritten again for convenience:

$$\Delta Y_t = \alpha_c + \gamma_c t + (\rho_c - 1)Y_{t-1} + \sum_{i=1}^{p-1} \varphi_i \Delta Y_{t-i} + u_t \qquad u_t \sim IID(0, \sigma^2) \tag{6.1}$$

where y_t is the series under consideration, t is a time trend, and u_t are white noise residuals. The optimum lag length p is chosen from the Bayesian information criterion (BIC). Throughout, hypothesis tests are carried out at the 5% significance level.

The results are presented in Table 6.1. The τ_τ-test implies that the null hypothesis of a unit root is accepted in all series except for the real paddy price, lnPPAD, rainfall, lnRAIN, and the risk variables, lnCVP and lnSDP, which appear to be I(0). The Φ_3-statistic is then estimated to test the joint null hypothesis of a unit root and no trend. This null in all series is accepted for those series except for lnPPAD, lnRAIN, lnCVP and lnSDP which appear trend stationary and the results from the τ_τ-test are supported.

We then perform ADF-tests to examine the null without trend. The τ_μ-test implies that the null is again rejected for lnPPAD, lnRAIN, lnCVP and lnSDP, and also for the palm oil price, lnPPALM. The joint null of a unit root and no constant using the F-statistic, Φ_1, is rejected for lnPPAD, lnPPALM, lnRAIN, lnCVP and lnSDP, and also for the rubber acreage being tapped, lnTAPA. This implies that the constant is significant under the null of a unit root and the standard t-statistic, instead of using the critical values from the DF-type distribution, is used to test the null applying in Table 5.2, 4a. The computed t-statistic of the coefficient of $lnTAPA_{t-1}$ is -4.20 with a critical value of 2.02 and the null of a unit root in lnTAPA is rejected. Thus, lnTAPA appears to be I(0). Removing the drift and trend from the null, we perform the τ-test which implies that the nulls of a unit root in lnPLTA and rubber production, lnQNT, are rejected and these series appear to be I(0).

We now perform ADF-tests on the first differences of the variables with a deterministic trend. The null that a variable contains two unit roots is tested against the alternative that it contains a unit root. The results indicate that the null of two unit roots for each variable is rejected. We conclude that the ADF-tests imply that lnPLTA, lnYLD, lnQNT, lnPNR, lnPFER and lnWAGE are I(1), while lnTAPA, lnPPAD, lnPPALM, lnTAPA and lnRAIN are I(0).

Table 6.2 Results of ADF-Tests

Variables	Obs.	Level					First Difference[51]	
		With trend		Without trend		Without trend and constant	With trend	
		τ_τ	Φ_3	τ_μ	Φ_1	τ	τ_τ	Φ_3
lnPLTA	47	-2.78 (2)	3.88	-0.93 (2)	3.93	3.68* (1)	-6.16* (0)	18.96†
lnTAPA	47	-1.72 (0)	3.72	-2.68** (2)	8.17††	1.95 (3)	-3.99* (2)	8.35†
lnYLD	47	-3.39 (0)	6.40	0.11 (0)	0.97	-1.08 (1)	-9.25*(0)	42.82†
lnQNT	47	-1.22 (5)	1.22	-1.10 (5)	2.95	3.27* (0)	-5.47* (4)	18.62†
lnPNR	47	-1.63 (0)	3.40	-2.03 (0)	2.06	-0.09 (0)	-6.06* (0)	18.48†
lnPPAD	47	-4.16* (1)	9.24†	-4.35* (1)	9.46††	0.27 (0)	-6.58*(1)	21.79†
lnPPALM	47	-3.04 (0)	5.18	-3.22* (0)	5.19††	0.13 (0)	-8.00* (0)	17.80†
lnPFER	47	-1.33 (0)	1.57	-1.78 (0)	1.73	0.48 (0)	-6.55* (1)	21.77†
lnWAGE	47	-2.34 (1)	2.81	-1.55 (1)	1.30	0.41 (0)	-5.69* (0)	16.21†
lnSUB	47	-2.63 (2)	3.72	-2.74 (2)	3.95	-0.67 (2)	-5.82* (1)	17.21†
lnRAIN	47	-5.78* (0)	16.74†	-5.70* (0)	16.22††	-0.27 (4)	-6.08* (3)	18.49†
lnCVP	47	-3.81* (0)	7.38†	-3.88* (0)	7.65††	-0.49 (0)	-6.96* (0)	24.37†
lnSDP	47	-3.93* (0)	7.70†	-3.93* (0)	7.92††	-0.83 (0)	-5.34* (5)	14.86†
Crit. value (n= 50)		-3.50	6.73	-2.93	4.86	-1.95	-3.50	6.73

Notes:
1) * denotes absence of unit root.
2) ** denotes absence of unit root based on t-statistic.
3) † denotes absence of unit root, with trend
4) †† denotes absence of unit root, with constant
5) The number of lags is given in parentheses.

To seek confirmation of the evidence obtained from the ADF-tests, we perform KPSS-tests where the null is stationary against the alternative of non-stationary. We perform these tests on all series in levels both with and without a deterministic trend. In a model with a trend, we find that the null of trend stationarity is rejected for all variables except for lnQNT, lnPPAD, lnPFER, lnRAIN, and lnCVP; but some variables exhibit borderline significance. In a model without a trend, the null of

[51] At this step, a trend variable should be excluded, but based on the Perron's (1988) testing procedure, we still keep it.

stationarity is accepted for lnPNR, lnPPAD, lnPPALM, lnPFER, lnSUB, lnRAIN, lnCVP, and lnSDP and these variables appear I(0).

Table 6.3 Results of KPSS-Tests

Variables	KPSS test with trend	KPSS test without trend
lnPLTA	0.19	1.00
lnTAPA	0.23	0.92
lnYLD	0.16	0.98
lnQNT	0.13*	1.03
lnPNR	0.15	0.16*
lnPPAD	0.08*	0.10*
lnPPALM	0.17	0.18*
lnPFER	0.16	0.43*
lnWAGE	0.16	0.61
lnSUB	0.17	0.18*
lnRAIN	0.06*	0.16*
lnCVP	0.10*	0.10*
lnSDP	0.16	0.20*
Critical Value	0.15	0.46

Note: * denotes absence of unit root.

The unit root test results are summarised in Table 6.4. Both ADF- and KPSS-tests indicate non-stationarity of lnPLTA, lnYLD and lnWAGE and we conclude that these variables are I(1). Similarly, both tests indicate that lnPPAD, lnRAIN, and lnCVP are I(0). For other series, the presence of a unit root is ambiguous. The ADF-test implies that lnTAPA is I(0) without a trend, but the KPSS-test indicates that it is I(1) with or without a trend. For lnQNT, the ADF-test implies that it is I(1) both with and without a trend, but the KPSS-test indicates that it is I(0) with a trend and I(1) without. The ADF-tests also imply that lnPNR, lnPFER, and lnSUB are I(1) both with and without a trend while KPSS-tests imply that these series are I(1) with a trend and I(0) without.

For lnPPALM, both ADF- and KPSS-tests imply that it is I(0) without a trend but I(1) with a trend. For the risk variable, lnSDP, the ADF-test implies that it is I(0) but the KPSS-test indicates that it is I(1) with a trend and I(0) without.

Table 6.4 Summary of Unit Root Tests

Variables	**ADF-Test**		**KPSS-Test**		**Decision**
	With trend	**Without trend**	**With trend**	**Without trend**	
lnPLTA	I(1)	I(1)	I(1)	I(1)	I(1)
lnTAPA	I(1)	I(0)	I(1)	I(1)	I(1)
lnQNT	I(1)	I(1)	I(0)	I(1)	I(1)
lnYLD	I(1)	I(1)	I(1)	I(1)	I(1)
lnPNR	I(1)	I(1)	I(1)	I(0)	I(1)
lnPPAD	I(0)	I(0)	I(0)	I(0)	I(0)
lnPPALM	I(1)	I(0)	I(1)	I(0)	I(0)
lnPFER	I(1)	I(1)	I(1)	I(0)	I(1)
lnWAGE	I(1)	I(1)	I(1)	I(1)	I(1)
lnSUB	I(1)	I(1)	I(1)	I(0)	I(1)
lnRAIN	I(0)	I(0)	I(0)	I(0)	I(0)
lnCVP	I(0)	I(0)	I(0)	I(0)	I(0)
lnSDP	I(0)	I(0)	I(1)	I(0)	I(0)

The discrepancy between the results of the two unit root tests may be a consequence of the computed statistics being close to critical values particularly in the case of KPSS-tests. For the purpose of subsequent analysis, it is widely accepted that it is better to assume initially that variables are non-stationary. The reason is that although an underlying series is actually stationary, regression results based on first differences (or error-correction mechanisms) are still valid and consistent, but they are less efficient. Conversely, if we postulate that a series is stationary whereas it is actually non-stationary, this error leads to inappropriate statistical inferences based on standard asymptotic results, that is, the spurious regression problem (Deb, 2003, p.14).

6.5 Summary and Conclusions

To examine the presence of unit root in each series, we perform the ADF test which tests the null of non-stationarity against the alternative of stationarity. Furthermore, to confirm the results of these tests, we also perform KPSS-tests which test the null of stationarity against the alternative of non-stationarity. Even though there are differences between the results of the two unit root tests, it is acceptable to assume primarily that variables are non-stationary. The unit root results in Table 6.4 indicate that the variables including lnPLTA, lnTAPA, lnQNT, lnYLD, lnPNR, lnPFER, lnWAGE and lnSUB are I(1) while some variables, lnPPAD, lnPPALM, lnRAIN, and lnCVP are I(0). For lnSDP we conclude that it is I(0) by reason of the usual characteristics of risk variables. These I(0) series cannot establish the long-run relationship between I(1) variables, but are permitted to come into the system as exogenous variables. We re-test for unit root each series using the LR-statistic in Johansen's multivariate framework. The unit root results imply that there is evidence of non-stationarity in these time series. Therefore, traditional regression analysis using these time series data in levels may produce spurious results. The next chapter we will examine the output and acreage-yield response models for natural rubber production in Thailand using Johanson's approach.

Chapter 7 Cointegration Results

7.1 Introduction

After establishing the order of integration of each series in Chapter 6, we perform cointegration tests. Two or more series are cointegrated if they are integrated of the same order and a linear combination of these series exists which is integrated to an order lower than the individual variables. In this study, we apply Johansen's (2002b; 2000) multivariate full information maximum likelihood procedure. Then, we obtain short- and long-run elasticities by transforming the model into a vector error correction model (VECM). Impulse response analysis is also performed to illustrate the path of adjustment to long-run equilibrium when the system is shocked. Two models for both output response and acreage-yield response are examined using annual data for 1962-2008. All computations reported are performed in CATS 2.0 in RATS 6.35 while impulse response analysis uses MALCOLM in RATS 5.11.

The chapter is organised as follows. Section 7.2 presents the tests for cointegration in both the output and acreage-yield response models. Section 7.3 presents results of the impulse response analysis. Section 7.4 compares the results here with those of previous studies. The final section summarises.

7.2 Cointegration Test Results

This section examines cointegration in both an output response and an acreage-yield response model. If cointegration exists, there is a meaningful long-run equilibrium relationship between variables, and formulating the relationship as a VECM provides consistent estimates of both long-run and short-run elasticities. To test for cointegration, we apply Johansen's (2002b; 2000) multivariate cointegration procedure.

7.2.1 The Output Response Model

From the theoretical economic model of output response in Chapter 4, Section 4.6.1 or Equation (4.90), we hypothesise that rubber output is a function of the real rubber price, lnPNR, the two real competing crop prices of paddy and/or palm oil, lnPPAD and lnPPALM, the real fertiliser price, lnPFER, the real wage rate, lnWAGE, the real net replanting subsidy, lnSUB, rainfall, lnRAIN, and risk variables, lnCVP or lnSDP. The two competing crop prices are included initially then jointly, but we could not find a cointegrating relationship and we exclude competing crop prices from further consideration. Even though the unit root tests suggest that lnPPAD and lnPPALM are stationary or I(0), the tests of stationarity based on the Johansen's cointegration approach indicate that the nulls of stationarity are rejected, so both variables appear here to be I(1). Therefore, we perform a cointegration test by setting lnPPAD and/or lnPPALM to be either I(0) or I(1) but no cointegrating vector is found. This may imply that there is no competing crop for rubber production. Similarly, we also exclude the wage rate, the subsidy, rainfall, and both risk variables because we could not find a cointegrating relationship (See Appendix 7.1 for cointegration results of these other models.)

We postulate that rubber output is a function of the real rubber price and the real fertiliser price only. Following Juselius (2006), we apply misspecification tests to examine the properties of the residuals of an unrestricted VAR. The results in Table 7.1 show that the trace correlation, which is an overall measure of goodness of fit, is 0.14. It is similar to R^2 in the traditional linear regression analysis (Juselius, 2006, p.73), that is, a large value is desirable. The Ljung-Box and the LM-tests indicate no autocorrelation up to second-order, but the multivariate Hansen-Doornik normality test shows non-normality. The first-order ARCH-test rejects the hypothesis of no heteroscedasticity, but that for second-order suggests that the null is accepted.

Table 7.1 Misspecification Tests for the Output Response Model without Dummies

Tests	Statistics
Trace Correlation	0.14
Tests for Autocorrelation	
Ljung-Box(11)	$\chi^2(90) = 71.85$ (0.92)
LM(1)	$\chi^2(9) = 15.37$ (0.08)
LM(2)	$\chi^2(9) = 10.72$ (0.30)
Test for Normality	$\chi^2(6) = 102.24$ (0.00)
Test for ARCH	
LM(1)	$\chi^2(36) = 56.68$ (0.01)
LM(2)	$\chi^2(72) = 84.84$ (0.14)

Note: p-values in the parentheses.

Four short-run impulse dummies for 1965, 1966, 1974 and 2008, which are denoted as D65, D66, D74 and D08, are included to improve the properties of the residuals. These dummies are selected based on the criterion that the standardised residuals exceed a threshold at 1.96 (the critical t value at the 0.05 confidence level). D74 and D08 can be interpreted as dummies for oil price shocks. Misspecification tests are again performed and the results are shown in Table 7.2. The trace correlation increases to 0.52. Even though the Ljung-Box test rejects the hypothesis of no autocorrelation, the LM-tests indicate no autocorrelation up to second-order. The

Hansen-Doornik test still implies non-normality; and ARCH-tests up to second-order imply no heteroscedasticity. Since the residuals are non-normal, significance tests should be treated with caution.

Table 7.2 Misspecification Tests for the Output Response Model with Dummies

Tests	Statistics
Trace Correlation	0.52
Tests for Autocorrelation	
Ljung-Box(11)	$\chi^2(90) = 131.78\ (0.00)$
LM(1)	$\chi^2(9) = 9.66\ (0.38)$
LM(2)	$\chi^2(9) = 5.69\ (0.77)$
Test for Normality	$\chi^2(6) = 31.01\ (0.00)$
Test for ARCH	
LM(1)	$\chi^2(36) = 50.47\ (0.06)$
LM(2)	$\chi^2(72) = 81.32\ (0.21)$

Note: p-values in the parentheses.

i) Lag Length Determination

The dynamics of the model are determined by lag length. The first step of Johansen's procedure is to select the order of, or the number of lags, in the VAR. For convenience, the VAR is rewritten as:

$$Z_t = A_1 Z_{t-1} + \ldots + A_k Z_{t-k} + u_t \tag{7.1}$$

The VAR lag length/reduction tests are performed with a maximum of five lags. The results in Table 7.3 indicate that the VAR with order one provides minimum values of the Schwarz Bayesian Criterion (SC) and the Hannan-Quinn Criterion (HQ). We also perform the LR-test for lag length determination. The results are shown in the second part of Table 7.3 and we expect the first hypotheses to be accepted and higher lags to be rejected, but the results are ambiguous. We therefore use only the SC and HQ criteria.

Table 7.3 Determining the Order of the VAR for the Output Response Model

Variables included in the unrestricted VAR : lnQNT lnPNR lnPFER
Deterministic and/or exogenous variables : Constant

Model	**SC**	**HQ**
VAR(5)	-9.91	-11.48
VAR(4)	-10.33	-11.67
VAR(3)	-10.86	-11.96
VAR(2)	-11.33	-12.20
VAR(1)	-11.67	-12.30
Lag Reduction Tests	**Statistics**	
VAR(4)<<VAR(5)	$\chi^2(9) = 15.85$ (0.07)	
VAR(3)<<VAR(5)	$\chi^2(18) = 27.39$ (0.07)	
VAR(3)<<VAR(4)	$\chi^2(9) = 11.54$ (0.24)	
VAR(2)<<VAR(5)	$\chi^2(27) = 41.01$ (0.04)	
VAR(2)<<VAR(4)	$\chi^2(18) = 25.15$ (0.12)	
VAR(2)<<VAR(3)	$\chi^2(9) = 13.62$ (0.14)	
VAR(1)<<VAR(5)	$\chi^2(36) = 60.37$ (0.01)	
VAR(1)<<VAR(4)	$\chi^2(27) = 44.52$ (0.02)	
VAR(1)<<VAR(3)	$\chi^2(18) = 32.98$ (0.02)	
VAR(1)<<VAR(2)	$\chi^2(9) = 19.37$ (0.02)	

Note: p-values in the parentheses.

ii) Reduced Rank Test

The next step in Johansen's procedure is to perform the reduced rank test using trace statistics to test for the presence and number of cointegrating vectors. The asymptotic distribution of the standard rank test statistics following Johansen (1995; 1988) may be poor due to the actual finite sample distribution and the Bartlett small sample correction of the trace test derived in Johansen (2002b; 2000) is used. This correction is also applied to hypothesis tests on $\boldsymbol{\beta}$. The results in Table 7.4 indicate one cointegrating vector and there is a unique long-run equilibrium relationship among the variables. Using the Pantula principle, Model 3, with an unrestricted constant and trend, is the preferred model. This means that TIMEt, as a proxy for technological change, is automatically excluded because this variable is only included in Model 4.

