School of Economics and Finance

# Productivity Growth and R&D Spending in Australian Broadacre Agriculture: Empirical Analyses by Using Alternative Approaches

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This thesis is presented for the Degree of
Doctor of Philosophy
of
Curtin University

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Dedicated

to

my late grandparents

# Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgement has been made. This thesis contains no material, which has been accepted for the award of any other degree or diploma in any university.

Md Farid Uddin Khan

12 April 2015

# List of publications from the thesis

**Journal Article:**

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# List of Acronyms

| | |
|---|---|
| ABARE | Australian Bureau of Agricultural and Resource Economics |
| ABARES | Australian Bureau of Agricultural and Resource Economics and Sciences |
| ABS | Australian Bureau of Statistics |
| ACIAR | Australian Centre for International Agricultural Research |
| ASEAN | Association of Southeast Asian Nations |
| BOM | Bureau of Meteorology |
| CSIRO | Commonwealth Science and Industrial Research Organization |
| DAFF | Department of Agriculture, Fisheries and Forestry |
| DEA | Data Envelopment Analysis |
| DF-GLS | Dickey Fuller-Generalized Least Squares |
| GDP | Gross Domestic Product |
| GRDC | Grain Research and Development Corporation |
| IPCC | Intergovernmental Panel on Climate Change |
| IRR | Internal Rate of Return |
| KPSS | Kwiatkowski, Phillips, Schmidt, and Shin |
| MIRR | Modified Internal Rate of Return |
| OECD | Organization for Economic Cooperation and Development |
| OME | Output-Oriented Mix Efficiency |
| OTE | Output-Oriented Technical Efficiency |
| R&D | Research and Development |
| RDCs | Rural Research and Development Corporations |
| SFA | Stochastic Frontier Analysis |
| TFP | Total Factor Productivity |
| VAR | Vector Autoregression |
| VECM | Vector Error Correction Model |

# Abstract

A decline in agricultural productivity in many developed countries including Australia in recent years has led to increased interest in exploring the role of public funding in agricultural research and development (R&D). To date, very few studies have reported on the effect of R&D expenditure on productivity growth in agriculture in Australia. Although there is some anecdotal evidence that the recent spells of droughts and the fall in R&D spending since the 1970s are the main causes of this productivity slowdown in Australia, there is a paucity of in-depth empirical analysis to support these observations. In response of this research gap, the study reported here seeks to analyse the relationship between R&D spending and productivity growth in Australian broadacre agriculture with appropriate data and methodologies. Analysis begins with computing and decomposing total factor productivity (TFP) of Australian broadacre agriculture. Following this is an investigation of the nexus between R&D expenditure and TFP growth, along with a calculation of the rates of return and a forecasting exercise. This study concludes with an examination of the impact of R&D on productivity by accommodating non-neutrality in the effects of R&D on productivity and by capturing the state-level heterogeneities.

In this research, data are analysed using both parametric and nonparametric approaches. The TFP growth is estimated and decomposed using the Färe-Primont productivity indexes, which satisfy all basic index number axioms that are economically relevant and do not require any price information. In addition, the relationship between public R&D and productivity growth is examined by using standard time series econometric methods, with special emphasis on cointegration and causality approaches. A few robustness checks are also performed to test the consistency of the empirical results. Moreover, the rates of return on public R&D are calculated by employing a novel Modified Internal Rate of Returns (MIRR) method. Finally, the state-level heterogeneities and non-neutrality in the effects of R&D are captured by using the novel semiparametric smooth coefficient method.

Findings here reveal that there is a clear movement towards slower TFP growth across the sample periods in broadacre agriculture in Australia. Further, decomposition of TFP growth shows that the declining growth in technical change is the main driver of this slowing productivity growth. Results also demonstrate that Australian states have turned out to be technically highly efficient, and the scale and mix of the changes in efficiency are the main drivers of the overall change in efficiency. This research also finds econometric evidence of a cointegrating relationship between R&D and productivity growth with a unidirectional causality running from R&D to TFP growth. A significant out-of-sample relationship exists between the public R&D and productivity in broadacre agriculture. This thesis also obtains a credible estimate of the rates of return on public research investment. Taking the state-level heterogeneities and non-neutrality into account, the empirical results show that once both the direct and the indirect impacts are taken into consideration, R&D spending significantly increases agricultural productivity in Australia. Moreover, there are substantial variations in the impacts of R&D on output across the states.

Decomposition analysis provides a comprehensive and distinctive understanding of productivity changes and associated public policies. In addition, the evidence of the existence of a long-term relationship between productivity and R&D sheds light on the direction for future policies in boosting public investment in R&D to enhance productivity growth in Australian agriculture. Finally, the observed state-level variations in the effects of R&D on productivity growth suggest that these variations need to be taken into account for policy formulation regarding investments in public R&D in agriculture.

**Key Words:** Total Factor Productivity (TFP); Färe-Primont Index; Broadacre Agriculture; Research and Development (R&D); Cointegration; Semiparametric Smooth Coefficient Model

**JEL Classifications:** C14, C20, C23, C32, D24, F10, Q16

# CHAPTER ONE

# Introduction

## 1.1 The Setting

Over the last few decades, efficiency and productivity analysis in agriculture has attracted considerable attention in the economic literature as well as from policymakers both in developed and developing countries (Battese and Coelli, 1995; Bravo-Ureta *et al*., 2007; O'Donnell, 2012b; Samarajeewa *et al*., 2011; Van Beveren, 2012). By enhancing productivity, firms as well as the industry can maintain or increase their competitiveness and market share. Attaining considerable growth in productivity is critical for an economy to move forward towards opportunity and prosperity. In Australia, productivity growth has also become an essential source of economic prosperity for the country (Salim and Islam, 2010). It makes a significant contribution to the gross domestic product (GDP) and it generates employment for a large number of people.

In the global context, the recent concern has been that productivity is falling, particularly in developed economies (Pardey *et al*., 2013). This has implications for their domestic food security and rural livelihoods as well as for the food security in developing countries, where growing populations will continue to increase their demand for food in the coming decades (Pardey *et al*., 2006). Recent studies suggest that productivity growth in at least some sectors, including the cropping sector of Australian agriculture, has slowed over the past decade compared to the earlier periods (Nossal and Sheng, 2010). This decline in agricultural productivity has significant implications for the well-being of Australia's rural community and the prosperity to the economy as a whole. It has renewed interest in productivity analysis, particularly in investigating the possible causes of this decline.

Historically, investment in research and development has been playing an important role in achieving and continuing productivity growth in agriculture. Many studies have been conducted globally to examine the impact of R&D on productivity growth in the agricultural sector (Alene, 2010; Alston *et al*., 2011; Bervejillo *et al*., 2012; Mullen, 2010; Pardey *et al*., 2013; Salim and Islam, 2010). A large number of these studies provide the empirical evidence that investment in R&D is one of the main sources of productivity growth to the economy (Coe and Helpman, 1995; Griliches, 1979; Hall and Scobie, 2006). It brings about a more effective use of existing resources and thereby raises the productivity level. Studies focusing on Australian agriculture also show evidence on the contribution to the investment in agricultural R&D and related policies to the improvements in agricultural productivity throughout the Twentieth Century (Mullen, 2010; Salim and Islam, 2010). They indicate that promoting public investment in R&D in agriculture is particularly essential because of the inability of small producers to gain much economic benefit from individual R&D investment as their farm products are largely uniform and non-rival. Further, public R&D has significant intra- and inter-industry spillover and other regional and rural benefits.

Despite its remarkable contribution to productivity gains, the public investment in agricultural R&D in Australia has been slowing in recent decades (Hunt *et al*., 2014; Mullen, 2010). In particular, the slowing trend in the total public expenditure in agricultural R&D since the mid-1970s has raised concern and initiated discussion among researchers and practitioners. This long-term slowdown in public investment in agricultural research could be the cause of the recent slowdown in productivity growth in Australian agriculture. Therefore, the decline in agricultural productivity, both domestically and globally, has renewed interest in the need for increased attention to improving efficiency and productivity so that agriculture can contribute to meeting the growing food needs globally.

According to the Australian Productivity Commission report (2011), future productivity growth requires more attention to public investment in agricultural R&D to make this sector more competitive in both domestic and global markets. This suggests that to prosper and grasp global opportunities in agriculture it is important to focus more on increased research and development investment in the future. In these circumstances, it is important to estimate and explain the components of productivity changes and to explore the role of public funding in agricultural R&D in agricultural productivity by calculating the returns on such expenditure.