Table 7.4 Johansen Cointegration Results for the Output Response Model

Variables included in the unrestricted VAR : lnQNT lnPNR lnPFER
Deterministic and/or exogenous variables : Constant D65 D66 D74 D08

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	3	70.65 (0.00)	40.57 (0.00)	51.10 (0.00)
1	2	28.54 (0.00)	12.21 (0.15)*	18.20 (0.34)
2	1	4.57 (0.35)	4.51 (0.03)	4.94 (0.61)

Notes: 1) p-values in the parentheses.
2) * indicates where the null is accepted for the first time moving through the table row by row from left-to-right.

iii) Johansen Normalised Estimates

The normalised rubber output equation is:

$$lnQNT = 3.04lnPNR - 7.64lnPFER \tag{7.2}$$

The parameter estimates in an identified cointegrating relationship such as (7.2) can be interpreted as *ceteris paribus* estimates of long-run elasticities (Johansen, 2005). Those in (7.2), i.e., 3.04 and -7.64, are estimated long-run elasticities of rubber output with respect to own price and to the fertiliser price, respectively, and both have *a priori* expected signs. We apply misspecification tests to examine the properties of the residuals in (7.2) and the results are shown in Table 7.5. The trace correlation is 0.47; the Ljung-Box test rejects the null of non-autocorrelation but the LM-test for up to second-order does not; the Hansen-Doornik test implies non-normality; and the first-order ARCH-test rejects the hypothesis of no heteroscedasticity, but that for second-order suggests that the null is accepted.

Table 7.5 Misspecification Tests for the Output Response Model

Tests	**Statistics**
Trace Correlation	0.47
Tests for Autocorrelation	
Ljung-Box(11)	$\chi^2(96) = 125.32\ (0.02)$
LM(1)	$\chi^2(9) = 6.26\ (0.71)$
LM(2)	$\chi^2(9) = 10.25\ (0.33)$
Test for Normality	$\chi^2(6) = 25.21\ (0.00)$
Test for ARCH	
LM(1)	$\chi^2(36) = 59.44\ (0.01)$
LM(2)	$\chi^2(72) = 85.64\ (0.13)$

Note: p-values in the parentheses.

iv) Hypothesis Testing

Given cointegration, we test three types of restrictions on the parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ and the results are shown in Table 7.6. First, we test the null of stationarity for each variable using LR-statistics, that is, $\beta_{PNR} = \beta_{PFER} = 0$, $\beta_{QNT} = \beta_{PFER} = 0$, and $\beta_{QNT} = \beta_{PNR} = 0$. Results indicate that all nulls are rejected and all variables are non-stationary. Second, we test the nulls of variable exclusion, that is, $\beta_{QNT} = 0$, $\beta_{PNR} = 0$, and, $\beta_{PFER} = 0$: all nulls are rejected and all coefficients are significant. Third, the nulls of weak exogeneity are tested, that is, $\beta_{QNT} = 0$, $\alpha_{PNR} = 0$, and $\alpha_{PFER} = 0$, and results suggest that the null for lnPFER is rejected while those for lnQNT and lnPNR are accepted, and we conclude that lnQNT and lnPNR are weakly exogenous.

Table 7.6 Hypothesis Testing for Output Response Model

Tests	H_0	LR-Statistics
Test of Stationarity		
lnQNT	$\beta_{PNR} = \beta_{PFER} = 0$	24.46 (0.00)
lnPNR	$\beta_{QNT} = \beta_{PFER} = 0$	20.43 (0.00)
lnPFER	$\beta_{QNT} = \beta_{PNR} = 0$	15.57 (0.00)
Test of Variable Exclusion		
lnQNT	$\beta_{QNT} = 0$	6.75 (0.01)
lnPNR	$\beta_{PNR} = 0$	7.99 (0.01)
lnPFER	$\beta_{PFER} = 0$	19.19 (0.00)
Test of Weak Exogeneity		
lnQNT	$\alpha_{QNT} = 0$	0.28 (0.60)
lnPNR	$\alpha_{PNR} = 0$	20.43 (0.34)
lnPFER	$\alpha_{PFER} = 0$	15.57 (0.00)

Note: p-values in the parentheses.

v) Weak Exogeneity and the Partial Model

Since lnQNT and lnPNR are weakly exogenous, it is possible to obtain a more appropriate partial model by conditioning on lnPNR. The partial model is estimated with one lag and one cointegrating vector.[52] After normalising the long-run cointegrating vector on lnQNT, we obtain the cointegrating vector:

$$\text{lnQNT} = -8.03\text{lnPFER} + 2.94\text{lnPNR} \tag{7.3}$$

The long-run price elasticity of rubber output is estimated to be 2.94 and has the *a priori* expected sign while the long-run elasticity of rubber output to fertiliser price is estimated to be -8.03 and is negative as expected. Misspecification tests are applied to check the properties of the residuals and the results are shown in Table 7.7.

[52] Even though it is unnecessary to perform the lag length test and the cointegration rank test again, the VAR lag length test and Johansen's reduced rank test applied on the partial output model also indicate one lag and one cointegrating vector, and Model 3, with a restricted constant and no trend, is appropriate.

Table 7.7 Misspecification Tests for the Output Response Model (in the Partial System)

Tests	Statistics
Trace Correlation	0.69
Tests for Autocorrelation	
Ljung-Box(11)	$\chi^2(42) = 73.83$ (0.00)
LM(1)	$\chi^2(4) = 1.22$ (0.88)
LM(2)	$\chi^2(4) = 5.02$ (0.29)
Test for Normality	$\chi^2(4) = 24.02$ (0.00)
Test for ARCH	
LM(1)	$\chi^2(9) = 11.82$ (0.22)
LM(2)	$\chi^2(18) = 24.37$ (0.14)

Note: p-values in the parentheses.

The trace correlation is 0.69 which is higher than that in the full model. Although the Ljung-Box test implies autocorrelation, the LM-test for up to second-order indicates its absence. The Hansen-Doornik test again indicates non-normality. The second-order ARCH-test reveals no heteroscedasticity. Thus, the properties of the residuals generally improve but non-normality remains.

Once more, we perform three hypothesis tests on the partial output response model and the results are shown in Table 7.8. In the partial model, there are two stationarity tests and two weak exogeneity tests, since lnPNR has been already set to be an exogenous variable. Testing for stationarity of each variable, that is $\beta_{PFER} = 0$ and $\beta_{QNT} = 0$, indicates that the nulls are rejected and we conclude that both lnQNT and lnPFER are non-stationary. The nulls of variable exclusion, that is, $\beta_{QNT} = 0$, $\beta_{PFER} = 0$, and $\beta_{PNR} = 0$, are rejected and all coefficients are significant. The null of weak exogeneity of lnQNT, that is, $\alpha_{QNT} = 0$ is accepted while that of lnPFER, that is, $\alpha_{PFER} = 0$ is rejected. This result implies that lnQNT is a weakly exogenous variable and since lnQNT is the dependent variable, we go no further and conclude that an appropriate output response model is not found. Thus, an output supply response model appears inappropriate to explain supply response of rubber production of Thailand.

Table 7.8 Hypothesis Tests for the Partial Output Response Model

Tests	H_0	LR-Statistics
Test of Stationarity		
lnQNT	$\beta_{PFER} = 0$	19.13 (0.00)
lnPFER	$\beta_{QNT} = 0$	6.13 (0.01)
Test of Individual exclusion		
lnQNT	$\beta_{QNT} = 0$	6.13 (0.01)
lnPFER	$\beta_{PFER} = 0$	19.13 (0.00)
lnPNR	$\beta_{PNR} = 0$	7.11 (0.01)
Test of Weak exogeneity		
lnQNT	$\alpha_{QNT} = 0$	0.53 (0.47)
lnPFER	$\alpha_{PFER} = 0$	17.08 (0.00)

Note: p-values in the parentheses.

7.2.2 The Acreage-Yield Response Model

The acreage-yield response model consists of two sub-models for the responses of acreage and yield. According to the theoretical economic model of acreage response in Chapter 4, Section 4.6.2 or Equation (4.98), we hypothesise that the planted rubber acreage, lnPLTA, or the acreage being tapped, lnTAPA, is a function of the real rubber price, lnPNR, the real competing crop prices of paddy and/or palm oil, lnPPAD and lnPPALM, the real wage rate, lnWAGE, the real net replanting subsidy, lnSUB, and risk factors, lnCVP or lnSDP. As in the output response model, the two competing crop prices are excluded from further consideration since we could not find a cointegrating relationship which includes them. Further, we eliminate the wage rate, and risk variables for the same reason. (See Appendix 7.2 for cointegration results of these other models.) As a result, rubber acreage is assumed to be a function only of its own price and the replanting subsidy. Misspecification tests are applied to examine the properties of the residuals of the unrestricted VAR and the results are shown in Table 7.9. The trace correlation is 0.24; the Ljung-Box and the first-order LM-tests accept the hypothesis of no autocorrelation, but the second-order LM-test rejects the null; the Hansen-Doornik test implies non-normality; and ARCH-tests up to second-order imply evidence of heteroscedasticity.

Table 7.9 Misspecification Tests for the Acreage Response Model without Dummies

Tests	Statistics
Trace Correlation	0.24
Tests for Autocorrelation	
Ljung-Box(11)	χ^2 (90) = 92.45 (0.41)
LM(1)	χ^2 (9) = 10.91 (0.28)
LM(2)	χ^2 (9) = 28.25 (0.00)
Test for Normality	χ^2 (6) = 34.92 (0.00)
Test for ARCH	
LM(1)	χ^2 (36) = 52.83 (0.04)
LM(2)	χ^2 (72) = 132.26 (0.00)

Note: p-values in the parentheses.

Two short-run impulse dummies, D65 and D67, are included to improve statistical credentials. Misspecification tests on the residuals in Table 7.10 are generally acceptable: the trace correlation is 0.46; the Ljung-Box test indicates some autocorrelation, but LM-tests indicate no autocorrelation up to second-order; the

Hansen-Doornik test implies normality; and the ARCH-tests up to second-order imply no evidence of heteroscedasticity.

Table 7.10 Misspecification Tests for the Acreage Response Model with Dummies

Tests	Statistics
Trace Correlation	0.46
Tests for Autocorrelation	
Ljung-Box(11)	$\chi^2(90) = 168.95$ (0.00)
LM(1)	$\chi^2(9) = 16.22$ (0.06)
LM(2)	$\chi^2(9) = 12.64$ (0.18)
Test for Normality	$\chi^2(6) = 8.77$ (0.19)
Test for ARCH	
LM(1)	$\chi^2(36) = 21.11$ (0.98)
LM(2)	$\chi^2(72) = 91.46$ (0.06)

Note: p-values in the parentheses.

As an alternative to the planted acreage response model, we consider a tapped rubber acreage response model but we find no cointegrating relationship. Thus, the planted acreage response model appears more appropriate for explaining farmers' behaviour than the tapped acreage response model and we discard the latter. (See Appendix 7.3 for cointegration results of models using lnTAPA.)

According to the theoretical economic model of acreage-yield response in Chapter 4, Section 4.6.2 or Equation (4.105), we hypothesise that rubber yield, lnYLD, is expected to be a function of the rubber price, the competing crop prices of paddy and/or palm oil, lnPPAD and lnPPALM, the fertiliser price, lnPFER, the wage rate, lnWAGE, rainfall, lnRAIN, and risk variables, lnCVP and/or lnSDP. However, we find that the rubber price, both competing crop prices, the wage rate, and risk variables have no effect on rubber yield, and we postulate yield to be a function of the fertiliser price and rainfall only. (See Appendix 7.4 for cointegration results of these other models). It might be argued then that the replanting subsidy programme could induce technological change in rubber production. New technology possibly spread to rubber farmers via farmers joining the replanting programme because they have more opportunities to access high-yielding rubber varieties, fertilisers, new information, and other supports. Therefore, we include lnSUB into the yield response model but we could not find a cointegrating vector among variables. Misspecification tests are performed to examine the properties of the residuals. The results in Table 7.11 show that the trace correlation is low at 0.08; both Ljung-Box and LM-tests indicate no autocorrelation up to second-order; the Hansen-Doornik test implies non-normality; and ARCH-tests up to second-order imply no evidence of heteroscedasticity.

Table 7.11 Misspecification Tests for the Yield Response Model without Dummies

Tests	Statistics
Trace Correlation	0.08
Tests for Autocorrelation	
Ljung-Box(11)	$\chi^2(40) = 29.07\ (0.90)$
LM(1)	$\chi^2(4) = 6.93\ (0.14)$
LM(2)	$\chi^2(4) = 6.88\ (0.14)$
Test for Normality	$\chi^2(4) = 96.42\ (0.00)$
Test for ARCH	
LM(1)	$\chi^2(9) = 12.15\ (0.21)$
LM(2)	$\chi^2(18) = 16.03\ (0.59)$

Note: p-values in the parentheses.

Four short-run impulse dummies, D65, D66, D74 and D08, are included to improve statistical credentials. All misspecification tests on the residuals in Table 7.12 are acceptable except that for normality: the trace correlation is 0.64; both Ljung-Box and LM-tests indicate no autocorrelation up to second-order; the Hansen-Doornik test implies non-normality; and ARCH-tests up to second-order imply no heteroscedasticity. Since the residuals are non-normal, significance tests should be treated with caution.

Table 7.12 Misspecification Tests for the Yield Response Model with Dummies

Tests	Statistics
Trace Correlation	0.64
Tests for Autocorrelation	
Ljung-Box(11)	χ^2 (40) = 378.26 (0.59)
LM(1)	χ^2 (4) = 2.55 (0.64)
LM(2)	χ^2 (4) = 5.44 (0.25)
Test for Normality	χ^2 (4) = 29.38 (0.00)
Test for ARCH	
LM(1)	χ^2 (9) = 1.04 (1.00)
LM(2)	χ^2 (18) = 17.47 (0.49)

Note: p-values in the parentheses.

i) Lag Length Determination

Lag length/reduction tests are performed with a maximum of five lags. The results for the acreage and yield response models are reported in Tables 7.13 and 7.14. SC and HQ imply in both cases that a VAR of order one is appropriate, although LR-tests are ambiguous.

Table 7.13 Determining the Order of the VAR for the Acreage Response Model

Variables included in the unrestricted VAR	:	lnPLTA lnPNR lnSUB
Deterministic and/or exogenous variables	:	Constant D65 D67

Model	**SC**	**HQ**
VAR(5)	-12.855	-14.270
VAR(4)	-13.520	-14.699
VAR(3)	-14.029	-14.973
VAR(2)	-14.361	-15.069
VAR(1)	-14.793	-15.265

Lag Reduction Tests	**Statistics**
VAR(4)<<VAR(5)	χ^2 (9) = 5.69 (0.77)
VAR(3)<<VAR(5)	χ^2 (18) = 17.95 (0.46)
VAR(3)<<VAR(4)	χ^2 (9) = 12.26 (0.20)
VAR(2)<<VAR(5)	χ^2 (27) = 37.63 (0.08)
VAR(2)<<VAR(4)	χ^2 (18) = 31.94 (0.02)
VAR(2)<<VAR(3)	χ^2 (9) = 19.68 (0.02)
VAR(1)<<VAR(5)	χ^2 (36) = 53.13 (0.03)
VAR(1)<<VAR(4)	χ^2 (27) = 47.44 (0.01)
VAR(1)<<VAR(3)	χ^2 (18) = 35.18 (0.01)
VAR(1)<<VAR(2)	χ^2 (9) = 15.50 (0.08)

Note: p-values in the parentheses.

Table 7.14 Determining the Order of the VAR for the Yield Response Model

Variables included in the unrestricted VAR	:	lnYLD lnPFER
Deterministic and/or exogenous variables	:	Constant lnRAIN D65 D66 D74 D08

Model	**SC**	**HQ**
VAR(5)	-7.296	-8.135
VAR(4)	-7.548	-8.282
VAR(3)	-7.720	-8.349
VAR(2)	-7.844	-8.368
VAR(1)	-8.105	-8.524

Lag Reduction Tests	**Statistics**
VAR(4)<<VAR(5)	χ^2 (4) = 4.36 (0.36)
VAR(3)<<VAR(5)	χ^2 (8) = 12.12 (0.15)
VAR(3)<<VAR(4)	χ^2 (4) = 7.76 (0.10)
VAR(2)<<VAR(5)	χ^2 (12) = 21.84 (0.04)
VAR(2)<<VAR(4)	χ^2 (8) = 17.48 (0.03)
VAR(2)<<VAR(3)	χ^2 (4) = 9.72 (0.05)
VAR(1)<<VAR(5)	χ^2 (16) = 25.84 (0.06)
VAR(1)<<VAR(4)	χ^2 (12) = 21.48 (0.04)
VAR(1)<<VAR(3)	χ^2 (8) = 13.72 (0.09)
VAR(1)<<VAR(2)	χ^2 (4) = 4.01 (0.41)

Note: p-values in the parentheses.

ii) Reduced Rank Test

The reduced rank test using trace statistics is performed to test for the presence and number of cointegrating vectors. Results in Tables 7.15 and 7.16 show that the acreage and yield response models both have one cointegrating vector and each has a unique long-run equilibrium relationship. Following the Pantula principle, Model 2, with a restricted constant and no trend, is appropriate for both. Similar to the output response model, TIMEt is automatically excluded.

Table 7.15 Johansen Cointegration Results for the Acreage Response Model

Variables included in the unrestricted VAR	:	lnPLTA lnPNR lnSUB
Deterministic and/or exogenous variables	:	Constant D65 D67

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	3	80.38 (0.00)	51.00 (0.00)	68.00 (0.00)
1	2	6.18 (0.94)*	3.51 (0.93)	11.78 (0.82)
2	1	0.35 (0.96)	0.13 (0.72)	2.79 (0.89)

Notes: as for Table 7.4.

Table 7.16 Johansen Cointegration Results for the Yield Response Model

Variables included in the unrestricted VAR	:	lnYLD lnPFER
Deterministic and/or exogenous variables	:	Constant RAIN D65 D66 D74 D08

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	2	26.56 (0.00)	24.48 (0.00)	30.68 (0.01)
1	1	0.61 (0.98)*	0.58 (0.45)	4.53 (0.67)

Notes: as for Table 7.4.

iii) Johansen Normalised Estimates

Unique cointegrating vectors, normalised on lnPLTA in the acreage response model and on lnYLD in the yield response model, are:

$$\ln PLTA = -12.87 + 2.14\ln PNR + 0.63\ln SUB \quad (7.4)$$

and:

$$\ln YLD = 80.22 - 5.50\ln PFER \quad (7.5)$$

The long-run price elasticity of acreage response in (7.4) has the expected sign and is estimated to be 2.14, while the long-run elasticity of acreage with respect to the subsidy also has the expected sign and is estimated to be 0.63. Similarly, the estimated yield elasticity with respect to fertiliser price is negative as expected and is -5.50. That is, when the fertiliser price increases, fertiliser use decreases and rubber productivity falls. In the acreage response model, the coefficients, including those on D65 and D67, are all significant. In the yield response model, the coefficients on the short-run impulse dummies are significant for D65 and D66, but those on D74 and D08 are insignificant but they remain in the model to improve the properties of the residuals.

To examine the residuals, we apply misspecification tests and the results for both models are shown in Tables 7.17 and 7.18. In the acreage response model, the trace correlation is low at 0.42; the Ljung-Box test rejects the null of non-autocorrelation but the LM-test indicates no autocorrelation up to second-order; the Hansen-Doornik test indicates that the residuals are normally distributed; and ARCH-tests up to second-order indicate no heteroscedasticity. All misspecification tests except the Ljung-Box test are satisfactory. However, the low trace correlation test suggests that the planted acreage response model may not be an adequate description of the data. In the yield response model, all misspecification tests on the residuals are acceptable except that for normality: the trace correlation is 0.63; both Ljung-Box and LM-tests indicate no autocorrelation up to second-order; the Hansen-Doornik test implies non-normality; and ARCH-tests up to second-order imply no heteroscedasticity. Since the residuals are non-normal, significance tests should be treated with caution.

Table 7.17 Misspecification Tests for the Acreage Response Model

Tests	Statistics
Trace Correlation	0.42
Tests for Autocorrelation	
Ljung-Box(11)	$\chi^2(96) = 178.88$ (0.00)
LM(1)	$\chi^2(9) = 15.10$ (0.09)
LM(2)	$\chi^2(9) = 11.92$ (0.22)
Test for Normality	$\chi^2(6) = 6.74$ (0.35)
Test for ARCH	
LM(1)	$\chi^2(36) = 23.30$ (0.95)
LM(2)	$\chi^2(72) = 92.32$ (0.05)

Note: p-values in the parentheses.

Table 7.18 Misspecification Tests for the Yield Response Model

Tests	Statistics
Trace Correlation	0.63
Tests for Autocorrelation	
Ljung-Box(11)	$\chi^2(42) = 37.36$ (0.68)
LM(1)	$\chi^2(4) = 2.32$ (0.68)
LM(2)	$\chi^2(4) = 5.47$ (0.24)
Test for Normality	$\chi^2(4) = 27.43$ (0.00)
Test for ARCH	
LM(1)	$\chi^2(9) = 1.89$ (0.99)
LM(2)	$\chi^2(18) = 19.03$ (0.39)

Note: p-values in the parentheses.

iv) Hypothesis Testing

Given cointegration in each sub-model, we apply three hypothesis tests. Results for the acreage model are presented in Table 7.19. First, we re-examine the stationarity of each variable testing the three nulls that $\beta_{PNR} = \beta_{SUB} = 0$, $\beta_{PLTA} = \beta_{SUB} = 0$ and $\beta_{PLTA} = \beta_{PNR} = 0$ using LR-statistics, and results show that all tests are rejected and all variables have a unit root. Second, we test the nulls of individual exclusion, that is,

$\beta_{PLTA} = 0$, $\beta_{PNR} = 0$, and $\beta_{SUB} = 0$, and results show that all hypotheses are rejected and all coefficients are significant. Third, the nulls of weak exogeneity are tested, that is, $\alpha_{PLTA} = 0$, $\alpha_{PNR} = 0$, and $\alpha_{SUB} = 0$, and results imply that those for lnPLTA and lnSUB are rejected, but that for lnPNR is accepted. Thus, lnPNR is weakly exogenous which implies that price is not responsive to acreage and this reflects the fact that the domestic rubber price is mainly determined by the world rubber price.

Table 7.19 Hypothesis Testing for the Acreage Response Model

Tests	H_0	LR-Statistics
Test of Stationarity		
lnPLTA	$\beta_{PNR} = \beta_{SUB} = 0$	36.72 (0.00)
lnPNR	$\beta_{PLTA} = \beta_{SUB} = 0$	16.33 (0.00)
lnSUB	$\beta_{PLTA} = \beta_{PNR} = 0$	44.11 (0.00)
Test of Variable exclusion		
lnPLTA	$\beta_{PLTA} = 0$	8.11 (0.00)
lnPNR	$\beta_{PNR} = 0$	36.11 (0.00)
lnSUB	$\beta_{SUB} = 0$	5.19 (0.02)
Test of Weak exogeneity		
lnPLTA	$\alpha_{PLTA} = 0$	67.58 (0.00)
lnPNR	$\alpha_{PNR} = 0$	0.43 (0.51)
lnSUB	$\alpha_{SUB} = 0$	4.21 (0.04)

Note: p-values in the parentheses.

Results of hypothesis testing in the yield response model are shown in Table 7.20. First, we test for stationarity (and variable exclusion) of each variable, lnYLD and lnPFER, that is, $\beta_{PFER} = 0$ and $\beta_{YLD} = 0$. Results show that both nulls are rejected and both variables are non-stationarity. The nulls of weak exogeneity, that is, $\alpha_{YLD} = 0$ and $\alpha_{PFER} = 0$ are both rejected and it is appropriate to set either variable as the dependent variable.

Table 7.20 Hypothesis Testing for the Yield Response Model

Tests	H_0	LR-Statistics
Test of Stationarity		
lnYLD	$\beta_{PFER} = 0$	23.60 (0.00)
lnPFER	$\beta_{YLD} = 0$	7.07 (0.01)
Test of Variable exclusion		
lnYLD	$\beta_{YLD} = 0$	7.07 (0.01)
lnPFER	$\beta_{PFER} = 0$	23.60 (0.00)
Test of Weak exogeneity		
lnYLD	$\alpha_{YLD} = 0$	9.87 (0.00)
lnPFER	$\alpha_{PFER} = 0$	11.93 (0.00)

Note: p-values in the parentheses.

v) Weak Exogeneity and the Partial Model

The acreage response model is now formulated as a partial system by conditioning on the weakly exogenous rubber price. As with the full model, the partial model is estimated with one lag and one cointegrating vector.[53] After normalising the long-run cointegrating vector on lnPLTA, the long-run equilibrium relationship is:

$$\ln PLTA = -13.36 + 0.65 \ln SUB + 2.16 \ln PNR \tag{7.6}$$

The estimate of the own price elasticity of planted rubber acreage is positive and is 2.16 while the estimate of the long-run elasticity of planted rubber acreage with respect to the replanting subsidy is positive and is 0.65. Both estimates are similar in magnitudes to those in the full model and our model appears robust. We also apply misspecification tests on the residuals in the partial model and the results are shown in Table 7.21. The trace correlation is 0.66; Ljung-Box and LM-tests for up to second-order indicate no autocorrelation; the Hansen-Doornik test indicates that the residuals

[53] Again, the VAR lag length test and the Johansen reduced rank test on the partial output model indicate one lag, one cointegrating vector exists, and Model 2 is appropriate.

are normally distributed; and the first-order ARCH test indicates no heteroscedasticity, but the test for second-order rejects the null. These misspecification tests imply reasonably well-behaved residuals. Compared with the misspecification tests in the full system, the trace correlation value increases, autocorrelation tests improve, residuals are still normal, and the first-order ARCH test shows no heteroscedasticity even though the null for second-order is rejected. In general, the partial model appears to be a better representation of the data than the full system.

Table 7.21 Misspecification Tests for the Acreage Response Model (in the Partial System)

Tests	Statistics
Trace Correlation	0.66
Tests for Autocorrelation	
Ljung-Box(11)	$\chi^2(42) = 49.15\ (0.21)$
LM(1)	$\chi^2(4) = 5.50\ (0.24)$
LM(2)	$\chi^2(4) = 5.17\ (0.27)$
Test for Normality	$\chi^2(4) = 6.97\ (0.14)$
Test for ARCH	
LM(1)	$\chi^2(9) = 8.27\ (0.51)$
LM(2)	$\chi^2(18) = 46.76\ (0.00)$

Note: p-values in the parentheses.

We now re-test the hypotheses on the partial acreage response model and results are presented in Table 7.22. In the partial acreage response model, there are two stationarity tests and two weak exogeneity tests, since lnPNR has been already set to be an exogenous variable.

Table 7.22 Hypothesis Tests for the Partial Acreage Response Model

Tests	**H_0**	**LR-Statistics**
Stationarity		
lnPLTA	$\beta_{SUB} = 0$	5.45 (0.02)
lnSUB	$\beta_{PLTA} = 0$	7.83 (0.01)
Variable exclusion		
lnPLTA	$\beta_{PLTA} = 0$	7.83 (0.01)
lnSUB	$\beta_{SUB} = 0$	5.45 (0.02)
lnPNR	$\beta_{PNR} = 0$	35.68 (0.00)
Weak exogeneity		
lnPLTA	$\alpha_{PLTA} = 0$	73.68 (0.00)
lnSUB	$\alpha_{SUB} = 0$	4.01 (0.05)

Note: p-values in the parentheses.

The nulls of stationarity of each variable, lnPLTA and lnSUB, that is, $\beta_{SUB} = 0$ and $\beta_{PLTA} = 0$, indicate that both are rejected and lnPLTA and lnSUB are non-stationarity. The nulls of variable exclusion, that is, $\beta_{PLTA} = 0$ and $\beta_{SUB} = 0$, are both rejected and all coefficients are significant. The nulls of weak exogeneity, that is, $\alpha_{PLTA} = 0$ and $\alpha_{SUB} = 0$ is rejected for lnPLTA but is accepted for lnSUB where the p-value is borderline. Nevertheless, we cannot formulate a model by conditioning lnSUB to be weakly exogenous (as in the case of lnPNR in the acreage response model) since the Johansen's framework requires at least two dependent variables.

In an attempt to improve model specification, we also performed Perron's (1997) unit root test on lnSUB where the null is of a unit root with an endogenous break. The result from using the innovational outlier model with a change in the intercept indicates a unit root and a break in 1994, while the result using the innovational outlier model with a change in both the intercept and slope suggests a unit root and a break in 1988. We can observe further from Figure 6.9 that a break might occur in

1980. We, therefore, perform cointegration tests on the acreage response model with all three breaks separately but in no case is a cointegrating vector found.

vi) The VECM Estimates

Since cointegration exists in both acreage and yield response models, we can specify VECMs to capture short- and long-run dynamics (Engle and Granger, 1987). Table 7.23 shows the VECM estimates for the acreage response model where planted rubber acreage is dependent on own price and the replanting subsidy. The coefficients on lnPNR and lnSUB have *a proiri* expected signs and are significant. The price elasticities of acreage planted in the short and long run are estimated to be 0.03 and 2.16 which imply that a 1% increase in own price increases acreage by 0.03% in the short run and by 2.16% in the long run. Low estimated short-run and high long-run elasticities of acreage response imply that rubber farmers in Thailand can only adjust planted area in the short run in response to a price change by a small amount, whereas they can make substantial adjustments in the long run. The slow adjustment in the short run may be caused by farmers facing significant adjustment costs of investment. Further, adjustment is possibly restricted because inputs like labour and capital are relatively inflexible in the short run. The estimated short-run elasticity of rubber acreage in response to replanting subsidy implies that there is no acreage response to changes in the subsidy in the short run while the estimated long-run elasticity is 0.65 where a 1% increase in the subsidy increases rubber acreage by 0.65% in the long run. The replanting subsidy is a major determinant of acreage response.

Table 7.23 The VECM Results for the Acreage Response Model (in the Partial System)

Regressors	Coefficients	
	Short-run	Long-run
Constant		-13.36 (3.30)
lnSUB		0.65 (-2.51)
lnPNR		2.16 (-7.52)
$\Delta \ln SUB$	-	
$\Delta \ln PNR$	0.03 (2.26)	
D65	-0.07 (-4.64)	
D67	0.12 (7.044)	
EC (α)	-0.03 (-13.92)	

Note: t-statistics in the parentheses.

The coefficient on the error correction term, α, measures the speed of adjustment towards long-run equilibrium and is -0.03. It has the *a priori* expected sign and is significant and indicates that the previous year's disequilibrium of acreage from the long-run equilibrium is corrected by about 3% in the current year. This slow speed of adjustment may be the consequence of the significant adjustment costs and inflexible adjustment of inputs in the short run. The influence of these factors is reflected in the short-run price elasticity of acreage planted as noted above.

Table 7.24 reports the VECM estimates for the yield response model. Results indicate that yield is dependent on the fertiliser price only. The coefficient of lnPFER has the *a priori* expected sign and is significant. The long-run elasticity of yield in response to fertiliser price is estimated to be -5.50 and a 1% increases in the fertiliser price decreases rubber yield by 5.50% in the long run. This high estimated long-run elasticity of yield with respect to the fertiliser price implies that rubber yield is highly affected by the fertiliser price. If the fertiliser price increases, fertiliser use declines and yield falls substantially. However, the consequences of a rise in the fertiliser price on yield in the short run cannot be measured because of the perennial characteristics of rubber, that is, rubber trees do not respond in the short run to fertiliser use but rather, they take time to realise the effect of changing fertiliser application.

Table 7.24 The VECM Results for the Yield Response Model

Regressors	Short-run	Long-run
Constant		80.22 (-5.79)
lnPFER		-5.50 (7.34)
$\Delta \ln PFER$	-	
lnRAIN	-0.10 (-3.20)	
D65	-0.52 (-7.91)	
D66	0.55 (8.24)	
D74	0.02 (0.26)	
D08	0.08 (1.12)	
EC (α)	-0.03 (-3.35)	

Note: t-statistics in the parentheses.

Rainfall causes a significant negative effect on yield in the short run and a 1% increase in rainfall decreases the rubber yield by 0.10%. This suggests that rainfall is essential for tree growth, but to prevent diseases, it is appropriate to tap only when the bark of the tree is dry. Therefore, rainfall interrupts tapping and causes decreasing productivity. The coefficient on the error correction term is -0.03 and it has the *a priori* expected sign and is significant. It indicates adjustment of 3% of the previous year's deviation of yield from the long-run equilibrium takes place in the current year. This slow adjustment might be the effect of the perennial production characteristics of rubber.

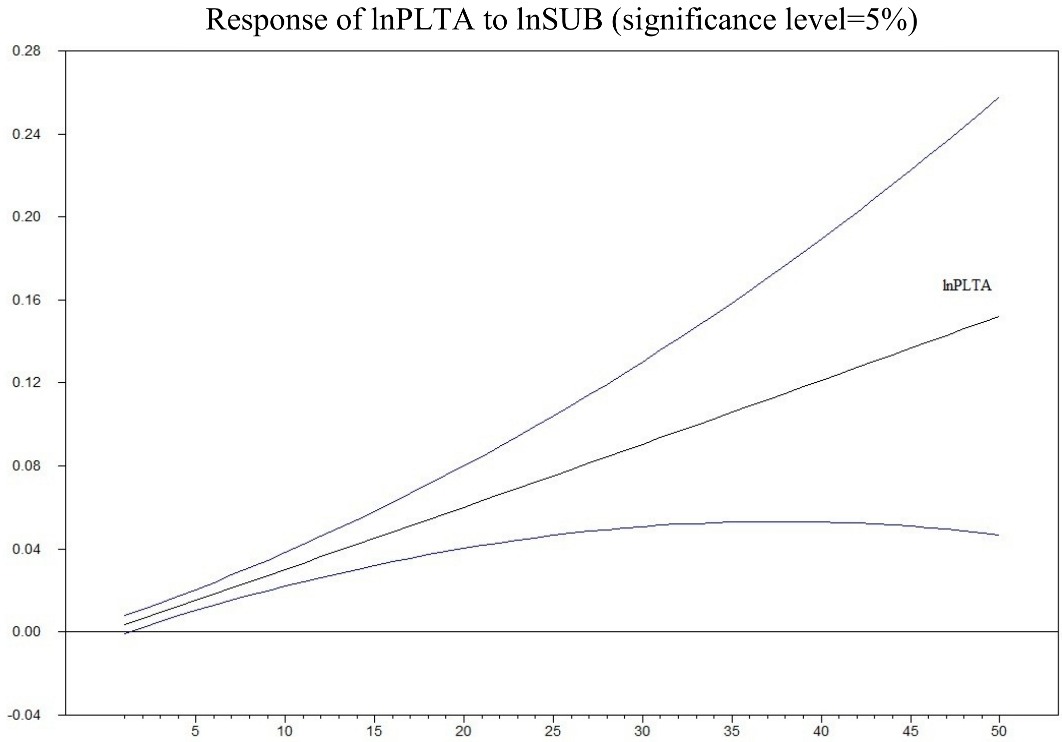
7.3 Impulse Response Analysis

Impulse response function analysis is now applied to both acreage and yield equations to assess the effect a shock in a specific variable and the response of others. A VECM for each is reformulated into the equivalent VAR in levels and orthogonal impulse response functions are calculated using the Choleski decomposition.

i) The Acreage Response Model

In the acreage response model, the ordering for the Choleski decomposition is lnSUB and lnPLTA. This implies that there is no contemporaneous effect of a one-unit shock in lnPLTA on lnSUB, but there is an indirect effect in that lagged values of lnPLTA affect the contemporaneous values of lnSUB. The impulse response functions are illustrated for a 50-year time horizon with 95% confidence intervals in Figure 7.1. Since each series is expressed in logarithms, the vertical axis can be interpreted as approximate percentage changes. Thus, a one standard error shock in the replanting subsidy (approximately 16%) leads to a continual increase in the rubber acreage and lnPLTA does not converge to a long-run equilibrium. This might imply instability of the system. Since rubber price is a weakly exogenous variable, we cannot examine the effect of a shock in price on planted acreage.