## 1.2 Productivity Growth and R&D in Agriculture

Australian agriculture is primarily based on extensive cropping and livestock farming activity, which is generally known as 'broadacre'[1] agriculture. Australian broadacre agriculture has long been recognized as a significant contributor to both the country's agricultural growth and economic growth, generating more than 85 per cent of the country's gross value of agricultural production. One of the distinguishing features of broadacre agriculture is the jointness in the production process that arises due to interdependence in production processes and technology (Ahammad and Islam, 2004; Salim and Islam, 2010).

A large number of empirical studies of agricultural productivity in Australia have found increases in agricultural productivity measured by total factor productivity (hereafter, TFP) over the last 50 years. Using country-level data, Males *et al*. (1990) have estimated an average TFP growth of 2.2 per cent per annum in Australian broadacre agriculture over the period 1978 to 1989. Disaggregating the sample size into different enterprise types they have found that the productivity growth rate varies between average rates of 2.2 per cent and 5.5 per cent per annum across enterprise types.

Extending this dataset to 1994, Knopke *et al*. (1995) also find that the productivity growth in the crop industry slowed to 4.6 per cent per annum while the average productivity growth in broadacre agriculture remained at 2.7 per cent per annum for the period 1978 to 1994. Dividing farms into three groups, they also find that scale matters significantly in productivity growth variations. Similarly, using a farm-level dataset covering the period from 1953 to 1988, Mullen and Cox (1995) have estimated an average rate of productivity growth of 2.3 per cent per annum. Further, extending their dataset to 1994, Mullen and Cox (1996) have compared measures of productivity growth based on different approaches and have found an average TFP

[1] Agriculture comprises farming activities, which are mainly engaged in producing crops, meat and wool.

growth of 2.5 per cent for the period 1953–1994, which is a bit higher than their previous estimate for the period 1953–1988.

Though Australian agriculture has experienced an upward trend in productivity over the last six decades, slower growth has been observed in recent decades. Particularly in the 2000s, productivity growth stopped or even negative productivity growth was experienced according to ABS productivity estimates (ABS, 2008). Nossal and Sheng (2010) estimate TFP growth in broadacre agriculture of 1.4 per cent per annum for the period from 1977–78 to 2007–08. But over the recent period from 1997–98 to 2007–08, they estimate the rate of productivity growth to have declined to – 1.3 per cent per annum.

Moreover, the empirical evidence regarding factors that determine the slowing TFP growth in Australian agriculture is very sparse. Mullen and various co-authors have conducted a series of econometric researches in Australian agricultural productivity. Using a unique dataset, they have found research and development to be an important factor of productivity in Australian agriculture. Their studies have reported estimates of the rates of return on research and development spending ranging from 15 to 40 per cent in broadacre agriculture over the period 1953 to 1994 (Mullen and Cox, 1996; Mullen *et al*., 1996). Later, Mullen (2007) has revisited their previous studies by extending their previous dataset to 2003 and has found no indication of declining rates of return over the years 1953–2003.

However, these studies suffer from poor time-series properties and fail to confirm the existence of a stable cointegrating relationship between research and development and productivity. From the previous studies of productivity growth, it is difficult to properly assess whether the productivity change is from improving the rate of technical progress or from improving levels of either technical or scale and mix efficiency. Further, the conventional measures of productivity indexes do not take the sources to productivity growth into account, which can lead to poor public policy. Moreover, previous studies often have an industry-specific or region-specific focus.

Similarly, there is limited empirical evidence of the effects of R&D spending on productivity in Australian agriculture. Although some studies indicate that public

R&D investment in agriculture contributes to TFP growth, this has not been explored deeply or tested empirically. In addition, these estimates do not accommodate heterogeneity in the effect of R&D on the productivity across states in Australia. States in Australia are heterogeneous in terms of their economic development, geographical locations, and resource endowments, which need to be accounted in the relationship between R&D and productivity. Moreover, the spillover effects from R&D to agricultural productivity have also been ignored in the literature on the impact of agricultural R&D in Australia, which may produce an omitted variable bias in the estimated effects of public R&D (Alston, 2002; Schimmelpfennig and Thirtle, 1994). Finally, the previous studies of productivity analysis in Australian broadacre agriculture hardly acknowledge or take the effects of changed climatic variations into account in their empirical analysis.

## 1.3 Research Objectives and Methodology

The main objective of this empirical thesis is to estimate and explore the agricultural productivity growth and its major determinants in Australian broadacre agriculture. In pursuit of achieving this objective, this thesis aims to achieve the following specific research objectives:

1. To measure and decompose total factor productivity (TFP) growth in agriculture
2. To examine the long-run relationship between public research and development (R&D) and productivity growth
3. To estimate the rates of return on R&D in agricultural productivity
4. To explore the effects of R&D on productivity growth using a novel semi-parametric smooth coefficient model.

To achieve these research objectives this thesis performs empirical analyses by using alternative approaches. Firstly, this thesis calculates and decomposes the TFP growth by following the Färe-Primont productivity index recently proposed by O'Donnell (2014). This index can be used to make reliable multi-lateral and multi-temporal comparisons, which makes it more reliable than the other index measures applied in productivity analyses. This is one of the standard approaches in productivity literature that can be decomposed exhaustively into recognizable components, especially in nonparametric specifications, without requiring data on prices (Färe *et al*., 1994; Lovell, 2003).

Secondly, using standard time-series econometrics this thesis investigates the nexus between research and development expenditure and productivity growth using the country-level time-series dataset for the period 1953 to 2009. A set of standard unit root tests, including the Augmented Dickey Fuller, the Dickey Fuller-Generalized Least Squares (DF-GLS), the Phillips-Perron and the KPSS (Kwiatkowski, Phillips, Schmidt, and Shin) tests, are employed to examine time-series properties of all series. Moreover, the Zivot-Andrews unit root test is applied to check for the robustness of these standard unit root results, even after allowing structural breaks.

In addition, this thesis applies a cointegration test proposed by Johansen and Juselius (1990) to investigate the cointegrating relationship between R&D and productivity growth. The cointegration test proposed by Gregory and Hansen (1996) is applied to establish the evidence of a cointegrating relationship between R&D and productivity, even with unknown structural breaks. In addition, the Granger causality test is used to shed light on the direction of possible causality between R&D and TFP growth along with the Toda-Yamamoto Granger non-causality test for the robustness check. Further, this thesis employs a novel and conceptually superior method than the conventional internal rate of return (IRR) called the modified internal rate of return (MIRR) to obtain a credible estimate of returns on the public research investment.

Finally, in order to capture important differences in the effect of R&D on productivity that are supposed to arise from socio-economic, geographic and resource differences across states, this thesis uses a novel semiparametric smooth coefficient approach as proposed by Li *et al*. (2002). The novelty of this method lies in the fact that it captures non-linearity and cross-effects of the environment variable in a production framework by expressing both the intercept and slope coefficients as unknown functions of environment variables such as R&D. The uniqueness of this method makes it superior to the standard production function framework which fails to capture geographical differences and differences in resource endowments.

One limitation that is important to state at the outset is that this thesis utilizes different sets of available data in each of its empirical analyses in pursuit of providing a comprehensive understanding of the dynamics of productivity. The data used in the three key empirical chapters vary in accordance with the research objectives and availability of suitable data. Firstly, I use state-level data from 1990 to 2011 to estimate and decompose productivity indexes. These data comprise six major inputs; land, labour, capital, fertilizer, materials and services and rainfall; and four outputs; crops, livestock, wool and other output variables. I also include rainfall variable as an environmental input of broadacre agriculture production from the concern that rainfall variability may have influence on broadacre agriculture in Australia.

Secondly, after estimating the productivity indexes and its components, this thesis investigates the long-run drivers of the productivity changes in Australian agriculture. Considering that the short time period for which state-level data are available is unsuitable to employ standard time-series techniques, this thesis rather uses the country-level time-series data for the period 1953 to 2009. Following recent time-series studies, four variables namely total factor productivity, domestic public investments in R&D, foreign public investments in R&D and farmers' level of education are used in this analysis to explore the possible links and directions between these variables.

Finally, the credibility of time-series findings is always questioned because of the lack of theoretical foundation of its techniques, like VARs and ECMs, and the possible biases of the omission of relevant variables (Pardey and Craig, 1989; Thirtle *et al*, 2002). Besides, analysis using country-level aggregate data has a limitation of not allowing potential heterogeneity across the states and non-neutrality in the effects. Considering these limitations and concern, this thesis also uses an up-to-date nonparametric technique applied to the state-level agricultural input, output and R&D data to find a plausible estimate of the effects of R&D on productivity growth. It uses data from 1995 to 2007as the state-level R&D data are available only for this period.

## 1.4 Significance of the Research

Australia's agriculture makes a remarkable contribution to its economy by producing high-quality food, employing workers and earning from its exports. It also makes a significant contribution to global agriculture in terms of feeding the world population, particularly in the Asia-Pacific region where around two-thirds of the people are experiencing food insecurity due to their low incomes and other circumstances. In this region, particularly in developing countries, Australia plays a major role in their agriculture by enhancing the productivity and profitability of smallholder farmers.

Recently, new opportunities have emerged for Australian agriculture due to the increasing food demand in developing countries, particularly in Asia, as a result of their rapid economic growth and growing population. In addition, the rising commodity price in the global market has also been an opportunity for the export-focused Australian agriculture. Given its strong natural resource base in terms of geographic location and skilled workforce, Australia can help meet this growing demand and can make the most of these export opportunities.

However, these possibilities cannot be taken for granted as evidence shows that Australian businesses have to face intense competition from other exporting countries and also due to the fact that major developing countries are increasing their investments in agriculture. Moreover, by achieving strong growth, other sectors of the Australian economy are also out-competing Australian agriculture for scarce resources. This suggests that Australian agriculture is experiencing increased competition both in global markets and in its internal markets for essential resources. Making the most of opportunities presented by future growth in global food demand depends on Australia's ability to maintain competitiveness, which can be achieved through productivity improvements (Gray *et al*., 2014). Similarly, some recent studies have also recommended seeking productivity breakthroughs in Australia's broadacre industries to address the current and emerging constraints in the country (Keating and Carberry, 2010; Mullen, 2007).

In the face of such domestic and global challenges with declining productivity growth and increasing global demand for foods, Australia needs to focus on its agricultural productivity growth. This research aims to provide significant information that may assist policymakers in framing agricultural policies in several ways. Firstly, it explores different components of productivity growth, which contain important information on efficient use and management of agricultural resources in production. Secondly, by exploring the long-term determinants of productivity growth this study provides policy information in relation to improving from the recent productivity declines. Finally, this study provides separate estimation of the effects of R&D on productivity across different states to provide further direction for future policies on investments in R&D in Australia.

This thesis also makes several empirical contributions to the productivity literature. It employs the Färe-Primont index, which satisfies a number of important axioms from index number theory, including the identity and transitivity axioms, to compute and decompose productivity changes using state-level data. It identifies and estimates the main drivers of productivity growth in Australian broadacre agriculture. It applies a novel and conceptually superior method than the conventional internal rate of return (IRR) called the modified internal rate of return (MIRR) to obtain a credible estimate of returns to public research investment. Finally, it applies a semiparametric smooth coefficient approach to investigate the effects of R&D on TFP, enabling observation-specific heterogeneities and non-neutrality using state-level data. This is one of the first studies to apply this nonparametric approach in the agriculture context, which is supposed to broaden our understanding of the effects of R&D, particularly through recognizing and measuring the heterogeneity in its effects.

## 1.5 Structure of the Research

This thesis consists of six chapters including this introductory chapter. The rest of the thesis is organized as follows:

Chapter 2 presents an overview of Australia's agriculture sector and discusses its contribution to the Australian economy in terms of the value added to the economy, agricultural exports and the employment opportunities it creates. It also gives a brief review of Australian agricultural development, focusing more on the productivity performance and research and development investments in Australia's agriculture.

Chapter 3 estimates and exhaustively decomposes TFP changes into different finer measures of components of the productivity changes in Australian broadacre agriculture by using the Färe-Primont index of total factor productivity over the period 1990 to 2011. This chapter finds the trend in productivity growth in broadacre agriculture and identifies the main components of change in productivity growth. Further, it estimates TFP across states and over different sub-periods to see the variations of the estimates across states.

Chapter 4 investigates the nexus between research and development expenditure and productivity growth in Australian broadacre agriculture using country-level time-series data for the period 1953 to 2009. It examines the evidence of cointegrating and causal relationships between R&D and productivity by applying error correction model and Granger causality test. Moreover, it computes and analyses different measures of rates of return on the public investments in agricultural R&D using methodologically justified and plausible measures.

Chapter 5 analyses the impact of R&D on the productivity of Australia's broadacre farming in a flexible manner using the semiparametric smooth coefficient model proposed by Li *et al*. (2002). The novelty of this approach over the standard production function model is that it accommodates non-neutrality in the framework and captures heterogeneity across observations. Utilizing a state-level average farm dataset covering the period 1995 to 2007, this chapter captures both the direct and the indirect effects of R&D expenditures on productivity growth.

Chapter 6 concludes this thesis, presenting key findings of the empirical analyses undertaken in this study with some policy implications from the findings. It also mentions some limitations along with directions for future research.

# CHAPTER TWO

## Overview of Australia's Agriculture Sector

### 2.1 Introduction

Australia is the world's sixth-largest country by total area and is located in the Southern Hemisphere between the Indian and South Pacific Oceans. The country comprises the mainland of the Australian continent, the southern island state of Tasmania and numerous small islands. There are six states and two mainland territories in Australia. The states are New South Wales (NSW), Queensland (QLD), South Australia (SA), Tasmania (TAS), Victoria (VIC) and Western Australia (WA). The Australian Capital Territory (ACT) and the Northern Territory (NT) are the two territories, which in most ways function as states. It is one of the driest inhabited continents around the world, with over 70 per cent of its total land area being either semi-arid ($P<0.66E$ to $P>0.2E$, where $P$ is the annual rainfall and $E$ is potential evaporation) or arid ($P<0.2E$) and only around 10 per cent of the total land area is suitable for cropping and pastures (Wolf, 2009). These cultivable lands are not sufficiently fertile and need fertilizers and/or legumes to make them suitable for agricultural production.

The recent declines in agricultural productivity growth and the potential climate-change effects have increased the focus on the productivity of farms for Australian farm management in the twenty-first century (Mullen, 2007). Besides, the growing world population, increasing living standards and changing patterns of consumption are raising the global demand for agricultural products. Furthermore, the global necessity to reduce carbon emissions is also raising the concern over global food security. Under these circumstances, because of its strategic position in the economy and its implications for the world economy, it is important for Australian agriculture to seek opportunities for productivity breakthroughs.

In Australia, food security is also a concern, although there is a debate over this issue. A range of relevant issues stimulate the debate, indicating that certain groups of Australians are insecure regarding food, and many suffer nutrition-related health problems such as obesity (Farmar-Bowers *et al*., 2013). These suggest that the issues of food equity and access are the main issues concerning Australian food security. They do not arise from a lack of food, rather they are mainly due to the poor affordability of nutritious food for the underprivileged groups in society. A number of future possibilities, including the uncertainties of climate change, globalization and growing competition for resources both in Australia and globally, make the problems more complex. There has been concern over the future ability of Australian farmers to efficiently use the land, water and human resources to continue to offer adequate food, while preserving the ecology and maintaining the biodiversity in the environment and in soil.

This chapter presents an overview of Australia's agriculture sector and discusses its contribution to the Australian economy with respect to the value added to the economy, agricultural exports and the employment opportunities it creates. It also discusses the critical role that agricultural productivity plays in the continued success of this sector. Moreover, some recent opportunities and challenges faced by Australian agriculture are also discussed along with the possible threats of climate change and declining public investment in R&D.

This chapter is outlined as follows. The following section gives a brief review of Australian agricultural development. Section 2.3 provides an overview of natural resources and climate associated with agriculture. Section 2.4 discusses the contribution of the agriculture sector to the Australian economy. Section 2.5 presents a brief discussion of the productivity performance of agriculture. Section 2.6 looks at key trends in Australia's research and development investments in agriculture. Section 2.7 explores climate change and its effects on Australian agriculture, followed by a discussion about how Australia's agriculture policy reforms contribute to the R&D in Section 2.8. The final section concludes the chapter.

## 2.2 Agricultural Development in Australia

Australia initiated its scientific or modern agriculture in the late nineteenth and early twentieth century, introducing new techniques for farming, performing wheat breeding, using superphosphate fertilizers and promoting mechanization (Barr and Cary, 1992). The technique of ley farming by growing pasture legumes in rotation revolutionized Australian agriculture in maintaining soil conservation. In particular, it helped to counteract the depletion of soil organic matter for acidic soils in Victoria and alkaline soils in South Australia.