Figure 7.1 Impulse Responses to one Standard Error Shock in the Subsidy

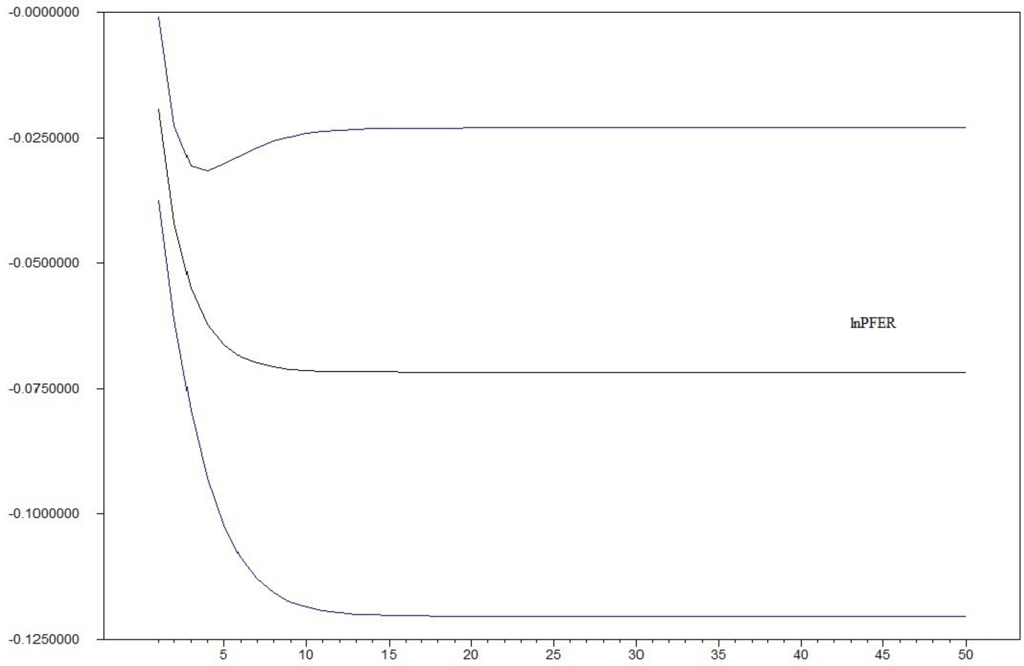


ii) The Yield Response Model

In the yield response model, the ordering for the Choleski decomposition is lnFER and lnYLD so a one-unit shock in lnYLD has no contemporaneous effect on lnPFER but lagged values of lnYLD affect indirectly the contemporaneous values of lnFER. Figure 7.2 illustrates this impulse response function for a 50-year time horizon with 95% confidence intervals. It shows that a one standard error shock in the fertiliser price (approximately 13%) causes an initial decrease, as expected, of 2% in the yield, dropping to 7% in the seventh year when it reaches the long-run equilibrium. This implies that if the fertiliser price increases, farmers decrease the amount of fertiliser used which then causes a temporary fall in rubber yield. The rationale for the result of a permanent decrease is that fertiliser use is generally correlated with good management practice but this is not modelled empirically.

Figure 7.2 Impulse Responses to one Standard Error Shock in the Fertiliser Price

Response of lnYLD to lnPFER (significance level=5%)



7.4 Comparison with Previous Studies

A comparison of the estimated elasticities from this study with those from previous studies is presented in Table 7.25. Most of the studies reviewed in Chapter 3 report low estimated short-run price elasticities for rubber acreage and this study supports that evidence. The estimated short-run price elasticity for rubber acreage planted in this study is 0.03, which is lower than the estimated short-run price elasticity of new planting in Stifel (1973) and the estimated short-run price elasticities of tappable area in Sakarindr (1979). Different methodologies and variables may be the cause of differences between the estimated elasticities here and those in previous studies. In addition, Stifel (1973) covers the early stage of development of rubber production in Thailand when there was a plentiful area suitable for rubber planting, and this might be the reason for the significant high estimated elasticity there. The estimated short-run price elasticity of rubber acreage in this study is close to those in Suwanakul and Wailes (1987) and Yibngamcharoensuk (1988), but it is higher than that found by Aroonsiriporn (1989). In the long run, Suwanakul and Wailes (1987) estimate a long-run price elasticity of rubber tappable acreage of 0.31, which is considerably greater than their estimate in the short run. Similarly, the result in this study shows that the estimated long-run price elasticity of rubber acreage planted is 2.16, which is significantly higher than that in the short run. The reason is that farmers can more easily adjust their planting or have fewer restrictions on planting in the long run, and this situation is supported by the very low adjustment coefficient for acreage. The estimated long-run price elasticity of rubber planted acreage in this study is also higher than the estimate obtained from Suwanakul and Wailes (1987).

In the yield equation, we could not estimate the yield elasticity with respect to price and this implies that rubber yield does not respond to changes in price. It might be argued that rubber yield could be altered if farmers changed their cultivated system, such as tapping frequency and intensity and the number of trees tapped per acreage, in response to rubber price fluctuation. However, farmers have not generally changed their cultivated behaviour from the standard system because unusual practices may damage the trees. Furthermore, since farmers mostly depend on rubber tree cultivation for cash, they have to tap the trees even when the rubber price decreases, although they may not tap trees on marginal land. This suggests that the mature rubber acreage is normally tapped at full or nearly full capacity, as we assume in our acreage-yield model where $TAPA_t = MA_t$ (Chapter 4, section 4.6.2), and it may be difficult for farmers to change the number of tree tapped per acreage when price increases. Thus, it seems reasonable that yield is not affected significantly by rubber price. Instead, yield reacts significantly to the fertiliser price in the long run. However, the productivity of perennials like rubber trees for any given level of inputs depends on a biologically-determined life-cycle. In the output response model, an appropriate cointegrating vector is not found and we cannot estimate the price elasticity of rubber output.

Table 7.25 Comparison of Estimated Price Elasticities of Rubber Acreage, Yield, and Output in Thailand

Author	Period of study	Acreage		Yield		Output		
		Short-Run	**Long-Run**	**Short Run**	**Long Run**	**Short Run**	**Medium Run**	**Long Run**
Behrman (1971)	1947-1965					0.409 and 0.037	-	0.189
Stifel (1973)	1913-1941 1926-1937 1950-1968	0.80*	- -			 0.771 0.15	- -	- -
Dowling (1979)	1915-1939 1950-1971 1950-1975					0.092-0.176 0.165-0.265	0.639-0.906 1.556-1.917	1.205-1.533 1.752-2.641
Grilli (1979)	1955-1975		-		-	0.25	-	-
Sakarindr (1979)	1955-1972	0.1052, -0.1002, and 0.5805**	-		-	0.1173, 0.1127, and 0.1292	-	-
Man and Blandford (1980)	1960-1977					0.644	-	1.452
Jumpasut (1981)	1947-1979 1970-1979					Aggregate: 0.59 South East: -0.22 South: 0.17	-	0.25 -0.12 0.08
Hataiseree (1983)	1964-1980					0.21	-	-
Meyanathan (1983)	1972-1976					0.02	-	-
Tan (1984)	1956-1978					0.395	3.954	6.714
Suwanakul and Wailes (1987)	1954-1983	0.03**	0.31	0.18	0.25	0.21		0.56
Yibngamcharoensuk (1988)	1964-1983 1966–1983 1969-1983	0.047***	-	- 0.137 -	-	 0.114 and 0.112	-	-
Aroonsiriporn (1989)	1966-1986	0.002**	-		-		-	-
Div. of Agric. Econ. Research (1989)	1961-1976		-		-	0.236	-	-
Changkid (1982)	1979-1987	-	-	-	-	0.41	-	-
Burger and Smit (1997)	1974-1993							0.25
Pipitkul (2003)	1975-2002	-	-	-	-	0.08	-	-
This study	1962-2008	0.03***	2.16	-	-	-	-	-

Notes: 1) * indicates new planting; 2) ** indicates tappable area; and 3) *** indicates planted area.

7.5 Summary

In this chapter, we estimate output, acreage, and yield responses of rubber in Thailand using annual data for 1962-2008. Since most of variables are non-stationary, a traditional time series analysis may produce spurious regression results and a cointegration approach is more appropriate to estimate both short- and long-run supply responses. Johansen's cointegration approach is used to estimate the acreage-yield and output response models, and we find that a unique long-run relationship exists, one for the output response model and one each for the acreage and yield response models. Three tests are applied to all equations. The stationary test suggests that all variables in each equation have a unit root. The variable exclusion test confirms that all coefficients in each equation are significant. However, weak exogeneity tests show that the rubber price, both in the acreage and output equations, is weakly exogenous. We therefore reformulate the acreage and output equations by setting the rubber price to be weakly exogenous. Output in the output response model then becomes weakly exogenous and there is no long-run output relationship. Thus, an output supply response model appears inappropriate to explain supply response of rubber production of Thailand. The preferred model is then comprised of acreage and yield responses.

In the acreage response model, we find a unique long-run relationship between the planted area, the rubber price, and the fertiliser price. The long-run price elasticity of rubber acreage planted is estimated to be 2.16, which is higher than those in previous studies, while the estimated elasticity of rubber acreage planted in response to a change in the subsidy is 0.65. The VECM shows that the estimated short-run price elasticity of rubber acreage planted is very low at 0.03. We also find that there is a unique long-run relationship between rubber yield, the fertiliser price, and rainfall in the yield response model. However, the residuals are non-normal which might affect statistical inference. The long-run elasticity of rubber yield with respect to the fertiliser price is estimated to be -5.50 while the rubber price has no effect on yield. In the VECM, rainfall has a negative effect on rubber yield at -0.10. Impulse response analysis shows that a shock to the replanting subsidy leads to a continual increase in the rubber acreage, and this might imply instability of the model. A one standard error shock in the fertiliser price causes a decrease of 7% in the rubber yield after seven years; this effect is permanent and the rubber yield takes around seven years to return to long-run equilibrium.

Appendix 7.1 Cointegration Results for Output Response Models

Table 7.26 Output Response Model 1 with One Lag[54]

Variables included in the unrestricted VAR	:	lnQNT lnPNR lnPPAD lnPFER lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant
Lag	:	1 (SC)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	98.03 (0.11)*	92.34 (0.08)	122.61 (0.02)
1	5	60.76 (0.45)	55.07 (0.42)	74.738 (0.33)
2	4	33.34 (0.80)	28.39 (0.80)	46.53 (0.58)

Notes: 1) p-values in the parentheses.
2) * indicates where the null is accepted for the first time moving through the table row by row from left-to-right.

Table 7.27 Output Response Model 1 with Five Lags

Variables included in the unrestricted VAR	:	lnQNT lnPNR lnPPAD lnPFER lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant
Lag	:	5 (HQ)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	301.11 (0.00)	280.08 (0.00)	332.19 (0.00)
1	5	199.58 (0.00)	179.56 (0.00)	207.39 (0.00)
2	4	110.19 (0.00)	93.81 (0.00)	114.12 (0.00)
3	3	52.25 (0.00)	37.49 (0.01)	56.20 (0.00)
4	2	26.12 (0.01)	13.42 (0.10)*	21.76 (0.15)
5	1	6.94 (0.13)	1.08 (0.30)	5.31 (0.56)

Note: as for Table 7.26.

[54] Throughout the appendices, models are numbered sequentially and the numbers 1-5 do not correspond with the numbered models embedded in Johansen's framework. The most parsimonious lags are selected according to either the Schwarz Bayesian Criterion (SC) and/or the Hannan-Quinn Criterion (HQ).

Table 7.28 Output Response Model 2 with One lag

Variables included in the unrestricted VAR	:	lnQNT lnPNR lnPPALM lnPFER lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant
Lag	:	1 (SC)

Hypotheses		Trace Test		
H_0: r	H_1: (n-r)	Model 2	Model 3	Model 4
0	6	93.50 (0.20)*	86.09 (0.19)	113.74 (0.09)
1	5	53.14 (0.76)	46.54 (0.78)	67.41 (0.61)
2	4	28.73 (0.94)	26.87 (0.86)	43.67 (0.41)

Note: as for Table 7.26.

Table 7.29 Output Response Model 2 with Five lags

Variables included in the unrestricted VAR	:	lnQNT lnPNR lnPPALM lnPFER lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant
Lag	:	5 (HQ)

Hypotheses		Trace Test		
H_0: r	H_1: (n-r)	Model 2	Model 3	Model 4
0	6	296.32 (0.00)	278.66 (0.00)	316.16 (0.00)
1	5	156.18 (0.00)	149.69 (0.00)	182.79 (0.00)
2	4	90.87 (0.00)	88.15 (0.00)	119.12 (0.00)
3	3	44.34 (0.00)	42.58 (0.00)	69.54 (0.00)
4	2	13.84 (0.31)*	13.10 (0.11)	24.61 (0.07)
5	1	5.42 (0.25)	4.82 (0.03)	6.31 (0.43)

Note: as for Table 7.26.

Table 7.30 Output Response Model 3 with One Lag

Variables included in the unrestricted VAR	:	lnQNT lnPNR lnPPAD lnPPALM lnPFER lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant
Lag	:	1 (SC)

Hypotheses		Trace Test		
H_0: r	H_1: (n-r)	Model 2	Model 3	Model 4
0	7	122.44 (0.21)*	114.87 (0.19)	145.15 (0.10)
1	6	81.41 (0.58)	74.33 (0.57)	97.90 (0.45)
2	5	54.77 (0.69)	47.95 (0.72)	66.59 (0.64)

Note: as for Table 7.26.

Table 7.31 Output Response Model 3 with Two lags

Variables included in the unrestricted VAR	:	lnQNT lnPNR lnPPAD lnPPALM lnPFER lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant
Lag	:	2 (HQ)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	7	123.69 (0.19)*	118.19 (0.13)	136.47 (0.24)
1	6	90.05 (0.29)	84.62 (0.23)	99.02 (0.41)
2	5	63.16 (0.37)	57.45 (0.32)	70.82 (0.48)

Note: as for Table 7.26.

Table 7.32 Output Response Model 4 with One lag

Variables included in the unrestricted VAR	:	lnQNT lnPNR lnPPAD lnPFER lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnCVP
Lag	:	1 (SC)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	93.52 (0.20)*	87.62 (0.16)	119.34 (0.04)
1	5	61.40 (0.42)	55.54 (0.40)	74.09 (0.36)
2	4	34.23 (0.76)	28.95 (0.77)	46.17 (0.60)

Notes: as for Table 7.26.

Table 7.33 Output Response Model 4 with Five Lags

Variables included in the unrestricted VAR	:	lnQNT lnPNR lnPPAD lnPFER lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnCVP
Lag	:	5 (HQ)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	315.56 (0.00)	287.58 (0.00)	342.40 (0.00)
1	5	201.96 (0.00)	180.50 (0.00)	221.48 (0.00)
2	4	109.42 (0.00)	89.40 (0.00)	128.44 (0.00)
3	3	49.57 (0.00)	30.84 (0.04)	50.54 (0.01)
4	2	22.92 (0.02)	4.59 (0.85)*	10.70 (0.89)
5	1	3.51 (0.50)	0.51 (0.47)	3.01 (0.87)

Note: as for Table 7.26.

Table 7.34 Output Response Model 5 with One Lag

Variables included in the unrestricted VAR	:	lnQNT lnPNR lnPPALM lnPFER lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnCVP
Lag	:	1 (SC)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	87.84 (0.36)*	80.84 (0.34)	110.67 (0.13)
1	5	53.60 (0.74)	46.97 (0.76)	66.68 (0.64)
2	4	29.16 (0.93)	27.01 (0.85)	43.51 (0.72)

Note: as for Table 7.26.

Table 7.35 Output Response Model 5 with Five Lags

Variables included in the unrestricted VAR	:	lnQNT lnPNR lnPPALM lnPFER lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnCVP
Lag	:	5 (HQ)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	305.79 (0.00)	288.14 (0.00)	328.58 (0.00)
1	5	160.96 (0.00)	153.71 (0.00)	186.57 (0.00)
2	4	94.86 (0.00)	89.519 (0.00)	118.39 (0.00)
3	3	38.62 (0.02)	36.66 (0.01)	64.04 (0.00)
4	2	10.43 (0.60)*	9.17 (0.36)	18.16 (0.34)
5	1	2.53 (0.68)	1.31 (0.25)	5.60 (0.52)

Note: as for Table 7.26.

Table 7.36 Output Response Model 6 with One Lag

Variables included in the unrestricted VAR	:	lnQNT lnPNR lnPPAD lnPPALM lnPFER lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnCVP
Lag	:	1 (SC)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	7	116.86 (0.35)*	109.55 (0.31)	141.25 (0.15)
1	6	82.01 (0.55)	74.82 (0.55)	97.17 (0.47)
2	5	55.62 (0.66)	48.76 (0.69)	66.70 (0.64)

Note: as for Table 7.26.

Table 7.37 Output Response Model 6 with Four Lags

Variables included in the unrestricted VAR		:	lnQNT lnPNR lnPPAD lnPPALM lnPFER lnWAGE lnSUB	
Deterministic and/or exogenous variables		:	Constant lnCVP	
Lag		:	4 (HQ)	
Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	7	208.48 (0.00)	201.99 (0.00)	239.03 (0.00)
1	6	99.79 (0.09)*	90.23 (0.11)	130.86 (0.01)
2	5	65.39 (0.28)	56.27 (0.37)	75.60 (0.31)
5	4	36.97 (0.63)	30.79 (0.68)	38.50 (0.89)

Note: as for Table 7.26.

Unique cointegrating vectors, normalised on lnQNT in the Output Response Model 6 with four lags is:

$$\ln QNT = -9.04 - 0.43\ln PNR + 1.59\ln PPAD + 0.27\ln PPALM - 0.77\ln PFER + 3.30\ln WAGE - 1.34\ln SUB \quad (7.7)$$

This equation shows wrong signs for lnPNR, lnPFER, lnWAGE, and lnSUB and we discard this model.

Table 7.38 Output Response Model 7 with One Lag

Variables included in the unrestricted VAR		:	lnQNT lnPNR lnPPAD lnPFER lnWAGE lnSUB	
Deterministic and/or exogenous variables		:	Constant lnSDP	
Lag		:	1 (SC)	
Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	97.83 (0.12)*	92.45 (0.08)	124.22 (0.02)
1	5	63.30 (0.35)	58.29 (0.29)	78.03 (0.23)
2	4	36.08 (0.67)	31.23 (0.66)	49.80 (0.43)

Note: as for Table 7.26.

Table 7.39 Output Response Model 7 with Five Lags

Variables included in the unrestricted VAR	:	lnQNT lnPNR lnPPAD lnPFER lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnSDP
Lag	:	5 (HQ)

Hypotheses		Trace Test		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	320.82 (0.00)	293.63 (0.00)	345.71 (0.00)
1	5	202.14 (0.00)	181.30 (0.00)	222.79 (0.00)
2	4	109.33 (0.00)	89.18 (0.00)	130.43 (0.00)
3	3	51.20 (0.00)	32.24 (0.03)	54.24 (0.00)
4	2	24.33 (0.01)	5.65 (0.74)*	12.93 (0.75)
5	1	5.36 (0.26)	0.20 (0.65)	5.375 (0.55)

Note: as for Table 7.26.

Table 7.40 Output Response Model 8 with One Lag

Variables included in the unrestricted VAR	:	lnQNT lnPNR lnPPALM lnPFER lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnSDP
Lag	:	1 (SC)

Hypotheses		Trace Test		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	90.51 (0.28)*	84.64 (0.28)	114.73 (0.07)
1	5	54.68 (0.70)	48.80 (0.69)	69.77 (0.52)
2	4	30.98 (0.88)	28.89 (0.77)	45.33 (0.63)

Note: as for Table 7.26.