Australia experienced almost a continuous upward trend in crop yield during the 20th century (Angus and van Herwaarden, 2001). In particular, a substantial improvement has been observed in crop productivity since the 1950s after the introduction of pasture legumes to supplement superphosphate and the development of the ley farming system. Later, a series of innovations and farm practices, including improvements in cropping practices (such as crop rotation and soil fertility management) and disease-resistant and improved quality of crop and pasture varieties led to continued improvement in the productivity of mixed farming systems.

The concept of sustainable farming was introduced and practised in Australian agriculture in the 1980s with the main goal of changing its operation to set strong foundations for the future. It focuses on producing more with fewer resources by increasing agricultural productivity and reducing its environmental impact. An improved efficiency by using resources and innovative farm and industry practices could help extract more from less and ensure productivity gains in Australia's agriculture. There has been significant progress in achieving sustainable farming practices across Australia, including efficient and sustainable water use, appropriate use of phosphorus, proper soil management, and maintenance of a high level of biodiversity in the soil and the environment to ensure sustainable agriculture in the future.

Despite the increases in productivity in Australian agriculture, while maintaining the natural resource base and ecosystem benefits, the gap still remains between potential and actual farm yield. Recently, Australian broadacre farms have been experiencing a period of uncomfortable changes due to concern over the profitability of family farming, the issue of animal welfare and other global/local concerns. In last two decades, the numbers of sheep have declined in the mixed farming zone and in the wheat-sheep belt due to the recent trend of crop specialization and the declining/ageing farming workforce in Australia (Figure 2.3). Moreover, a spell of dry seasons in recent periods along with the threat of possible climate change has strongly affected crop production. Recently, levels of water storage in the Murray-Darling Basin of south-eastern Australia have reached a record low level (ABC News, 2014). This may be due to the ongoing drought conditions, over allocation of water resources, and competition for water allocation between irrigation farmers, environmental water holders and community users. All these changes might cause problems for the social well-being of Australian rural communities.

## 2.3 Natural Resources and Climate

Australia's broadacre dryland agriculture[2] operates mainly within the latitudes from 21 to 37 °S (Figure 2.1(a)), which receive approximately 300–600 mm of annual rainfall. It is characterized by the moisture deficit of its soil, low variable rainfall, high evaporation, and long wet and dry periods (Carberry *et al*., 2011). The reliability of achieving 175mm of rainfall during the winter growing season of April to October shows the rainfall limitations for agriculture production (Figure 2.1(b)). As broadacre agriculture relies on rainfall for water, the variations in rainfall reliability introduce risk to agriculture and natural resource management and cause variations in productivity in agriculture from year to year (Laughlin *et al*., 2003). In this situation, managing the risks from rainfall variability and optimizing the use of resources to reach the water-limited potential yield has been an ongoing concern in the Australian agricultural sector.

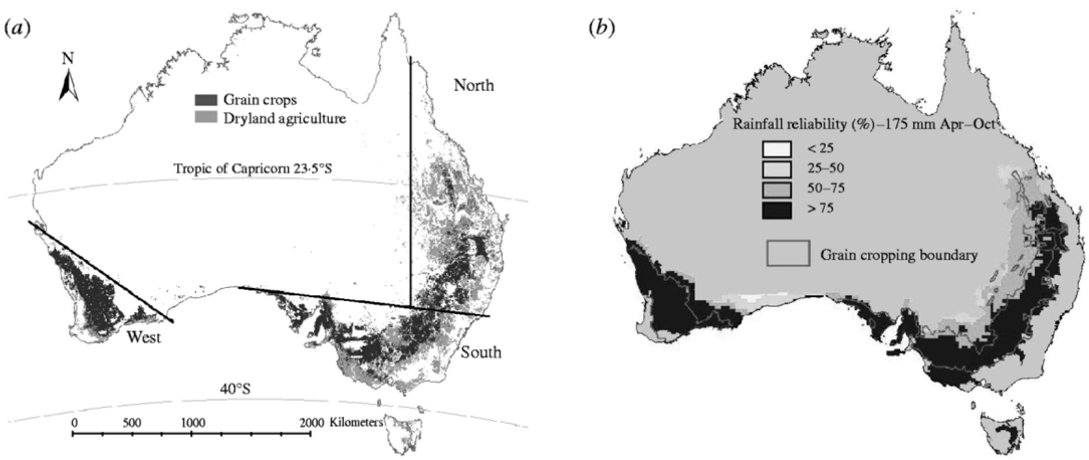
### *2.3.1 Agricultural Zone*

The Australian Bureau of Agricultural and Resource Economics has mapped Australian agriculture into three national zones on the basis of the use of land (Figure 2.2). They are the high-rainfall zone, the wheat-sheep zone and the pastoral zone.

[2] It does not include extensive livestock grazing in arid regions.

The absence of cropping in the high-rainfall zone is the main feature distinguishing it from its neighbouring wheat-sheep zone (Table 2.1).

**Figure 2.1: (a) Distribution of broadacre dryland agriculture in Australia, overlaid with dryland grain cropping areas. (b) Rainfall reliability for dryland grain production**




Source: Adopted from Carberry *et al*. (2011). Note: Lines on the map demarcate the three broad dryland agricultural regions in Australia: Western Region, Southern Region and Northern Region.

The high-rainfall zone lies between the coast and the wheat-sheep zone and produces mainly wool, dairy and beef. The wheat-sheep zone or wheat belt is the most prosperous zone that contributes to Australia being a dominant wheat-producing nation. This zone is also used for other cropping and the grazing for sheep. The pastoral zone, consisting of the inner and largely semi-arid regions with less fertile soils and low rainfall, is used for large-scale pastoral activities, including grazing of beef cattle and sheep. It produces mainly beef, wool, lamb and mutton. Like the high-rainfall zone, the pastoral zone is also distinguished by the absence of cropping; they are both almost solely used for grazing.

### *2.3.2 Broadacre Sector of Australian Agriculture: Types of Industries*

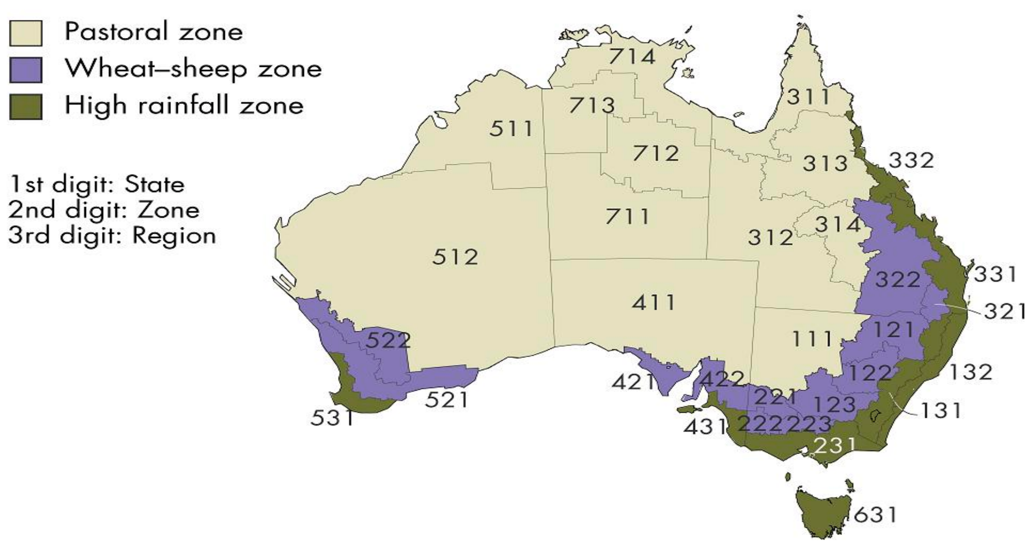
The broadacre farm sector of Australian agriculture covers dryland cropping and livestock farms, which produce grain, sheep, beef cattle and/or a mixture of these. They account for around 90 per cent of all agricultural land operated in Australia

(ABARES, 2014). Horticulture, vegetables, dairy and industrial crops are not included in this sector. This sector consists of five industry types:

**Table 2.1: Rainfall patterns across the main agricultural zones and production types**

| Zone | Rainfall | Products |
|---|---|---|
| High rainfall zone | The median annual rainfall is over 600 mm. | Sheep and cattle graze pastures. |
| Wheat-Sheep mixed farming zone. | Expected moderate rainfall ranges annually from 300 to 600 mm in WA, 400 to 600 mm in southern Australia, and 500 to 700 mm in Queensland. | Cereal crops, legumes, oilseeds, sorghum and soybeans to wool, sheep meat and beef production |
| Pastoral semi-arid grazing zone | Average annual rainfall is less than 300 mm in WA and less than 500 mm in Queensland. | No sown crops or pastures. |

**Figure 2.2: Map of Australia showing Australian broadacre zones and regions**




Source: Adopted from http://apps.daff.gov.au/AGSURF/regions.html accessed on 21.11.2014. Note: The states' numerical order 1 to 7 represents NSW, VIC, QLD, SA, WA, TAS and NT.

Firstly, the **wheat and other crops industry**, which includes specialized farms engaged mainly in growing cereal grains, coarse grains, pulses, rice and oilseeds. Secondly, the **mixed livestock-crops industry**, which includes farms engaged mainly in producing sheep and/or beef cattle along with broadacre crops, including cereal grains, coarse grains, oilseeds and/or pulses. Mixed livestock-crop farms account for most wool and sheep meat production in Australia. Thirdly, the **sheep industry**, which includes farms engaged mainly in producing sheep and wool. Around 30 per cent of Australia's wool is produced in this industry. Fourth is the **beef industry**, where the farms are engaged mainly in running beef cattle. Consisting of many small farms, this industry currently accounts for around 65 per cent of Australia's beef production. Finally, the **sheep–beef industry**, which includes farms engaged mainly in running both sheep and beef cattle. This industry consists of many small farms.

## 2.4 Contribution to the Economy

The agriculture industry makes an important contribution to the Australian economy by improving its rural livelihoods, creating job opportunities and earning export income. The significance of this industry in the Australian economy can be presented in various ways. One of the measures of the significance of this industry is its contribution to the gross domestic product (GDP). In 2012–13, Australian agriculture produced $34.9 billion in current prices, which accounts for more than 2 per cent of Australia's total GDP (Table 2.2).

Another important significance is that the agriculture sector is also an important source of employment in rural Australia. As of 2012–13, the total number of people employed in agriculture was 321.1 thousand, although this is the lowest number of employments since 2006–07 (Table 2.3). Including affiliated food and fibre industries, this figure goes up over 1.6 million in Australia. Since 2001, there has been a declining trend in the monthly employments in Australian agriculture (Figure 2.3). This reduction of the workforce in the agricultural sector has occurred during the series of droughts experienced over most of Australia since 2005 or 2007, which has severely affected Australian agriculture (ABS, 2008).

**Table 2.2: Annual industry gross value added in percentage**

| | 2006–07 | 2007–08 | 2008–09 | 2009–10 | 2010–11 | 2011–12 | 2012–13 |
|---|---|---|---|---|---|---|---|
| Agriculture, forestry and fishing | 2.0 | 2.1 | 2.4 | 2.4 | 2.4 | 2.4 | 2.3 |
| Mining | 6.6 | 6.6 | 6.7 | 7.0 | 7.0 | 7.3 | 7.7 |
| Manufacturing | 8.1 | 8.1 | 7.5 | 7.4 | 7.2 | 7.0 | 6.7 |
| Electricity, gas, water and waste services | 3.1 | 2.9 | 3.0 | 3.0 | 3.0 | 2.9 | 2.9 |
| Construction | 7.1 | 7.3 | 7.4 | 7.3 | 7.4 | 7.9 | 7.9 |
| Services | 48.9 | 48.9 | 49.1 | 49.0 | 49.4 | 49.2 | 49.1 |
| Other | 17.6 | 17.5 | 17.5 | 17.4 | 17.1 | 17.0 | 17.1 |
| Gross Domestic Product ($billions) | 1299 | 1347 | 1370 | 1397 | 1430 | 1483 | 1520 |

Source: Australian Bureau of Statistics (catalogue no. 5206.037)

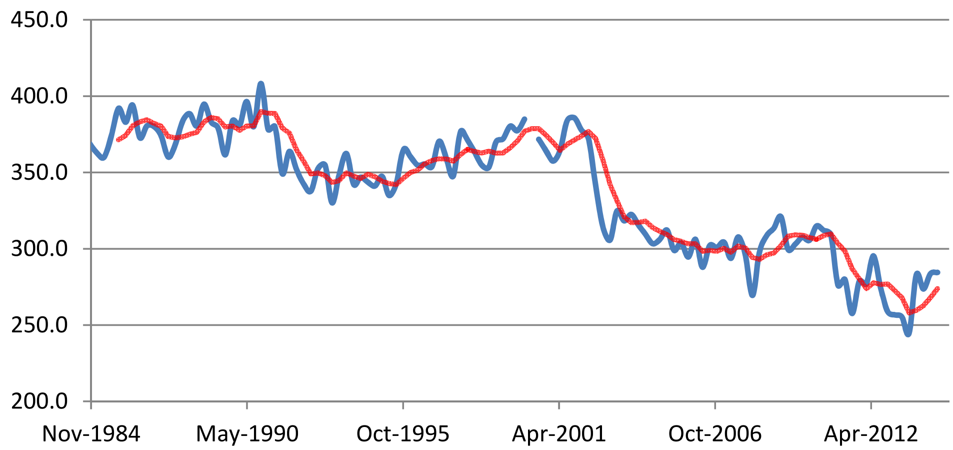
**Table 2.3: Sectoral distribution of employment ('000)**

| | 2007–08 | 2008–09 | 2009–10 | 2010–11 | 2011–12 | 2012–13 |
|---|---|---|---|---|---|---|
| Agriculture, forestry and fishing | 354.98 | 362.58 | 368.57 | 349.82 | 334.61 | 321.08 |
| Mining | 146.17 | 169.73 | 172.52 | 204.25 | 249.39 | 266.16 |
| Manufacturing | 1062.66 | 1028.52 | 1003.52 | 986.36 | 954.74 | 954.39 |
| Other industries | 9144.22 | 9338.35 | 9458.57 | 9749.51 | 9880.61 | 10021.77 |
| Total | 10708.04 | 10899.18 | 11003.19 | 11289.95 | 11419.35 | 11563.41 |

Source: ABARES; Agricultural Commodities, 2014

Australia's agriculture sector covers a broad range of activities varying from extensive pastoral and cropping to intensive livestock and horticultural production. It utilizes more than 50 per cent of Australia's land area that largely consists of vast arid and semi-arid regions (ABS, 2012). Because of its relative abundance in land, Australia has a comparative advantage in extensive broadacre agriculture (essentially non-irrigated crops, cattle and sheep), which contributed around 56 per cent of the gross value of agricultural production in 2012–13 (Figure 2.4). Around 53 per cent of Australia's agricultural businesses are engaged in broadacre activities, including beef cattle farming, sheep farming, grain growing, or a mixture of two or more of these farming types (ABARES, 2014). Broadacre farms can be classified largely into three types: crop specialists (more than 80 per cent of the farm used for cropping); mixed-farming enterprises (40 per cent to 80 per cent of the farm used for cropping); and livestock specialists (less than 40 per cent of the farm used for cropping).

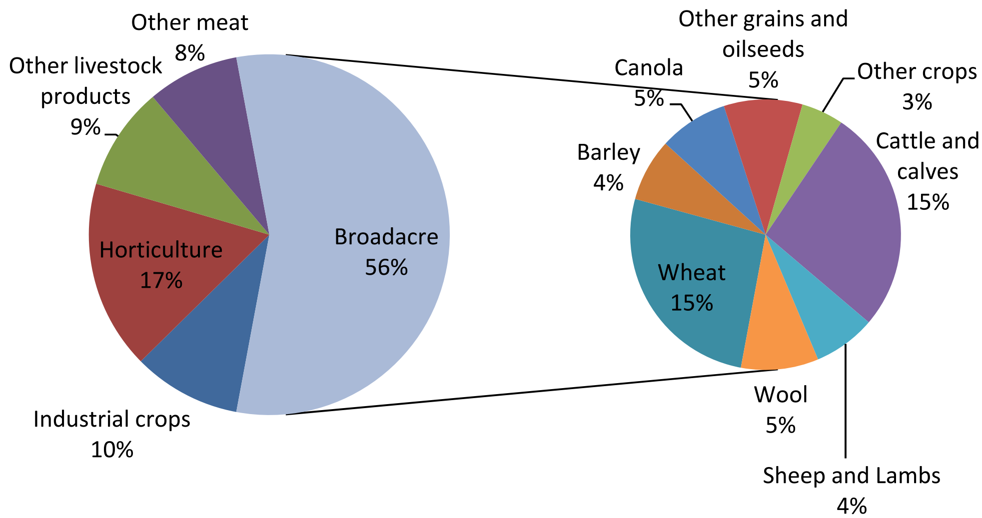
**Figure 2.3: Total employment in the agricultural sector (thousands of persons)**




Source: Australian Bureau of Statistics (catalogue no. 6291.0.55.003)