Table 7.41 Output Response Model 8 with Five Lags

Variables included in the unrestricted VAR	:	lnQNT lnPNR lnPPALM lnPFER lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnSDP
Lag	:	5 (HQ)

Hypotheses		Trace Test		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	305.30 (0.00)	288.68 (0.00)	328.83 (0.00)
1	5	162.26 (0.00)	155.32 (0.00)	187.20 (0.00)
2	4	95.63 (0.00)	90.25 (0.00)	118.75 (0.00)
3	3	40.55 (0.00)	38.84 (0.00)	65.66 (0.00)
4	3	10.35 (0.61)*	9.31 (0.34)	19.53 (0.26)
5	2	2.47 (0.69)	1.46 (0.23)	5.74 (0.50)

Note: as for Table 7.26.

Table 7.42 Output Response Model 9 with One Lag

Variables included in the unrestricted VAR	:	lnQNT lnPNR lnPPAD lnPPALM lnPFER lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnSDP
Lag	:	1 (SC)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	120.45 (0.25)*	114.14 (0.20)	145.93 (0.09)
1	5	83.65 (0.50)	77.38 (0.49)	100.84 (0.36)
2	4	57.14 (0.60)	50.85 (0.60)	70.00. (0.51)

Note: as for Table 7.26.

Table 7.43 Output Response Model 9 with Four Lags

Variables included in the unrestricted VAR	:	lnQNT lnPNR lnPPAD lnPPALM lnPFER lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnCVP
Lag	:	4 (HQ)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	7	206.68 (0.00)	201.83 (0.00)	239.02 (0.00)
1	6	96.14 (0.15)*	89.11 (0.13)	133.39 (0.00)
2	5	67.22 (0.22)	57.25 (0.32)	74.73 (0.34)
5	4	38.12 (0.57)	31.59 (0.64))	39.84 (0.85)

Note: as for Table 7.26.

Appendix 7.2 Cointegration Results for (Planted) Acreage Response Models

Table 7.44 Acreage Response Model 10 (Planted Acreage) with One Lag

Variables included in the unrestricted VAR	:	lnPLTA lnPNR lnPPAD lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant
Lag	:	1 (SC and HQ)

Hypotheses		Trace Test		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	5	133.81 (0.00)	108.41 (0.00)	124.24 (0.00)
1	4	63.78 (0.01)	58.39 (0.00)	74.22 (0.00)
2	3	31.16 (0.13)*	26.58 (0.15)	37.68 (0.15)

Note: as for Table 7.26.

Table 7.45 Acreage Response Model 11 (Planted Acreage) with One Lag

Variables included in the unrestricted VAR	:	lnPLTA lnPNR lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant
Lag	:	1 (SC and HQ)

Hypotheses		Trace Test		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	5	122.19 (0.00)	97.49 (0.00)	111.47 (0.00)
1	4	62.34 (0.00)	58.19 (0.00)	68.31 (0.02)
2	3	30.17 (0.16)*	26.53 (0.12)	36.80 (0.18)

Note: as for Table 7.26.

Table 7.46 Acreage Response Model 12 (Planted Acreage) with One Lag

Variables included in the unrestricted VAR	:	lnPLTA lnPNR lnPPAD lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant
Lag	:	1 (SC)

Hypotheses		Trace Test		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	158.44 (0.00)	133.07 (0.00)	148.64 (0.00)
1	5	89.32 (0.00)	83.28 (0.00)	99.09 (0.01)
2	4	53.40 (0.06)*	48.52 (0.04)	60.94 (0.08)

Note: as for Table 7.26.

Table 7.47 Acreage Response Model 12 (Planted Acreage) with Five Lags

Variables included in the unrestricted VAR	:	lnPLTA lnPNR lnPPAD lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant
Lag	:	5 (HQ)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	279.11 (0.00)	263.45 (0.00)	308.06 (0.00)
1	5	151.50 (0.00)	142.86 (0.00)	186.53 (0.00)
2	4	83.14 (0.00)	74.93 (0.00)	109.62 (0.00)
3	3	32.61 (0.09)*	24.88 (0.17)	59.16 (0.00)

Note: as for Table 7.26.

Table 7.48 Acreage Response Model 13 (Planted Acreage) with One Lag

Variables included in the unrestricted VAR	:	lnPLTA lnPNR lnPPAD lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnCVP
Lag	:	1 (SC and HQ)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	5	113.72 (0.00)	106.70 (0.00)	121.11 (0.00)
1	4	61.04 (0.01)	56.42 (0.01)*	71.00 (0.01)
2	3	28.44 (0.23)	27.16 (0.10)	35.86 (0.21)

Note: as for Table 7.26.

Table 7.49 Acreage Response Model 14 (Planted Acreage) with One Lag

Variables included in the unrestricted VAR	:	lnPLTA lnPNR lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnCVP
Lag	:	1 (SC and HQ)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	5	101.75 (0.00)	95.12 (0.00)	108.33 (0.00)
1	4	58.49 (0.02)	56.47 (0.01)*	65.56 (0.03)
2	3	28.09 (0.24)	27.62 (0.09)	36.97 (0.19)

Note: as for Table 7.26.

Table 7.50 Acreage Response Model 15 (Planted Acreage) with One Lag

Variables included in the unrestricted VAR	:	lnPLTA lnPNR lnPPAD lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnCVP
Lag	:	1 (SC)

Hypotheses		Trace Test		
H_0: r	H_1: (n-r)	Model 2	Model 3	Model 4
0	6	138.79 (0.00)	130.88 (0.00)	145.43 (0.00)
1	5	86.80 (0.01)	80.72 (0.00)	95.50 (0.01)
2	4	50.90 (0.09)*	49.56 (0.03)	59.64 (0.11)

Note: as for Table 7.26.

Table 7.51 Acreage Response Model 15 (Planted Acreage) with Five Lags

Variables included in the unrestricted VAR	:	lnPLTA lnPNR lnPPAD lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnCVP
Lag	:	5 (HQ)

Hypotheses		Trace Test		
H_0: r	H_1: (n-r)	Model 2	Model 3	Model 4
0	6	347.17 (0.00)	335.31 (0.00)	411.11 (0.00)
1	5	185.39 (0.00)	174.12 (0.00)	216.74 (0.00)
2	4	100.51 (0.00)	89.28 (0.00)	130.52 (0.00)
3	3	47.73 (0.00)	39.26 (0.00)	74.43 (0.00)
4	2	21.29 (0.03)	18.78 (0.01)	31.54 (0.01)
5	1	8.73 (0.06)*	7.62 (0.01)	11.14 (0.08)

Note: as for Table 7.26.

Table 7.52 Acreage Response Model 16 (Planted Acreage) with One Lag

Variables included in the unrestricted VAR	:	lnPLTA lnPNR lnPPAD lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnSDP
Lag	:	1 (SC and HQ)

Hypotheses		Trace Test		
H_0: r	H_1: (n-r)	Model 2	Model 3	Model 4
0	5	110.33 (0.00)	106.35 (0.00)	120.25 (0.00)
1	4	60.79 (0.01)	57.40 (0.00)	71.47 (0.01)
2	3	28.77 (0.21)*	26.14 (0.13)	34.96 (0.25)

Note: as for Table 7.26.

Table 7.53 Acreage Response Model 17 (Planted Acreage) with One Lag

Variables included in the unrestricted VAR	:	lnPLTA lnPNR lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnSDP
Lag	:	1 (SC and HQ)

Hypotheses		Trace Test		
H_0: r	H_1: (n-r)	Model 2	Model 3	Model 4
0	5	98.75 (0.00)	94.16 (0.00)	106.81 (0.00)
1	4	59.68 (0.01)	55.09 (0.01)	64.07 (0.05)*
2	3	28.49 (0.22)	26.46 (0.12)	35.40 (0.23)

Note: as for Table 7.26.

The unique cointegrating vector normalised on lnPLTA in the planted acreage response model is

$$lnPLTA = 0.13lnPNR + 0.12lnPPALM + 0.17lnWAGE - 0.16lnSUB + 0.1Time \quad (7.8)$$

This equation shows wrong signs on lnWAGE and lnSUB and we discard this model.

Table 7.54 Acreage Response Model 18 (Planted Acreage) with One Lag

Variables included in the unrestricted VAR	:	lnPLTA lnPNR lnPPAD lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnSDP
Lag	:	1 (SC)

Hypotheses		Trace Test		
H_0: r	H_1: (n-r)	Model 2	Model 3	Model 4
0	6	135.19 (0.00)	130.39 (0.00)	144.44 (0.00)
1	5	85.92 (0.01)	81.99 (0.00)	96.26 (0.01)
2	4	50.84 (0.09)*	48.38 (0.04)	58.45 (0.13)

Note: as for Table 7.26.

Appendix 7.3 Cointegration Results for (Tapped) Acreage Response Models

Table 7.55 Acreage Response Model 1 (Acreage Being Tapped) with One Lag

Variables included in the unrestricted VAR	:	lnTAPA lnPNR lnPPAD lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant
Lag	:	1 (SC)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	5	77.06 (0.05)*	68.95 (0.06)	55.52 (0.05)
1	4	45.38 (0.24)	38.56 (0.28)	56.18 (0.18)
2	3	21.91 (0.60)	15.29 (0.77)	33.15 (0.33)

Note: as for Table 7.26.

Table 7.56 Acreage Response Model 1 (Acreage Being Tapped) with Two Lags

Variables included in the unrestricted VAR	:	lnTAPA lnPNR lnPPAD lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant
Lag	:	2 (HQ)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	5	87.56 (0.01)	76.41 (0.01)	94.94 (0.02)
1	4	49.82 (0.11)*	43.00 (0.13)	61.04 (0.08)
2	3	23.52 (0.50)	18.10 (0.57)	34.26 (0.26)

Note: as for Table 7.26.

The unique cointegrating vector normalised on lnTAPA in the acreage being tapped model is:

$$\ln TAPA = 8.1 - 0.20\ln PNR + 0.54\ln PPAD + 1.08\ln WAGE - 0.93\ln SUB \quad (7.9)$$

This equation shows wrong signs on lnPNR, lnWAGE, and lnSUB and we discard this model.

Table 7.57 Acreage Response Model 2 (Acreage Being Tapped) with One Lag

Variables included in the unrestricted VAR	:	lnTAPA lnPNR lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant
Lag	:	1 (SC and HQ)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	3	70.37 (0.14)*	62.41 (0.17)	76.39 (0.28)
1	2	44.63 (0.27)	36.59 (0.37)	48.88 (0.47)
2	1	21.99 (0.60)	14.22 (0.83)	26.33 (0.72)

Note: as for Table 7.26.

Table 7.58 Acreage Response Model 3 (Acreage Being Tapped) with One Lag

Variables included in the unrestricted VAR	:	lnTAPA lnPNR lnPPAD lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant
Lag	:	1 (SC)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	3	101.59 (0.07)	93.55 (0.07)	114.18 (0.08)
1	2	68.48 (0.19)	61.23 (0.20)*	81.35 (0.15)
2	1	43.37 (0.32)	36.76 (0.36)	55.14 (0.22)

Note: as for Table 7.26.

Table 7.59 Acreage Response Model 3 (Acreage Being Tapped) with Five Lags

Variables included in the unrestricted VAR	:	lnTAPA lnPNR lnPPAD lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant
Lag	:	5 (HQ)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	250.76 (0.00)	238.14 (0.00)	323.11 (0.00)
1	5	143.31 (0.00)	131.46 (0.00)	196.36 (0.00)
2	4	65.23 (0.00)	59.60 (0.00)	114.41 (0.00)
3	3	30.85 (0.14)*	25.24 (0.16)	57.31 (0.00)
4	2	12.17 (0.44)	6.62 (0.63)	23.97 (0.08)

Note: as for Table 7.26.

Table 7.60 Acreage Response Model 4 (Acreage Being Tapped) with One Lag

Variables included in the unrestricted VAR	:	lnTAPA lnPNR lnPPAD lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnCVP
Lag	:	1 SC

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	5	77.33 (0.08)*	69.41 (0.05)	83.63 (0.11)
1	4	42.86 (0.34)	38.35 (0.29)	50.79 (0.38)
2	3	19.46 (0.76)	15.43 (0.46)	27.54 (0.64)

Note: as for Table 7.26.

Table 7.61 Acreage Response Model 4 (Acreage Being Tapped) with Two Lags

Variables included in the unrestricted VAR	:	lnTAPA lnPNR lnPPAD lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnCVP
Lag	:	2 (HQ)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	5	83.59 (0.01)	81.24 (0.00)	96.35 (0.01)
1	4	47.60 (0.17) *	45.48 (0.08)	60.51 (0.09)
2	3	20.55 (0.69)	18.42 (0.55)	33.30 (0.33)

Note: as for Table 7.26.

The unique cointegrating vector normalised on lnTAPA in the acreage being tapped model is:

$$\ln TAPA = 8.5 - 0.14\ln PNR + 0.48\ln PPAD + 1.1\ln WAGE - 1.01\ln SUB \quad (7.10)$$

This equation shows wrong signs on all explanatory variables and we discard this model.

Table 7.62 Acreage Response Model 5 (Acreage Being Tapped) with One Lag

Variables included in the unrestricted VAR	:	lnTAPA lnPNR lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnCVP
Lag	:	1 (SC and HQ)

Hypotheses		Trace Test		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	5	70.37 (0.14)*	62.41 (0.17)	76.39 (0.28)
1	4	44.63 (0.27)	36.59 (0.37)	48.88 (0.47)
2	3	21.99 (0.60)	14.22 (0.83)	26.33 (0.72)

Note: as for Table 7.26.

Table 7.63 Acreage Response Model 6 (Acreage Being Tapped) with One Lag

Variables included in the unrestricted VAR	:	lnTAPA lnPNR lnPPAD lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnCVP
Lag	:	1 (SC)

Hypotheses		Trace Test		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	98.78 (0.10)*	93.47 (0.07)	109.277 (0.15)
1	5	65.83 (0.26)	61.60 (0.19)	76.327 (0.28)
2	4	40.21 (0.47)	36.75 (0.36)	51.70 (0.34)

Note: as for Table 7.26.

Table 7.64 Acreage Response Model 6 (Acreage Being Tapped) with Five Lags

Variables included in the unrestricted VAR	:	lnTAPA lnPNR lnPPAD lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnCVP
Lag	:	5 (HQ)

Hypotheses		Trace Test		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	276.39 (0.00)	276.39 (0.00)	335.16 (0.00)
1	5	164.31 (0.00)	164.31 (0.00)	206.62 (0.00)
2	4	80.51 (0.00)	80.51 (0.00)	125.94 (0.00)
3	3	42.13 (0.01)	42.13 (0.01)	57.00 (0.00)
4	2	14.57 (0.26)*	14.57 (0.26)	18.76 (0.30)

Note: as for Table 7.26.

Table 7.65 Acreage Response Model 7 (Acreage Being Tapped) with One Lag

Variables included in the unrestricted VAR	:	lnTAPA lnPNR lnPPAD lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnSDP
Lag	:	1 (SC)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	5	76.08 (0.06)*	69.84 (0.05)	83.41 (0.11)
1	4	44.72 (0.26)	38.43 (0.29)	50.57 (0.39)
2	3	21.26 (0.65)	15.56 (0.75)	27.48 (0.66)

Note: as for Table 7.26.

Table 7.66 Acreage Response Model 7 (Acreage Being Tapped) with Two Lags

Variables included in the unrestricted VAR	:	lnTAPA lnPNR lnPPAD lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnSDP
Lag	:	2 (HQ)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	5	84.88 (0.01)	79.48 (0.01)	93.38 (0.02)
1	4	49.35 (0.12) *	44.61 (0.10)	58.51 (0.13)
2	3	22.79 (0.55)	18.46 (0.54)	32.20 (0.38)

Note: as for Table 7.26.

Table 7.67 Acreage Response Model 8 (Acreage Being Tapped) with One Lag

Variables included in the unrestricted VAR	:	lnTAPA lnPNR lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnSDP
Lag	:	1 (SC)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	5	67.80 (0.21)*	60.96 (0.21)	70.57 (0.49)
1	4	40.98 (0.43)	36.71 (0.37)	45.98 (0.60)
2	3	17.92 (0.84)	13.79 (0.85)	23.10 (0.87)

Note: as for Table 7.26.

Table 7.68 Acreage Response Model 9 (Acreage Being Tapped) with One Lag

Variables included in the unrestricted VAR	:	lnTAPA lnPNR lnPPAD lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnSDP
Lag	:	1 (SC)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	100.48 (0.08)*	93.40 (0.07)	108.46 (0.17)
1	5	67.79 (0.21)	60.96 (0.21)	75.26 (0.32)
2	4	41.86 (0.39)	36.73 (0.37)	51.25 (0.36)

Note: as for Table 7.26.

Table 7.69 Acreage Response Model 9 (Acreage Being Tapped) with Five Lags

Variables included in the unrestricted VAR	:	lnTAPA lnPNR lnPPAD lnPPALM lnWAGE lnSUB
Deterministic and/or exogenous variables	:	Constant lnSDP
Lag	:	5 (HQ)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	280.53 (0.00)	266.79 (0.00)	329.35 (0.00)
1	5	167.01 (0.00)	155.03 (0.00)	202.37 (0.00)
2	4	85.07 (0.00)	73.47 (0.00)	120.55 (0.00)
3	3	47.01 (0.00)	35.58 (0.00)	57.55 (0.00)
4	2	18.16 (0.10)*	6.77 (0.61)	19.72 (0.25)

Note: as for Table 7.26.

Appendix 7.4 Cointegration Results for Yield Response Models

Table 7.70 Yield Response Model 1 with One Lag

Variables included in the unrestricted VAR	:	lnYLD lnPNR lnPPAD lnPFER lnWAGE
Deterministic and/or exogenous variables	:	Constant lnRAIN
Lag	:	1 (SC and HQ)

Hypotheses		Trace Test		
H_0: r	H_1: (n-r)	Model 2	Model 3	Model 4
0	5	66.11 (0.26)*	60.23 (0.23)	81.47 (0.15)
1	4	36.09 (0.67)	31.29 (0.65)	47.97 (0.51)
2	3	16.14 (0.91)	15.79 (0.73)	28.29 (0.61)

Note: as for Table 7.26.

Table 7.71 Yield Response Model 2 with One Lag

Variables included in the unrestricted VAR	:	lnYLD lnPNR lnPPALM lnPFER lnWAGE
Deterministic and/or exogenous variables	:	Constant lnRAIN
Lag	:	1 (SC and HQ)

Hypotheses		Trace Test		
H_0: r	H_1: (n-r)	Model 2	Model 3	Model 4
0	5	58.17 (0.56)*	50.83 (0.60)	65.00 (0.70)
1	4	33.06 (0.81)	31.26 (0.66)	45.55 (0.62)
2	3	15.90 (0.92)	14.75 (0.80)	26.67 (0.70)

Note: as for Table 7.26.

Table 7.72 Yield Response Model 3 with One Lag

Variables included in the unrestricted VAR	:	lnYLD lnPNR lnPPAD lnPPALM lnPFER lnWAGE
Deterministic and/or exogenous variables	:	Constant lnRAIN
Lag	:	3 (SC)

Hypotheses		Trace Test		
H_0: r	H_1: (n-r)	Model 2	Model 3	Model 4
0	6	87.11 (0.38)*	79.55 (0.38)	101.03 (0.35)
1	5	57.75 (0.57)	50.49 (0.61)	66.88 (0.63)
2	4	32.62 (0.82)	30.93 (0.67)	47.54 (0.53)

Note: as for Table 7.26.

Table 7.73 Yield Response Model 3 with Five Lag

Variables included in the unrestricted VAR	:	lnYLD lnPNR lnPPAD lnPPALM lnPFER lnWAGE
Deterministic and/or exogenous variables	:	Constant lnRAIN
Lag	:	5 (HQ)

Hypotheses		Trace Test		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	253.98 (0.00)	233.94 (0.00)	294.45 (0.00)
1	5	150.95 (0.00)	135.39 (0.00)	192.67 (0.00)
2	4	74.28 (0.00)	64.98 (0.00)	115.58 (0.00)
3	3	28.36 (0.23)*	20.68 (0.39)	54.63 (0.00)
4	2	15.60 (0.20)	8.18 (0.45)	12.77 (0.76)
5	1	6.11 (0.19)	0.15 (0.70)	4.38 (0.69)

Note: as for Table 7.26.

Table 7.74 Yield Response Model 4 with One Lag

Variables included in the unrestricted VAR	:	lnYLD lnPNR lnPPAD lnPFER lnWAGE
Deterministic and/or exogenous variables	:	Constant lnRAIN lnCVP
Lag	:	1 (SC)

Hypotheses		Trace Test		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	65.01 (0.29)*	59.09 (0.27)	79.19 (0.20)
1	5	36.01 (0.68)	30.78 (0.68)	48.29 (0.50)
2	4	15.61 (0.93)	15.46 (0.75)	28.23 (0.61)

Note: as for Table 7.26.

Table 7.75 Yield Response Model 4 with One Lag

Variables included in the unrestricted VAR	:	lnYLD lnPNR lnPPAD lnPFER lnWAGE
Deterministic and/or exogenous variables	:	Constant lnRAIN lnCVP
Lag	:	5 (HQ)

Hypotheses		Trace Test		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	173.47 (0.00)	157.13 (0.00)	178.17 (0.00)
1	5	94.35 (0.00)	88.72 (0.00)	104.32 (0.00)
2	4	49.05 (0.00)	46.43 (0.00)	54.56 (0.00)
3	3	19.30 (0.07)*	18.39 (0.07)	24.49 (0.07)
4	1	6.38 (0.17)	6.35 (0.01)	6.38 (0.42)

Note: as for Table 7.26.

Table 7.76 Yield Response Model 5 with One Lag

Variables included in the unrestricted VAR	:	lnYLD lnPNR lnPPALM lnPFER lnWAGE
Deterministic and/or exogenous variables	:	Constant lnRAIN lnCVP
Lag	:	1 (SC and HQ)

Hypotheses		Trace Test		
H_0: r	H_1: (n-r)	Model 2	Model 3	Model 4
0	6	57.44 (0.59)*	50.40 (0.62)	64.28 (0.73)
1	5	32.51 (0.83)	30.59 (0.69)	44.039 (0.69)
2	4	15.34 (0.94)	14.60 (0.81)	27.74 (0.64)

Note: as for Table 7.26.

Table 7.77 Yield Response Model 6 with One Lag

Variables included in the unrestricted VAR	:	lnYLD lnPNR lnPPAD lnPPALM lnPFER lnWAGE
Deterministic and/or exogenous variables	:	Constant lnRAIN lnCVP
Lag	:	1 (SC)

Hypotheses		Trace Test		
H_0: r	H_1: (n-r)	Model 2	Model 3	Model 4
0	6	86.17 (0.41)*	78.83 (0.41)	99.97 (0.38)
1	5	57.72 (0.58)	50.45 (0.62)	67.73 (0.60)
2	4	32.71 (0.82)	30.65 (0.69)	47.22 (0.55)

Note: as for Table 7.26.

Table 7.78 Yield Response Model 6 with Five Lags

Variables included in the unrestricted VAR	:	lnYLD lnPNR lnPPAD lnPPALM lnPFER lnWAGE
Deterministic and/or exogenous variables	:	Constant lnRAIN lnCVP
Lag	:	5 (HQ)

Hypotheses		Trace Test		
H_0: r	H_1: (n-r)	Model 2	Model 3	Model 4
0	6	281.26 (0.00)	258.22 (0.00)	319.53 (0.00)
1	5	177.80 (0.00)	160.23 (0.00)	214.84 (0.00)
2	4	95.44 (0.00)	87.027 (0.00)	131.44 (0.00)
3	3	49.96 (0.00)	45.42 (0.00)	73.76 (0.00)
4	2	19.78 (0.06)*	19.64 (0.01)	33.23 (0.00)
5	1	7.48 (0.11)	7.41 (0.01)	8.07 (0.25)

Note: as for Table 7.26.

Table 7.79 Yield Response Model 7 with One Lag

Variables included in the unrestricted VAR	:	lnYLD lnPNR lnPPAD lnPFER lnWAGE		
Deterministic and/or exogenous variables	:	Constant lnRAIN lnSDP		
Lag	:	1 (SC)		

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	66.59 (0.24)*	61.39 (0.20)	81.29 (0.15)
1	5	37.26 (0.62)	32.10 (0.61)	50.03 (0.42)
2	4	15.75 (0.93)	15.57 (0.75)	30.02 (0.51)

Note: as for Table 7.26.

Table 7.80 Yield Response Model 7 with Five Lags

Variables included in the unrestricted VAR	:	lnYLD lnPNR lnPPAD lnPFER lnWAGE		
Deterministic and/or exogenous variables	:	Constant lnRAIN lnSDP		
Lag	:	5 (HQ)		

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	5	174.13 (0.00)	156.48 (0.00)	178.59 (0.00)
1	4	91.58 (0.00)	85.28 (0.00)	103.29 (0.00)
2	3	50.10 (0.00)	46.30 (0.00)	56.81 (0.00)
3	2	19.32 (0.07)*	17.47 (0.02)	25.82 (0.05)
4	1	6.12 (0.19)	5.86 (0.02)	6.11 (0.46)

Note: as for Table 7.26.

Table 7.81 Yield Response Model 8 with One Lag

Variables included in the unrestricted VAR	:	lnYLD lnPNR lnPPALM lnPFER lnWAGE		
Deterministic and/or exogenous variables	:	Constant lnRAIN lnSDP		
Lag	:	1 (SC)		

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	58.14 (0.56)*	52.26 (0.54)	66.27 (0.65)
1	5	34.45 (0.75)	32.40 (0.60)	45.72 (0.62)
2	4	14.89 (0.95)	14.31 (0.82)	27.78 (0.64)

Note: as for Table 7.26.

Table 7.82 Yield Response Model 9 with One Lag

Variables included in the unrestricted VAR	:	lnYLD lnPNR lnPPAD lnPPALM lnPFER lnWAGE
Deterministic and/or exogenous variables	:	Constant lnRAIN lnSDP
Lag	:	1 (SC)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	6	87.23 (0.38)*	80.99 (0.33)	101.92 (0.32)
1	5	58.11 (0.60)	51.84 (0.60)	69.635 (0.52)
2	4	34.51 (0.75)	31.95 (0.62)	48.48 (0.49)

Note: as for Table 7.26.

Table 7.83 Yield Response Model 9 with Five Lags

Variables included in the unrestricted VAR	:	lnYLD lnPNR lnPPAD lnPPALM lnPFER lnWAGE
Deterministic and/or exogenous variables	:	Constant lnRAIN lnSDP
Lag	:	5 (HQ)

Hypotheses		**Trace Test**		
H_0: r	**H_1: (n-r)**	**Model 2**	**Model 3**	**Model 4**
0	5	279.55 (0.00)	255.71 (0.00)	320.04 (0.00)
1	4	176.75 (0.00)	160.26 (0.00)	216.76 (0.00)
2	3	94.17 (0.00)	85.80 (0.00)	130.88 (0.00)
3	2	51.01 (0.00)	45.70 (0.00)	74.26 (0.00)
4	1	19.27 (0.07)*	18.82 (0.01)	34.45 (0.00)
4	1	6.89 (0.14)	6.44 (0.01)	7.58 (0.30)

Note: as for Table 7.26.

Chapter 8 Summary and Conclusions

8.1 Introduction

Thailand is the world's largest natural rubber producer and exporter and the rubber sector is an important source both of foreign revenue and domestic employment. To maintain and develop the economic performance of rubber production, the Thai government has applied various policies and measures including research in high-yielding varieties, good-practice harvesting systems and maintenance of trees, and teaching new technology to farmers. The key project is the replanting scheme which helps farmers both to replant old rubber holdings with high yielding varieties, and to introduce modern methods of cultivation. These circumstances have attracted the interest of agricultural economists, analysts and policymakers to study the response of Thailand's natural rubber farmers to economic incentives. The analysis of agricultural supply response to prices is important: from an understanding of the characteristics of supply response and estimates of supply elasticities, we can assess the effectiveness of existing policies and establish a baseline and foundation for developing new policies.

The major aim of this thesis is to examine the responsiveness of natural rubber farmers in Thailand to various factors. This study develops a methodological framework and then applies it to estimate the supply response of rubber in Thailand using cointegration analysis and annual time series data for 1962-2008. Specifically, the objectives are:

i) to specify an economic model of the supply response of rubber farmers in Thailand;

ii) to estimate the dynamic responsiveness of natural rubber supply with respect to changes in price, non-price factors, and risk, and to analyse the system's response to shocks; and

iii) to consider the economic implications of the empirical results for maintaining sustained and balance growth of rubber production in Thailand.

This chapter summarises the key results, and draws both conclusions and some policy implications. The remainder of the chapter is structured as follows. Section 8.2 presents a summary including the main results. Section 8.3 concludes and presents some policy implications. Section 8.4 highlights the contribution to the agricultural economics literature and considers the limitations of the study. Section 8.5 provides some suggestions for future research.

8.2 Summary and Main Results

Chapter 2 provides an overview of natural rubber production in Thailand. The rubber tree, *Hevea brasiliensis*, was first introduced into the South and then into Eastern regions and these two regions are designated as traditional areas. Since the 1960s, the rubber growing areas have continually increased and expanded into the North East and the North. The rubber tree takes approximately seven years to come to maturity after which it can produce for approximately 25 years. Rubber cultivation in Thailand mainly takes place on smallholdings and is labour-intensive with family members and paid workers who are normally employed on an output-sharing system. Farmers usually sell their products in the local rubber market. The Thai government intervenes in the rubber industry through various agencies. In particular, the Rubber Replanting

Aid programme plays a significant role in replacing low yield rubber trees and then replanting with modern, high yielding trees. The government also directly intervenes on occasion, particularly during 1992-2003 when the rubber price decrease, to control the rubber price in both domestic and international markets.

Chapter 3 reviews the approaches used in modelling supply response and focuses, in particular, on the supply response literature that relates to rubber production in Thailand. Two empirical approaches have been used in the literature, namely, econometric and programming approaches. Econometric approaches can be divided into direct methods, indirect or two-stage duality approaches, and cointegration approaches. Direct estimates, often using Nerlove's model, relate to estimating supply equations where supply is typically defined as a function of own price, other relevant prices, and non-price factors. Supply response studies of rubber in Thailand have mostly used directly estimated single-equation Nerlovian-type supply models, but difficulties arise from an inadequate dynamic structure, spurious results and biased results due to omitted relevant variables, especially risk. The cointegration approach overcomes the problem of spurious regression. Moreover, both short- and long-run elasticities can be estimated from an error correction model (ECM), which is considered to be a more theoretically accurate dynamic structure than Nerlovian models. However, it can be criticised for lacking a theoretical basis. Indirect or two-stage duality approaches have been used less frequently.

Chapter 4 discusses some aspects of the neo-classical theory of production as a tool for describing and interpreting the behaviour of farm producers, and hypotheses are developed. Agricultural supply response is influenced by both price and non-price variables. The prices include own price, the prices of competing crops, and prices of inputs while non-price variables include technology, weather conditions, and institutional variables such as government policies. Risk and uncertainty is also examined. We consider two models of natural rubber supply response: an output model, and an acreage-yield model. To illustrate the dynamic specification of agricultural production response, an ECM is applied.

Traditional econometric techniques are based on the assumption of stationary data, but most time series are non-stationary and there is the possibility that results are spurious. Chapter 5 introduces some concepts in modern time series analysis and presents an empirical methodology which tests both for unit roots and for cointegration. We test for unit roots using the augmented Dickey-Fuller (ADF) test which examines the null hypothesis of non-stationarity against the alternative of stationarity. The major difficulty of using the ADF-test is that it has poor size and power properties. Therefore, the KPSS-test, which tests the null of stationarity against the alternative of non-stationarity, is also applied. Cointegration exists where there is a long-run or equilibrium relationship(s) among the variables. There are two major cointegration approaches. The first is the Engle-Granger approach in single-equation models where an ADF-test is applied to test the order of integration of the residuals in a relationship estimated by ordinary least squared (OLS). Difficulties arise in the case of three or more variables when there may be more than one cointegrating vector, and the Engle-Granger procedure does not provide a systematic method for separate estimation. The other method is the Johansen approach which is a cointegration test in a multivariate system and this approach is used here. Based on a vector autoregression (VAR) model, it allows the estimation of all possible long-run cointegrating vectors among the variables. From the Granger representation theorem, cointegration implies that a vector error correction model (VECM) exists and it is possible to estimate the short-run structure. Impulse response analysis examines the response of one variable to an impulse or shock in another and provides insights into short- and long-run relations between the variables.

Chapter 6 presents the results of the unit root tests. While there is some ambiguity in the conclusions from the ADF- and KPSS-tests, we conclude the following. Natural logarithms of planted rubber acreage, lnPLTA, natural logarithms of rubber acreage being tapped, lnTAPA, natural logarithms of rubber output, lnQNT, natural logarithms of rubber yield, lnYLD, natural logarithms of real price of rubber, lnPNR, natural logarithms of real price of fertiliser, lnPFER, natural logarithms of real wage rate, lnWAGE, and natural logarithms of real net replanting subsidy per acreage, lnSUB are non-stationary I(1) variables. Natural logarithms of real price of paddy, lnPPAD, natural logarithms of real price of palm oil, lnPPALM, natural logarithms of average annual rainfall, lnRAIN, natural logarithms of coefficient of variation of real rubber price, lnCVP, and natural logarithms of standard deviation real rubber price, lnSDP, appear stationary I(0) variables. These stationary I(0) series cannot be included in a long-run relationship between non-stationary I(1) variables; they are included in the system as exogenous variables.

In Chapter 7, we present the results of both the output and acreage-yield response models. Using Johansen’s cointegration approach, we find that unique long-run relationships exists, one for the output response model and one each for the acreage and yield response models. Three tests are applied to all equations. A stationary test suggests that all variables in each equation have a unit root. A variable exclusion test confirms that all coefficients in each equation are significant. However, the rubber price in both acreage and output equations is weakly exogenous. We therefore reformulate the acreage and output equations by setting the rubber price to be weakly exogenous. Output in the output response model then becomes weakly exogenous and there is no long-run output relationship. Thus, an output supply response model appears inappropriate to explain supply response of rubber production of Thailand. The preferred model is one comprising of acreage and yield responses.

In the acreage model, we find a unique long-run relationship between the planted area, rubber price, and fertiliser price. The long-run price elasticity of rubber acreage planted is estimated to be 2.16, which is higher than those in previous studies, while the elasticity of rubber acreage planted in response to a change in the subsidy is estimated to be 0.65. Rubber price is weakly exogenous which implies that price is not responsive to acreage and this reflects the fact that the domestic rubber price is mainly determined by the world rubber price. The VECM shows that the estimated short-run price elasticity of rubber acreage planted is very low at 0.03. We also find that there is a unique long-run relationship between rubber yield, the fertiliser price, and rainfall in the yield response model. However, residuals are non-normal which might affect statistical inference. The long-run elasticity of yield with respect to the fertiliser price is estimated to be -5.50. As expected, the fertiliser price has a negative effect on yield: when the fertiliser price increases, fertiliser use decreases and rubber productivity falls. Fertiliser is important to the growth and productivity of rubber trees because soil quality is normally poor. Nutrition is also removed from the soil via rubber latex.Thus, the application of fertiliser is needed to balance soil quality. We also find that yield does not respond to changes in rubber price. It might be suggested that rubber yield might change if farmers adjust their cultivation methods, such as tapping frequency and intensity and the number of trees tapped per acreage, in response to rubber price changes. However, farmers do not generally change their cultivation practices from the standard system because unusual practices may damage trees. In general, farmers tap rubber trees even when the rubber price decreases because they rely on rubber tree cultivation for cash. However, they may not tap trees on marginal land. This implies that the mature rubber acreage is normally tapped at full or nearly full capacity, as we assume in our acreage-yield model where $TAPA_t = MA_t$. Thus, it seems reasonable that yield is not affected significantly by rubber price. In the VECM, rainfall has a negative effect on yield. Rainfall is necessary for tree growth, but to avoid diseases tapping is appropriate only when the bark of the tree is dry. Consequently, rainfall interrupts tapping and causes decreasing productivity.

Impulse response analysis shows that a shock in the replanting subsidy leads to a continual increase in the rubber acreage, and this might imply instability of model. A one standard error shock in the fertiliser price causes a decrease of 7% in the rubber yield; this effect is permanent and the rubber yield then takes around seven years to stabilise to new long-run equilibrium.