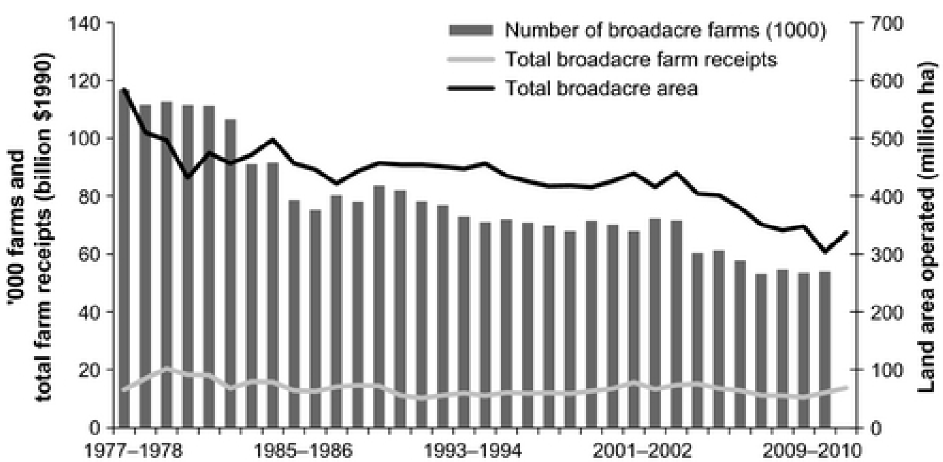
In 2011–2012, there were around 54,000 broadacre farms, which produced output to the gross value of $36.4 billion. This represents more than 90 per cent of the domestic food supply in Australia. More than 90 per cent of these agricultural farms are owned and operated by a family. One Australian farmer, on average, produces enough to feed around 600 people, and among these around two-thirds are located overseas. In the gross value of the agricultural production in Australia, commodities like cattle and calves slaughtering have contributed the highest value, followed by wheat, milk, vegetables, fruit and nuts, wool and cotton. However, there has been a negative trend in the number of broadacre farms and total land area operated in broadacre agriculture (Figure 2.5). The number of broadacre farms in Australia halved between 1977–1978 and 2011–2012, and the total land area operated by broadacre farmers also declined in the same period. Despite these declines, the gross value of output (in real terms) remained fairly steady.

**Figure 2.4: Share of gross value of Australia's agricultural production, by industry (2012–13)**




Sources: Derived by the author from ABARES data; Australian Bureau of Statistics

**Figure 2.5: Number of broadacre farms, and broadacre farm receipts and total broadacre land area operated (1977–1978 to 2010–2011)**

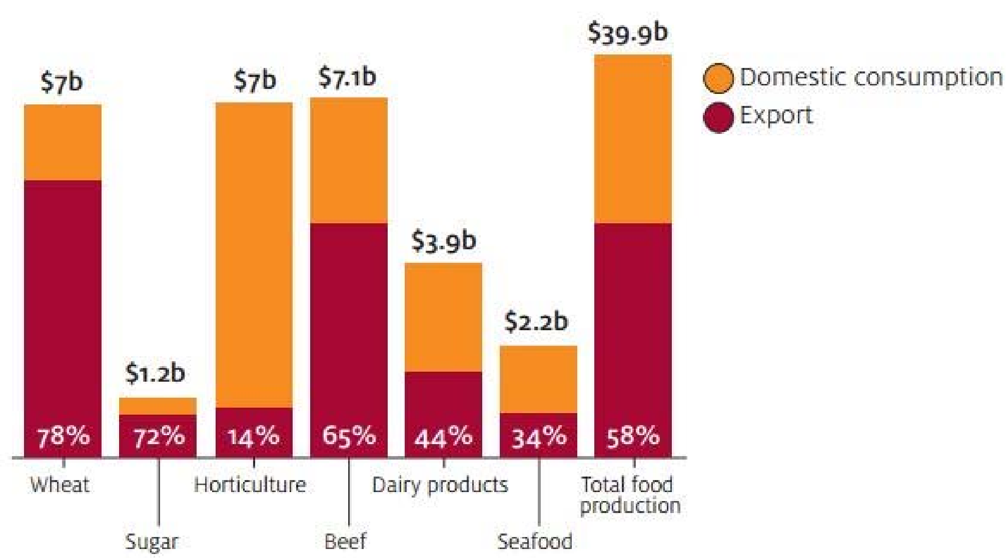



Source: ABARES AAGIS data. Adopted from Sheng *et al*. (2014)

### *2.4.1 Australian Food Production and Export*

Australian agriculture is highly export-focused and supports businesses and economic prosperity, employment and community well-being across Australia. Australian farmers typically export around 60 per cent of what they grow on their farms (ABARES, 2013). The average value of farm exports of Australian food products in 2010–11 to 2012–13 was valued at $39.9 billion. A large share of the products from these commodities is exported to global markets; in particular, the percentages of wheat, beef and dairy products exported are 78 per cent, 65 per cent and 44 per cent, respectively (Figure 2.6). According to Australian Bureau of Statistics (ABS) data, Australia exported around 58 per cent of the total value of food production averaged from 2010–11 to 2012–13, which amounted to some $23 billion. In the total export earnings during the same period, wheat and beef were the two largest agricultural exports and contributed around 23.8 per cent and 20.1 per cent of the value, respectively (Table 2.4).

**Figure 2.6: Percentage of food production exported, average for 2010–11 to 2012–13**




Source: ABARES; Australian Bureau of Statistics. Adopted from Agricultural Commodities, 2014

**Table 2.4: Percentage of food production exported for the top 12 commodities, three-year average (2010–11 to 2012–13)**

| Commodity | Gross Value of Production ($m) | Gross Value of Exports ($m) | Exports share % | Contribution to exports % |
|---|---|---|---|---|
| Wheat | 6 994 | 5 471 | 78 | 23.8 |
| Beef | 7 145 | 4 630 | 65 | 20.1 |
| Dairy | 3 869 | 1 686 | 44 | 7.3 |
| Sheep meat | 2 365 | 1 364 | 58 | 6.0 |
| Canola | 1 771 | 1 299 | 73 | 5.6 |
| Barley | 1 838 | 1 270 | 69 | 5.5 |
| Horticulture | 7 031 | 957 | 14 | 4.2 |
| Live cattle and sheep | 929 | 929 | 100 | 4.0 |
| Sugar cane | 1 190 | 853 | 72 | 3.7 |
| Pulses | 947 | 784 | 83 | 3.4 |
| Seafood | 2 214 | 747 | 34 | 3.2 |
| Wine grapes | 765 | 499 | 65 | 2.2 |
| Total food production | 39 914 | 23 011 | 57.65 | 100 |

Source: ABARES; Agricultural Commodities, 2014

**Table 2.5: Major destinations of Australia's agricultural exports (2011–12)**

| Country/region | Value of agricultural exports $m | % of value of exports |
|---|---|---|
| South-East Asia | 6945.36 | 19.1 |
| China | 6688.51 | 18.4 |
| Japan | 4363.78 | 12.0 |
| European Union 28 | 2899.00 | 8.0 |
| Korea, Rep. of | 2552.71 | 7.0 |
| Middle East | 2500.00 | 6.9 |
| United States | 2300.37 | 6.3 |
| New Zealand | 1471.33 | 4.1 |
| South Asia | 1435.89 | 4.0 |
| Africa | 1144.61 | 3.2 |
| Other | 3608.28 | 9.9 |
| Total | 36317.18 | 100.0 |