Comparing the estimated elasticities from this study with those from previous studies reviewed in Chapter 3, we find that most previous studies report low estimated short-run price elasticities for rubber acreage and this study supports that evidence. In the long run, farmers adjust their plantings, so estimated long-run elasticities are greater than those in the short run, and this situation is supported by the very low adjustment coefficient for acreage. The estimated short-run price elasticity of rubber planted acreage is inelastic but that in the long run is highly elastic. In the yield equation, we could not estimate the elasticity with respect to price and this suggests that yield does not respond to changes in price. In contrast, yield responds significantly to the fertiliser price in the long run, that is, when the fertiliser price increases, fertiliser use decrease and rubber productivity falls. Since an appropriate cointegrating vector is not found in the output response model, we cannot estimate the price elasticity of rubber output.

8.3 Conclusions and Policy Implication

This study provides strong evidence that Thai rubber farmers respond rationally to economic incentives in their production environment. Results show that the estimated elasticities of rubber acreage planted to own price is significant and positive, and price policies can be effective for achieving/influencing desired acreage. However, the low estimated short-run and high long-run price elasticities of acreage response suggest that rubber farmers only adjust planted area by a small amount in the short run in response to a price change, whereas they make substantial adjustments in the long run. This slow adjustment in the short run is caused by significant adjustment costs of investment. Further, adjustment is restricted because inputs like labour and capital are inflexible in the short run. Therefore, any form of pricing policy requires a long lead time to reach long run equilibrium. Not surprisingly, the impacts of changes in the prices of alternative crops like oil palm or paddy do not affect the acreage allocation between these crops. The reason is that the replanting subsidy significantly drives the new acreage of rubber and few rubber farmers revert to alternative crops. Therefore, the output prices of alternative crops are unimportant in decision-making. The implication here is that it might be appropriate to formulate a price policy for these crops based on a single crop since any change in the price of one crop has no effect on the acreage of other crops.

We find that small increases in the price of rubber lead to large increases in the planted rubber acreage. The policy implication is that if the government aims to increase rubber acreage, the rubber price should not be allowed to fall. In the domestic market, the government should develop markets particularly central rubber markets to improve price transmission to farmers thereby eliminating market tiers with associated margins. The government could also encourage the establishment of farmer groups, institutes or co-operatives both to increase their bargaining power and strengthen their business-management capacity. Another possible policy to sustain the rubber price is that the government should stimulate more domestic demand, which can be achieved by increasing domestic rubber utilisation for the production of value-added products rather than exporting as raw materials. This could decrease the dependency on the world market and might insulate farmers from world price fluctuations. Since the domestic rubber price is significantly influenced by the world price, the government needs to co-operate with other rubber producing countries to intervene in the world market when price falls.

The results also indicate the importance of the replanting subsidy. There is no acreage response to changes in the subsidy in the short run, but there is a small but significant response in the long run. Thus, the government can stimulate the expansion of acreage planted in the long run by increasing the replanting subsidy. This replanting subsidy is important to farmers because they face a temporary short fall of the income during the unproductive period before the newly planted rootstock matures and the subsidy mitigates against these. Moreover, participation in the replanting programme helps farmers to access to various training schemes and information about production and marketing. However, a concern is that the replanting programme fund is mainly obtained from the cess charged on rubber exporters; this resource allocation is sub-optimal since all rubber farmers pay the tax indirectly but the replanting programme benefits only farmers who join the replanting scheme.

In our yield response model, results indicate that an increase in the fertiliser price has a negative effect on yield. The Thai fertiliser industry cannot satisfy domestic demand because of a lack of raw materials and high costs of production, and fertiliser is mainly imported. Previously, the government subsidised fertilisers to rubber farmers in the replanting scheme, but there were complaints of late arrival of inputs and poor quality and this practice was stopped. Now, the government makes a payment directly to farmers for purchasing fertilisers. The policy implication is that a sufficient amount of good quality fertiliser at reasonable prices should be provided. To achieve this, the government could develop good quality fertiliser production, possibly to be sold at a subsidised price, to rubber farmers. Alternatively, the government could manage and promote competition among fertiliser producers and traders. Finally, research and development of organic fertilisers, indigenous sources of the plant nutrients (N, P and K) could be promoted. The application of organic fertilisers would help farmers to maintain low costs of production, and they would be less dependent on the world fertiliser market. However, chemical and organic fertiliser should be used jointly since both complement each other in improving soil quality.

Currently, it seems that the rubber growing areas in Thailand might not grow significantly as in the past due to land constraints, and yield growth will be increasingly important to the future of the sector. Thus, in cooperation with measures on fertilisers, the government should support research and development into rubber cultivation and harvesting, particularly those on integrated plantation, and then introduce this knowledge to farmers to improve productive efficiency and the quality of rubber products.

8.4 Contributions and Limitations of the Study

This study contributes to the understanding and knowledge of the specification and estimation of the behavioural relationships underlying rubber supply response in two key ways. This is the first study which applies modern time series econometrics to estimating the supply response of rubber in Thailand, and we show that the cointegration approach is suitable for the study of agricultural supply response of a perennial crop. Second, our results imply that an output response model is inadequate to describe natural rubber supply response in Thailand. By contrast, acreage and yield response models are appropriate and are to be preferred. Previous studies of rubber supply response in Thailand either estimate one or other of these models without making a comparison.

As in many econometric models, the supply response models developed here have some limitations. One is data constraints where series like new plantings, removals, land prices, and technical change such as high-yielding varieties usage, which reflect progress in rubber production, are not available. Some of the data used, i.e., the wage rate and the fertiliser price, are possibly of poor quality. A key omission from the empirical analysis is land prices which are an important factor in the acreage decision for rubber famers. If the price of land for growing rubber is high, as is the case in the Southern and Eastern regions where it is more than 8,000 US$/hectare in 2008, it is difficult for rubber farmers to expand the rubber acreage. This situation stimulates the rapid expansion of rubber areas in the Northeastern and Northern regions where the land is relatively cheaper. Misspecification error from the omission of relevant explanatory variables can lead to biased parameter estimates. Data limitations imply that Thailand must improve and maintain its agricultural statistics collecting service because meaningful analysis is impossible without reliable, high quality data. Another limitation is that the economic relationships in the model are approximated by simple log-linear functional forms, and this may pose problems in deterministic solutions or forecasting outside the historical data range. Also, the time series used here is relatively small and this leads to the estimated elasticities having less than optimal statistical credentials.

8.5 Future Research

Regardless of limitations, this study provides some answers to important topical policy questions about rubber supply response in Thailand which should be useful to government policymakers. In particular, the results can aid policymakers in their monitoring and directing of rubber production policies and in their formulation of appropriate strategies. Further analysis can be developed in four areas. First, if reliable data are available on, for example, new plantings and removals by age distribution, future studies could estimate more accurate elasticities. Second, the empirical model could be estimated for different rubber growing regions or provinces, as there may be different responses in each region. Panel cointegration models may be appropriate here. Third, since the rubber sector in Thailand has been influenced by a number of government interventions, exploring the effects of government programmes on the rubber sector empirically is an interesting and useful area for future research. Finally, it is hoped that the approach developed here could be used for analysis of the supply response of a wider-range of perennial crops.

References

Abdulai, A. and Rieder, P. (1995) 'The impact of agricultural price policy on cocoa supply in Ghana: an error correction estimation', *Journal of African Economics,* 4, (3), pp. 315 - 335.

Adesina, A. A. and Brorsen, B. W. (1987) 'A risk responsive acreage response function for millet in Niger', *Agricultural Economics,* 1, (3), pp. 229-239.

Ady, P. (1968) 'Supply functions in tropical agriculture', *Bulletin of the Oxford University Institute of Economics and Statistics,* 30, (2), pp. 157-188.

Akaike, H. (1973) 'Information theory and the extension of the Maximum Likelihood principle', in Petrov, B. N. and Csaki, F.(eds) *2nd International Symposium on Information Theory.* Akademial Kiado, Budapest, pp. 267-281.

Akiyama, T. and Trivedi, P. K. (1987a) *A New Global Tea Model: Specification, Estimation, and Simulation.* Washington D.C.: World Bank

Akiyama, T. and Trivedi, P. K. (1987b) 'Vintage production approach to perennial crop supply: an application to tea in major producing countries', *Journal of Econometrics,* 36, (1-2), pp. 133-161.

Alemu, Z. G., Oosterhuizen, K. and van Schalkwyk, H. D. (2003) 'Grain-supply response in Ethiopia: an error-correction approach ', *Agrekon* 42 (4), pp. 389-404.

Alias, M. and Tang, T. C. (2010) 'Supply response of Malaysian palm oil producers: impact of interest rate variations', *Oil Palm Industry Economic Journal* 5, (2), pp. 11-22.

Alias, M. H., Ali, A. M. and Rahman, M. A. (2001) 'The impact of government policy on the supply response of Malyasian Palm oil, rubber, and cocoa producers', *Utara Management Review,* 2, (1), pp. 41-64.

Almon, S. (1965) 'The distributed lag between capital appropriations and expenditures', *Econometrica,* 33, (1), pp. 178-196.

Alston, J. M., Carman, H. F., Christian, J. E., Dorfman, J., Murua, J.-R. and Sexton, R. J. (1995) *Optimal Reserve and Export Policies for the California Almond Industry: Theory, Econometrics and Simulations.* Davis: Giannini Foundation of Agricultural Economics, University of California (42).

Alston, J. M., Freebairn, J. W. and Quilkey, J. J. (1980) 'A model of supply response in the australian orange growing industry', *Australian Journal of Agricultural Economics,* 24, (3), pp. 248-267.

Arellano, C. and Pantula, S. G. (1995) 'Testing for trend stationarity versus difference stationarity', *Journal of Time Series Analysis,* 16, (2), pp. 147-164.

Aroonsiriporn, P. (1989) *The Impact of External Factors to the Demand and Supply of Natural Rubber in Thailand.* Master thesis. Kasetsart University.

Arrow, K. J. (1965) *Aspects of the Theory of Risk-bearing.* Helsinki: Yrjo Jahnssonin Sättio.

Arthannarong, V. (1994) *Farmer's Behavior in the Production of Rubber.* Master thesis. Chulalongkorn University.

Askari, H. and Cummings, J. T. (1976) *Agricultural Supply Response: A Survey of the Econometric Evidence.* New York: Praeger.

Banerjee, A. (1993) *Co-integration, Error Correction, and the Econometric Analysis of Non-stationary Data.* New York: Oxford University Press.

Baron, D. P. (1970) 'Price uncertainty, utility, and industry equilibrium in pure competition', *International Economic Review,* 11, (3), pp. 463-480.

Bateman, M. J. (1965) 'Aggregate and regional supply functions for Ghanaian cocoa, 1946-1962', *Journal of Farm Economics,* 47, (2), pp. 384-401.

Bateman, M. J. (1969) 'Supply relations for perennial crops in the less developed areas', in Wharton, C. R.(ed), *Subsistence Agriculture and Economic Development.* Chicago: Aldine Press, pp. 243 - 253.

Beattie, B. R. and Taylor, C. R. (1985) *The Economics of Production.* New York: Wiley.

Behrman, J. R. (1968) 'Monopolistic coca pricing', *American Journal of Agricultural Economics,* 50, (3), pp. 702-719.

Behrman, J. R. (1971) 'Econometric model simulations of the world rubber market, 1950 -1980', in Klein, L. R.(ed), *Essays in Industrial Economics.* Vol. 3 Philadelphia: Economics Research Unit, University of Pensylvania.

Blough, S. R. (1992) 'The relationship between power and level for generic unit root tests in finite samples', *Journal of Applied Econometrics,* 7, (3), pp. 295-308.

Box, G. E. P. and Jenkins, G. M. (1970) *Time Series Analysis: Forecasting and Control.* San Francisco: Holden-Day.

Box, G. E. P. and Jenkins, G. M. (1976) *Time Series Analysis: Forecasting and Control.*Rev. ed San Francisco: Holden-Day.

Brennan, J. P. (1980) *Some effects of risk on the suppy of wheat in Victoria.* Master thesis. University of Melbourne.

Brennan, J. P. (1982) 'The representation of risk in econometric models of supply: some observations', *Australian Journal of Agricultural Economics,* 26, (2), pp. 151-157.

Burger, K. and Smit, H. P. (1997) *The Natural Rubber Market : Review, Analysis, Policies and Outlook.* Cambridge: Woodhead.

Bushnell, P. G. and King, G. A. (1986) *The Domestic and Export Markets for California Almonds.* Davis: Giannini Foundation of Agricultural Economics, University of California (334).

Caner, M. and Kilian, L. (2001) 'Size distortions of tests of the null hypothesis of stationarity: evidence and implications for the PPP debate', *Journal of International Money and Finance,* 20, (5), pp. 639-657.

Carman, H. F. (1981) 'Income tax reform and California orchard development', *Western Journal of Agricultural Economics,* 6, (02), pp. 165-180.

Carman, H. F. and Craft, R. K. (1998) *An economic evaluation of California avocado industry marketing programs, 1961-1995.* Davis: Giannini Foundation of Agricultural Economics, University of California (345).

Centre for Agricultural Information Office of Agricultural Economics. (2009) *Thailand Foreign Agricultural Trade Statistics 2008*. [Online]. Available at: http://www.oae.go.th/main.php?filename=journal_all (Accessed: December 30, 2010).

Centre for Agricultural Information Office of Agricultural Economics. (2006) *Cost of Production of Major Crops.* Bangkok: Office of Agricultural Economics.

Centre for Agricultural Information Office of Agricultural Economics (n.d.) *Agricultural Economic Data*. Available at: http://www.oae.go.th/ewt_news.php?nid=4542 (Accessed: November 30, 2010).

Chavas, J.-P. and Holt, M. T. (1990) 'Acreage decisions under risk: the case of corn and soybeans', *American Journal of Agricultural Economics,* 72, (3), pp. 529-538.

Cheung, Y.-W. and Lai, K. S. (1993) 'Finite-sample sizes of Johansen's likelihood ratio tests for cointegration', *Oxford Bulletin of Economics & Statistics,* 55, (3), pp. 313-328.

Choi, I. (1994) 'Residual-based tests for the null of stationarity with applications to U.S. macroeconomic time Series', *Econometric Theory,* 10, (3/4), pp. 720-746.

Clay, J. (2003) *World Agriculture and the Environment : A Commodity-by-commodity Guide to Impacts and Practices.* Washington, D.C.: Island.

Cochrane, J. H. (1991) 'A critique of the application of unit root tests', *Journal of Economic Dynamics and Control,* 15, (2), pp. 275-284.

Colman, D. (1983) 'A review of the arts of supply response analysis', *Review of Marketing and Agricultural Economics,* 51, (3), pp. 201 - 230.

Colman, D. and Young, T. (1989) *Principles of Agricultural Economics: Markets and Prices in Less Developed Countries.* Cambridge: Cambridge University Press.

Deb, S. (2003) *Terms of Trade and Supply Response of Indian Agriculture: Analysis in Cointegration Framework.* Delhi: Centre for Development Economics, Delhi School of Economics (115).

Debertin, D. L. (1986) *Agricultural Production Economics.* New York: Macmillan.

DEFRA (2009) *Annex 7-International Grain Market*. Available at: www.defra.gov.uk/foodfarm/food/pdf/ag-price-annex%207.pdf (Accessed: October 16, 2009).

Dennis, J. G., Hansen, H., Johansen, S. and Juselius, K. (2006) *CATS in RATS. Cointegration Analysis of Time Series, Version 2.* Evanston: Estima.

Department of Agriculture (n.d.) *Plant Knowledge Base: Para Rubber*. Available at: http://210.246.186.28/pl_data/RUBBER/1STAT/st01.htmlata/RUBBER/1stat/st01.html (Accessed: January 15, 2008).

Dickey, D. A. and Fuller, W. A. (1979) 'Distribution of the estimators for autoregressive time series with a unit root', *Journal of the American Statistical Association,* 74, (366), pp. 427-431.

Dickey, D. A. and Fuller, W. A. (1981) 'Likelihood ratio statistics for autoregressive time series with a unit root', *Econometrica,* 49, (4), pp. 1057-1072.

Diebold, F. X. and Senhadji, A. S. (1996) 'The uncertain unit root in real GNP: comment', *American Economic Review,* 86, (5), pp. 1291-1298.

Division of Agricultural Economic Research. (1989) *The Study of Rubber's Demand.* Bangkok: Office of Agriculutural Economics

Doll, J. P. and Orazem, F. (1984) *Production Economics: Theory with Applications.*2nd ed New York: Wiley.

Doornik, J. A. (1998) 'Approximations to the asymptotic distributions of cointegration tests', *Journal of Economic Surveys,* 12, (5), pp. 573-593.

Doornik, J. A. (1999) 'Approximations to the asymptotic distributions of cointegration tests', in McAleer, M. and Oxley, L.(eds) *Practical Issues in Cointegration Analysis.* Oxford: Blackwell.

Dorfman, J. H. and Heien, D. (1989) 'The effects of uncertainty and adjustment costs on investment in the almond industry', *Review of Economics and Statistics,* 71, (2), pp. 263-274.

Dowling, J. M. (1979) 'The supply response of rubber in Thailand', *Southern Economic Journal,* 45, (3), pp. 795-805.

Durbin, J. and Koopman, S. J. (2001) *Time Series Analysis by State Space Methods.*2nd ed Oxford: Oxford University Press.

Ellis, F. (1988) *Peasant Economics: Farm Households and Agrarian Development.* Cambridge: Cambridge University Press.

Enders, W. (2010) *Applied Econometric Time Series.*3rd ed Hoboken: Wiley.

Engle, R. F. and Granger, C. W. J. (1987) 'Co-integration and error correction: Representation, estimation, and testing', *Econometrica,* 55, (2), pp. 251-276.

Estima. (2004) *RATS Version 6, Reference Manual.* Evanston: Estima.

Food and Agriculture Organisation (n.d.) *FAOSTAT* [Online]. Available at: http://faostat.fao.org/site/339/default.aspx (Accessed: June 30, 2009).

French, B. C. and Bressler, R. G. (1962) 'The lemon cycle', *Journal of Farm Economics,* 44, (4), pp. 1021-1036.

French, B. C. and King, G. A. (1988) *Dynamic Economic Relationships in the California Cling Peach Industry.* Davis: Giannini Foundation of Agricultural Economics, University of California (338).

French, B. C., King, G. A. and Minami, D. D. (1985) 'Planting and removal relationships for perennial crops: an application to cling peaches', *American Journal of Agricultural Economics,* 67, (2), pp. 215-223.

French, B. C. and Matthews, J. L. (1971) 'A supply response model for perennial crops', *American Journal of Agricultural Economics,* 53, (3), pp. 478-490.

French, B. C. and Nuckton, C. F. (1991) 'An empirical-analysis of economic-performance under the Marketing Order for raisins', *American Journal of Agricultural Economics,* 73, (3), pp. 581-593.

French, B. C. and Willett, L. S. (1989) *An Econometric Model of the U.S. Asparagus Industry.* Davis: Giannini Foundation of Agricultural Economics, Universtiy of California (340).

Fuller, W. A. (1976) *Introduction to Statistical Time Series.* New York: Wiley.

Ghatak, S. and Ingersent, K. A. (1984) *Agriculture and Economic Development.* Brighton: Wheatsheaf Books.

Granger, C. W. J. (1981) 'Some properties of time series data and their use in econometric model specification', *Journal of Econometrics,* 16, (1), pp. 121-130.

Granger, C. W. J. and Newbold, P. (1974) 'Spurious regressions in econometrics', *Journal of Econometrics,* 2, (2), pp. 111-120.

Greene, W. H. (2008) *Econometric Analysis.*6th ed Upper Saddle River: Pearson/Prentice Hall.

Grilli, E. R. (1979) *An Econometric Model of the World Rubber Economy.* Washington, D.C.: World Bank

Gujarati, D. N. and Porter, D. C. (2009) *Basic Econometrics.*5th (international) ed Boston: McGraw-Hill.

Hallam, D. and Zanoli, R. (1993) 'Error correction models and agricultural supply response', *European Review of Agricultural Economics,* 20, (2), pp. 151-166.

Hannan, E. J. and Quinn, B. G. (1979) 'The determination of the order of an autoregression', *Journal of the Royal Statistical Society. Series B (Methodological),* 41, (2), pp. 190-195.

Hansen, B. E. (1992) 'Efficient estimation and testing of cointegrating vectors in the presence of deterministic trends', *Journal of Econometrics,* 53, (1-3), pp. 87-121.

Harbo, I., Johansen, S., Nielsen, B. and Rahbek, A. (1998) 'Asymptotic inference on cointegrating rank in partial systems', *Journal of Business & Economic Statistics,* 16, (4), pp. 388-399.

Harris, R. and Sollis, R. (2005) *Applied Time Series Modelling and Forecasting.* Chichester: John Wiley & Sons.

Hartley, M. J., Nerlove, M. and Peters, R. K. (1987) 'An analysis of rubber supply in Sri Lanka', *American Journal of Agricultural Economics,* 69, (4), pp. 755-761.

Hataiseree, R. (1983) *An Economic Analysis of the Thai Natural Rubber Industry.* Master thesis. Thammasat University.

Hendry, D. F. and von Ungern-Sternberg, T. (1981) 'Liquidity and inflation effects on consumers' expenditure', in Deaton, A. and Stone, R.(eds) *Essays in the Theory and Measurement of Consumer Behaviour* Cambridge: Cambridge University Press, pp. 237-260.

Hennebery, S. R. and Tweeten, L. G. (1991) 'A review of international agricultural supply response', *Journal of International Food & Agribusiness Marketing,* 2, (3/4), pp. 49 - 68.

International Monetary Fund (n.d.) *International Financial Statistics (IFS)* [Online]. Available at: http://www.imfstatistics.org/imf/ (Accessed: November 15, 2008).

IRRDB (n.d.) *Hevea Brasiliensis: General Description* Available at: http://www.irrdb.com/irrdb/NaturalRubber/RubberTree/RubberTree.htm (Accessed: January 15, 2008).

International Rice Research Institute (n.d.) *World Rice Statisitces* [Online]. Available at: http://irri.org/our-science/social-science-economics/world-rice-statistics (Accessed: November 30, 2009).

Johansen, S. (1988) 'Statistical analysis of cointegration vectors', *Journal of Economic Dynamics and Control,* 12, (2-3), pp. 231-254.

Johansen, S. (1992) 'Testing weak exogeneity and the order of cointegration in UK money demand data', *Journal of Policy Modeling,* 14, (3), pp. 313-334.

Johansen, S. (1995) *Likelihood-based Inference in Cointegrated Vector Autoregressive Models.* Oxford: Oxford University Press.

Johansen, S. (2000) 'A Bartlett correction factor for tests on the cointegrating relations', *Econometric Theory,* 16, (5), pp. 740-778.

Johansen, S. (2002a) 'A small sample correction for tests of hypotheses on the cointegrating vectors', *Journal of Econometrics,* 111, (2), pp. 195-221.

Johansen, S. (2002b) 'A small sample correction for the test of cointegrating rank in the vector autoregressive model', *Econometrica,* 70, (5), pp. 1929-1961.

Johansen, S. (2005) 'Interpretation of cointegrating coefficients in the cointegrated vector autoregressive model', *Oxford Bulletin of Economics & Statistics,* 67, (1), pp. 93-104.

Johansen, S. and Juselius, K. (1990) 'Maximum likelihood estimation and inference on cointegration with applications to the demand for money', *Oxford Bulletin of Economics & Statistics,* 52, (2), pp. 169-210.

Johansen, S., Mosconi, R. and Nielsen, B. (2000) 'Cointegration analysis in the presence of structural breaks in the deterministic trend', *Econometrics Journal,* 3, (2), pp. 216-249.

Jumpasut, P. (1981) *The Natural Rubber Economy of Thaiand.* PhD thesis. University of Michigan.

Juselius, K. (2006) *The Cointegrated VAR Model: Methodology and Applications.* Oxford: Oxford University Press.

Just, R. E. (1974) 'An investigation of the importance of risk in farmers' decisions', *American Journal of Agricultural Economics,* 56, (1), pp. 14-25.

Just, R. E. and Zilberman, D. (1986) 'Does the law of supply hold under uncertainty?', *Economic Journal,* 96, (382), pp. 514-524.

Kaiyoorawong, S. and Yangdee, B. (2008) 'Right of rubber farmers in Thailand under free trade', [Online]. Available at: http://www.wrm.org.uy/countries/Thailand/Rights_of_rubber_farmers_in_Thailand.pdf (Accessed: September 15, 2010).

Kalaitzandonakes, N. G. and Shonkwiler, J. S. (1992) 'A state-space approach to perennial crop supply analysis', *American Journal of Agricultural Economics,* 74, (2), pp. 343-352.

Kinney, W., Carman, H. F., Green, R. and O'Connel, J. (1987) *An Analysis of Economic Adjustment in the California-Arizona Lemon Industry.* Davis: Giannini Foundation of Agricultural Economics, University of California (337).

Knapp, K. C. and Konyar, K. (1991) 'Perennial crop supply response: a Kalman filter approach', *American Journal of Agricultural Economics,* 73, (3), pp. 841-849.

Kraus, M., Lee, J. Y. and Koo, W. W. (1995) 'Program and non-program wheat acreage response to prices and risk', *Journal of Agricultural and Resource Economics,* 20, pp. 96-107.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P. and Shin, Y. (1992) 'Testing the null hypothesis of stationarity against the alternative of a unit root: how sure are we that economic time series have a unit root?', *Journal of Econometrics,* 54, (1-3), pp. 159-178.

Leybourne, S. J. and McCabe, B. P. M. (1994) 'A consistent test for a unit root', *Journal of Business & Economic Statistics,* 12, (2), pp. 157-166.

Lin, W. (1977) 'Measuring aggregate supply response under instability', *American Journal of Agricultural Economics,* 59, (5), pp. 903-907.

Lin, W. and Dismukes, R. (2007) 'Supply response under risk: implications for Counter-Cyclical Payments' production impact', *Review of Agricultural Economics,* 29, (1), pp. 64-86.

Lutkepohl, H. (2005) *New Introduction to Multiple Time Series Analysis.* Berlin: Springer.

Lutkepohl, H. and Reimers, H.-E. (1992) 'Impulse response analysis of cointegrated systems', *Journal of Economic Dynamics and Control,* 16, (1), pp. 53-78.

Lutkepohl, H. and Saikkonen, P. (1999) 'Order selection in testing for the cointegration rank of a VAR process', in Engle, R. F. and White, H.(eds) *Cointegration, Causality, and Forecasting.* Oxford: Oxford University Press.

Lutkepohl, H., Saikkonen, P. and Trenkler, C. (2001) 'Maximum eigenvalue versus trace tests for the cointegrating rank of a VAR process', *Econometrics Journal,* 4, (2), pp. 287-310.

MacKinnon, J. G. (1991) 'Critical values of cointegration tests', in Engle, R. F. and Granger, C. W. J.(eds) *Long-run Economic Relationships: Reading in Cointegration* New York: Oxford University Press.

MacLaren, D. (1983) 'The output response of the risk averse firm: some comparative statics for agricultural policy', *Journal of Agricultural Economics,* 34, (1), pp. 45-56.

Maddala, G. S. (1998) 'Recent developments in dynamic econometric modelling: a personal viewpoint', *Political Analysis,* 7, (1), pp. 59-87.

Maddala, G. S. (2001) *Introduction to Econometrics.*3rd ed ed Chichester: Wiley.

Maddala, G. S. and Kim, I.-M. (1998) *Unit roots, Cointegration, and Structural Change.* Cambridge: Cambridge University Press.

Man, A. B. and Blandford, D. (1980) *The Outlook for Natural Rubber in the 198O's* New York: Cornell University.

McKay, A., Morrissey, O. and Vaillant, C. (1999) 'Aggregate supply response in Tanzanian agriculture', *Journal of International Trade & Economic Development,* 8, (1), pp. 107-123.

Mesike, C. S., Okoh, R. N. and Inoni, O. E. (2010) 'Supply response of rubber farmers in Negeria: an application of vector error correction model', *Journal of American Science,* 6, (9), pp. 52-56.

Meyanathan, S. (1983) 'Monthly regional supply functions of natural rubber', *Developing Economies,* 21, (3), pp. 225-233.

Nabeya, S. and Tanaka, K. (1988) 'Asymptotic theory of a test for the constancy of regression coefficients against the random walk alternative', *The Annals of Statistics,* 16, (1), pp. 218-235.

National Natural Rubber Committee. (2010) *Natural Rubber Development Strategies 2009-2013*. [Online]. Available at: http://www.rubberthai.com/about/strategy.php (Accessed: October 25, 2010).

Nerlove, M. (1958) *The Dynamics of Supply: Estimation of Farmers' Response to Price.* Baltimore: The Johns Hopkins Press.

Nerlove, M. (1979) 'The dynamics of supply - retrospect and prospect', *American Journal of Agricultural Economics,* 61, (5), pp. 874-888.

Neumann, J. v. and Morgenstern, O. (1944) *Theory of Games and Economic Behaviour.* Princeton: Princeton University Press.

Nickell, S. (1985) 'Error correction, partial adjustment and all that: an expository note', *Oxford Bulletin of Economics & Statistics,* 47, (2), pp. 119-129.

Nowshirvani, V. (1968) *Agricultural Supply in India: Some Theoretical and Empirical Studies.* . PhD thesis. Massachusetts Institute of Technology.

Office of Agricultural Economics. (various years) *Agricultural Statistics of Thailand.* Bangkok: Office of Agricultural Economics.

Office of the Rubber Replanting Aid Fund (n.d.-a) *History of Para Rubber*. Available at: http://www.rubber.co.th/web/technique3.php (Accessed: June 15, 2008).

Office of the Rubber Replanting Aid Fund (n.d.-b) *ORRAF Responsibility*. Available at: http://www.rubber.co.th/web/about11.php (Accessed: November 30, 2008).

Office of the Rubber Replanting Aid Fund (n.d.-c) *Replanting Extension*. Available at: http://www.rubber.co.th/web/service1.php (Accessed: November 30, 2008).

Osterwald-Lenum, M. (1992) 'A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics', *Oxford Bulletin of Economics & Statistics,* 54, (3), pp. 461-472.

Ozanne, A. (1999) 'Perverse supply response in peasant agriculture: a review', *Oxford Development Studies,* 27, (2), pp. 251 - 270.

Park, J. Y. (1990) 'Testing for unit roots and cointegration by variable addition', in Fomby, T. and Rhodes, F.(eds) *Advances in Econometrics: Cointegration, Spurious Regressions and Unit Roots.* Greenwich: Jai Press.

Perron, P. (1988) 'Trends and random walks in macroeconomic time series: further evidence from a new approach', *Journal of Economic Dynamics and Control,* 12, (2-3), pp. 297-332.

Pesaran, M. H., Shin, Y. and Smith, R. J. (2000) 'Structural analysis of vector error correction models with exogenous I(1) variables', *Journal of Econometrics,* 97, (2), pp. 293-343.

Phillips, P. C. B. (1987) 'Time series regression with a unit root', *Econometrica,* 55, (2), pp. 277-301.

Phillips, P. C. B. and Ouliaris, S. (1990) 'Asymptotic properties of residual based tests for cointegration', *Econometrica,* 58, (1), pp. 165-193.

Pipitkul, P. (2003) 'Demand and supply of natural rubber of Thailand', *Journal of Agricultural Economics,* 22, (2), pp. 65-97.

Pratt, J. W. (1964) 'Risk aversion in the small and in the large', *Econometrica,* 32, (1/2), pp. 122-136.

Puapongsakorn, N., Suzuki, P. and Ranong, V. N. (2001) *An Economic Evaluation on the Rubber Replantation Program.* Bangkok: Thailand Development Research Institute.

Rae, A. N. and Carman, H. F. (1975) 'A model of New Zealand apple supply response to technological change', *Australian Journal of Agricultural Economics,* 19, (1), pp. 39-51.

Rao, J. M. (1989) 'Agricultural supply response: a survey', *Agricultural Economics,* 3, (1), pp. 1-22.

Reimers, H.-E. (1992) 'Comparisons of tests for multivariate cointegration', *Statistical Papers,* 33, pp. 335-359.

Rubber Research Institute (n.d.) *Thailand Rubber Statistics*. Available at: http://www.rubberthai.com/statistic/stat_index.htm (Accessed: November 9, 2010).

Rubber Research Institute. (various years) *Thailand Rubber Statistics.* Bangkok: Rubber Research Institute.

Rubber Research Institute Department of Agriculture. (2010) *Information on Rubber*. [Online]. Available at: http://www.rubberthai.com/about/data.php (Accessed: December 15, 2010).

Rudebusch, G. D. (1992) 'Trends and random walks in a macroeconomic time series: a re-examination', *International Economic Review,* 33, (3), pp. 661-680.

Rudebusch, G. D. (1993) 'The uncertain unit root in real GNP', *American Economic Review,* 83, (1), pp. 264-272.

Sadoulet, E. and de Janvry, A. (1995) *Quantitative Development Policy Analysis.* Baltimore: The Johns Hopkins University Press.

Said, S. E. and Dickey, D. A. (1984) 'Testing for unit roots in autoregressive-moving average models of unknown order', *Biometrika,* 71, (3), pp. 599-607.

Saikkonen, P. and Luukkonen, R. (1993) 'Testing for a moving average unit root in autoregressive integrated moving average models', *Journal of the American Statistical Association,* 88, (422), pp. 596-601.

Sakarindr, P. (1979) *An Econometric Study of Thai Rubber Industry and the World Rubber Market.* PhD thesis. Iowa State University.

Salmon, M. (1982) 'Error correction mechanisms', *Economic Journal,* 92, (367), pp. 615-629.

Sandmo, A. (1971) 'On the Theory of the Competitive Firm Under Price Uncertainty', *American Economic Review,* 61, (1), pp. 65-73.

Sargan, J. D. and Bhargava, A. (1983) 'Testing residuals from least squares regression for being generated by the Gaussian random walk', *Econometrica,* 51, (1), pp. 153-174.

Schwarz, G. (1978) 'Estimating the dimension of a model', *The Annals of Statistics,* 6, (2), pp. 461-464.

Schwert, G. W. (1987) 'Effects of model specification on tests for unit roots in macroeconomic data', *Journal of Monetary Economics,* 20, (1), pp. 73-103.

Schwert, G. W. (1989) 'Tests for unit roots: a Monte Carlo investigation', *Journal of Business & Economic Statistics,* 7, (2), pp. 147-159.

Sectoral Economics Programmes. (2001) *An Assessment of the Office of Rubber Replanting Aid Fund.* Bangkok: Thailand Development Research Institue

Stifel, L. D. (1973) 'Growth of rubber economy of southern Thailand', *Journal of Southeast Asian Studies,* 4, (1), pp. 107-132.

Suwanakul, S. and Wailes, E. J. (1987) 'Estimates of structural relationships for the world's rubber market with particular emphasis on Thailand's natural rubber industry', *Kasetsart Journal: Social Sciences,* 8, (2), pp. 173-188.

Suzuki, P. (2009) *Rubber Price Intervention: Rent-sharing and Economic Cost.* Faculty of Economics, Thammasat University, pp: 1-14.

Takayama, A. (1994) *Analytical Methods in Economics.* New York: Harvester Wheatsheaf.

Tan, C. S. (1984) *World Rubber Market Structure and Stabilisation: An Econometric Study.* Washington, D.C.: World Bank

Tanaka, K. (1990) 'Testing for a moving average unit root', *Econometric Theory,* 6, (4), pp. 433-444.

Tomek, W. G. and Robinson, K. L. (1981) *Agricultural Product Prices.*2d ed Ithaca: Cornell University Press.

Townsend, R. and Thirtle, C. (1997) 'Dynamic acreage response: an error correction model for maize and tobacco in Zimbabwe', in Rose, R., Tanner, C. and Belamy, M. A.(eds) *Issues in Agricultural Competitiveness: Markets and Policies: Proceedings of the 22nd International Conference of Agricultural Economists.* Aldershot: Ashgate.

Traill, B. (1978) 'Risk variables in econometric supply response models', *Journal of Agricultural Economics,* 29, (1), pp. 53-61.

UNCTAD (n.d.) *Information on Rubber*. Available at: http://www.unctad.org/infocomm/anglais/rubber/sitemap.htm#site (Accessed: October 5, 2008).

Weliwita, A. and Govindasamy, R. (1997) 'Supply response in the Northeastern fresh tomato market: cointegration and error correction analysis', *Agricultural and Resource Economics Review,* 26, (2), pp. 247-255.

West, K. D. (1988) 'On the Interpretation of near random-walk behavior in GNP', *American Economic Review,* 78, (1), pp. 202-209.

Wickens, M. R. and Greenfield, J. N. (1973) 'The econometrics of agricultural supply: an application to the world coffee market', *Review of Economics & Statistics,* 55, (4), pp. 433-440.

www.maps-thailand.com. (n.d.) *Travel Map of Thailand.*

Yibngamcharoensuk, S. (1988) *An Econometric Analysis of the Supply Response of Natural Rubber and Price Variation through Time in Thailand.* Master thesis. Kasetsart University.