Source: ABARES; Agricultural Commodities, 2014

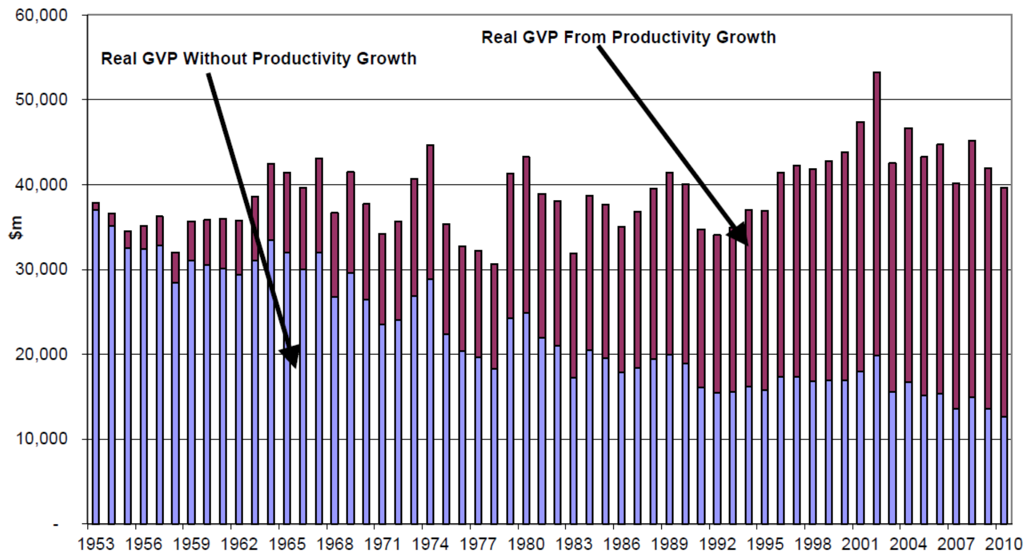
Regarding the destinations of Australian farm exports, there has been a shift in emphasis from Europe to Asian markets over the last few decades. An increasing demand for agricultural products has been observed in Asian markets, such as in China and in ASEAN countries due to their remarkable economic growth and growing population. In recent decades Asia has been an important destination for Australia's agricultural exports, accounting for more than 60 per cent of the value of total agricultural exports in 2011–12. The main destinations in Asia include South-East Asia (largely Indonesia), China, Japan and the Republic of Korea. Australia exports around 8 per cent, 7 per cent and 6 per cent of the value of its agricultural exports to the European Union, the Middle East and the United States, respectively (Table 2.5).

## 2.5 Australia's Productivity Performance in Agriculture

The Australian economy has experienced an upward trend in total factor productivity over the past two decades with an average rate at 1.4 per cent a year. Particularly in the 1990s, there was a strong TFP growth largely attributed to widespread microeconomic reforms during the same period (Gray *et al*., 2014). But, in the 2000s this productivity progress stopped and even experienced negative TFP growth in 2007–08 according to ABS productivity estimates (ABS, 2008). During this period, productivity slowed in most industries in Australia, with agriculture, mining and manufacturing industries contributing most to the slowdown. Similar stagnation in productivity growth was also observed in other OECD (Organization for Economic Cooperation and Development) countries (Nossal and Gooday, 2009).

Productivity growth has historically been important in achieving the output growth in Australian agriculture. In Figure 2.7, the red shaded top sections of the bars show the contribution of productivity growth to the real value of farm GVP, and the green shaded sections represent the real value of farm GVP without any productivity growth contribution. It is estimated that more than 70 per cent of the real GVP of agricultural production from 1953 to 2010 can be attributed to productivity growth, which is based on the average rate of productivity growth of 2 per cent per annum over the period 1953–2010 (Mullen and Keogh, 2013).

**Figure 2.7: The value of productivity growth to Australian agriculture, 1953–2010**

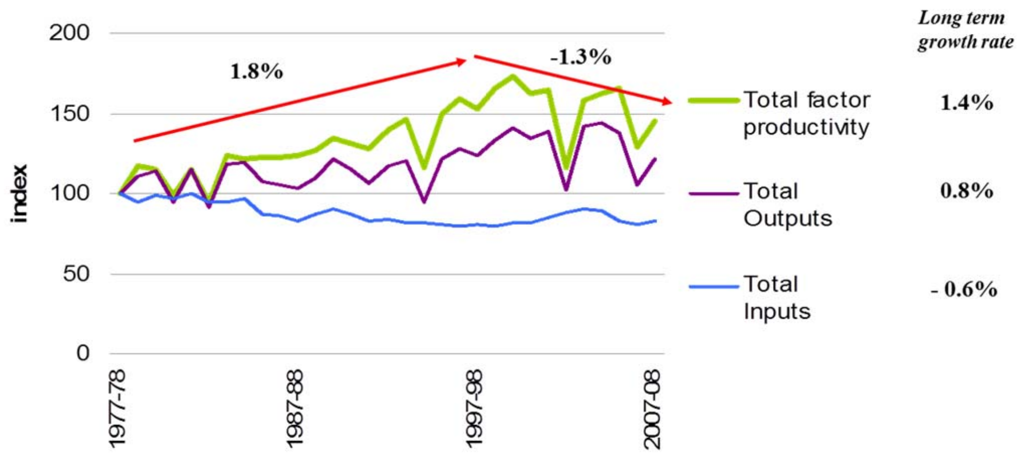



Source: Adopted from Mullen and Keogh (2013)

Whilst the past productivity gains since 1953 have provided significant benefits to the Australian economy, some recent concerns have brought this sector into the spotlight. Recent evidence suggests that productivity growth has slowed in Australian agriculture due to spells of bad weather and droughts over recent periods and the declining public investment in agricultural R&D since the 1970s. Figure 2.8 shows that broadacre productivity growth was stronger during the 1980s and 1990s, which enabled more output to be produced using fewer inputs. Nossal and Sheng (2010) estimated TFP growth in broadacre agriculture of 1.4 per cent per annum for the period from 1977–78 to 2007–08. During this period, broadacre farmers reduced their input use by 0.6 per cent a year and increased outputs by 0.8 per cent a year. However, over the recent period from 1997–98 to 2007–08, the rate of productivity growth is estimated to have declined to – 1.3 per cent per annum (Figure 2.8).

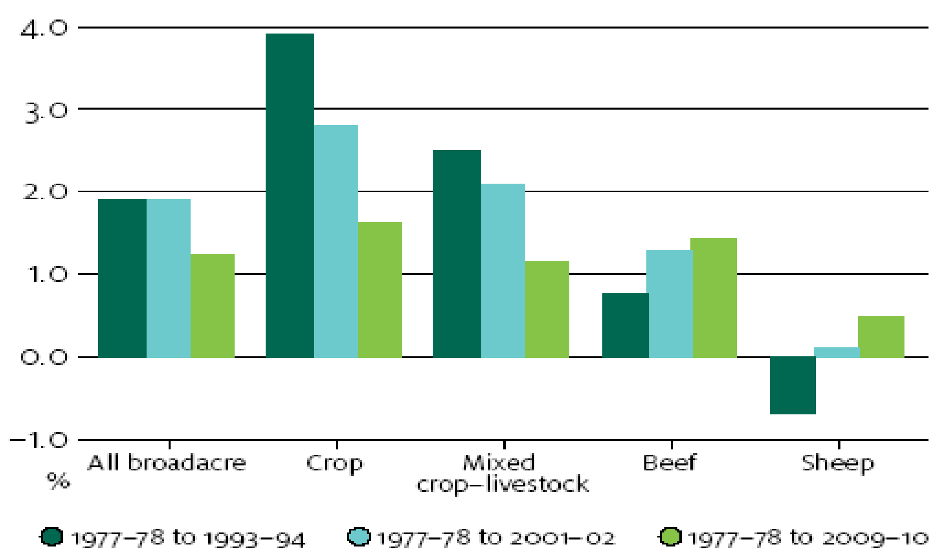
Specifically, in Australia, recent studies suggest that productivity growth, at least in some sectors of Australian agriculture, has slowed compared to earlier periods (DAFF, 2012; Sheng *et al*., 2010). In particular, productivity growth has slowed in the cropping and mixed crop-livestock sectors over the last few decades, although the rate of productivity growth in both the beef and sheep industries has increased over the same period (Figure 2.9). This suggests that the recent series of droughts may have had more effect on the cropping industry than on livestock industry.

**Figure 2.8: Productivity growth in Australian broadacre agriculture**




Source: Adopted from Sheng *et al*. (2010)

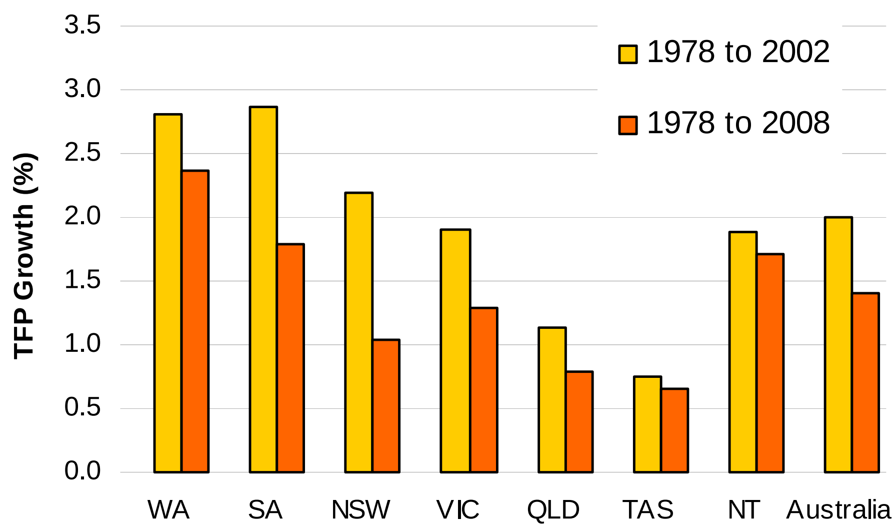
**Figure 2.9: Average annual broadacre TFP growth, by industry**




Source: DAFF, 2012; Australia's agriculture, fisheries and forestry at a glance, 2012

Moreover, Australian broadacre farms differ markedly across states in terms of productivity growth and financial performance. Productivity growth has been much stronger in Western Australia and South Australia than in the eastern states of New South Wales, Victoria, Queensland and Tasmania (Figure 2.10). Similarly, recently farm incomes have increased for farms in Western Australia and South Australia. On the other hand, a large fall in incomes has been reported for farms in regions of Queensland and New South Wales that have been subjected to severe drought conditions in recent years.

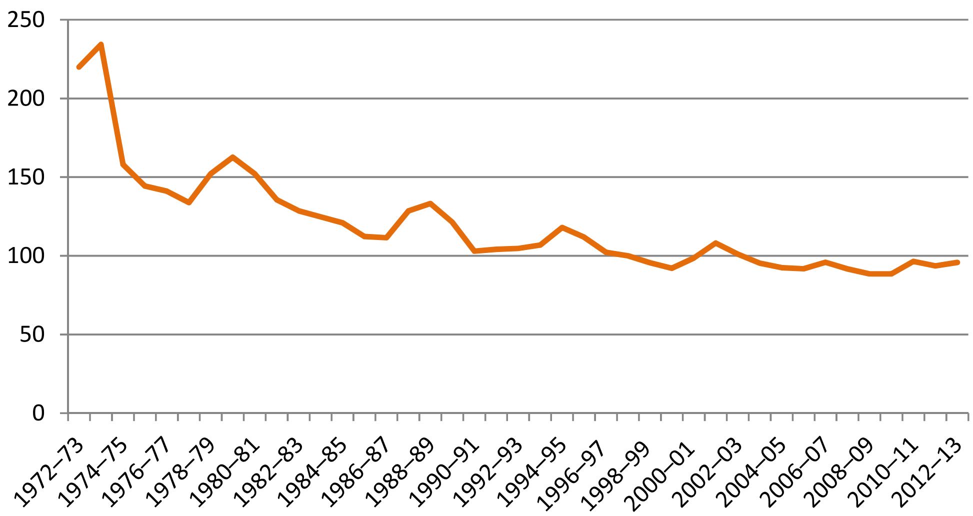
**Figure 2.10: State-level productivity change in broadacre agriculture**




Source: Adopted from Gooday (2010)

In addition, Australian farmers continue to face the challenge of long-term decline in the farmers' terms of trade in agriculture. It declined at an average annual rate of 1.68 per cent per annum over the period 1973–2013 (Figure 2.11). The long-term productivity growth has helped to offset this decline in the ratio of the prices farmers receive for their output to the prices paid for inputs. With the gains in efficiency and productivity, this sector also remains internationally competitive. This phenomenon in agriculture also illustrates the need for increasing attention to improving efficiency and productivity to ensure that the industry can meet the food needs of the growing world population while remaining internationally competitive in the future.

**Figure 2.11: Farmers' terms of trade in Australian agriculture: 1973–2013**




Source: ABARES; Australian Commodity Statistics, 2013

## 2.6 Research and Development in Australian Agriculture

Public investment in agricultural research and development[3] (R&D) has made a significant contribution to the improvement in the agricultural productivity growth, competitiveness and sustainability of Australia's agriculture (Productivity Commission, 2011). A study by Mullen (2007) shows that over the period 1994 to 2005, productivity growth in agriculture was higher than in any other sector of the Australian economy. The performance of Australian agriculture can also be compared favourably with agricultural sectors in other countries. For example, Rao *et al*. (2005) estimate a TFP growth rate of 2.0 per cent per annum over the period 1970 to 2000, which is similar to that of the USA and well above some other OECD countries. Therefore, despite a series of droughts and bad weather, fragile soils, variable climates and largely unsubsidized farming, Australian agriculture fared better than other sectors in the Australian economy or relative to the productivity

[3] Agricultural research and development (R&D) covers activities that results in new crop and pasture varieties and improved livestock types along with other activities that including improved fertilizer, weed management, efficient agricultural machinery, improved crop sowing and stored soil moisture. On the other hand, agriculture extension refers to activities related to delivering new information to farmers regarding new techniques and best practice farming (Black and Walker, 2009).

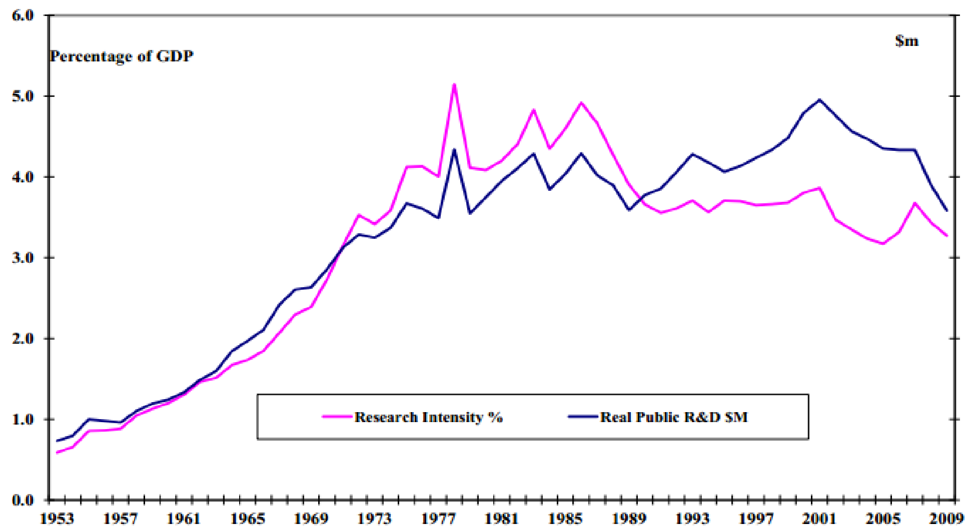
growth in the agricultural sectors of other countries (Carberry *et al*., 2011; Mullen, 2007).

This notable performance by Australian agriculture has been achieved through agricultural research leading to technology development and innovation. Over time, Australian farmers have adopted improved farming practices and disease-tolerant varieties, an integrated pest and weed management, crop rotation, conservation agriculture and breeding programmes. Adoption of these technologies and practices has historically supported the achievement of improved productivity growth, which has enabled farmers to achieve their production potential (Nossal and Sheng, 2010).

Although productivity has played a key role in promoting sustainable economic growth and improving the livelihoods of the rural community in Australia, the recent slowing of productivity raises interest among researchers and policy makers. The volatility and slowdown in broadacre productivity growth in the 1990s and 2000s could be explained by a decade of poor seasonal variations and drought conditions in Australia. A study shows that even after fully adjusting for climate variability, the estimated productivity has grown at an annual rate of 0.24 per cent since 2000 (Hughes *et al*., 2011).

This low productivity rate could be associated with the continuing decline in public investment in agricultural R&D since the 1970s. Figure 2.12 shows an upward trend in the total public expenditure in agricultural R&D up until the mid-1970s. Since then, expenditure growth has essentially been static, with a spike in investment in 2001 followed by falling investments. Likewise, agricultural research intensity (research investment as a percentage of agricultural GDP) grew strongly, reaching 5 per cent in the late 1970s, before declining markedly to a little more than 3 per cent in 2009. This is one of the key issues that needs to be focused on for future productivity growth, which contributes to the competitiveness of the agriculture sector, in both global and domestic markets (Productivity Commission, 2005). Recent studies have also suggested that seeking productivity breakthroughs is the greatest emerging opportunity for Australia's broadacre industries to address the current and emerging constraints they face (Keating and Carberry, 2010; Mullen, 2007).

**Figure 2.12: Real public investment and research intensity in Australian agricultural R&D**




Source: Adopted from Mullen (2013)

The results of some studies, for example Mullen and Cox (1995) and Sheng *et al*. (2014), suggest that the rates of return from public investment in R&D are reasonably high and vary between 15 and 40 per cent. These findings of high rates of return on research and development support the fact that Australia's agriculture industries are suffering from underinvestment in research and development. In addition, a recent report released by the Australian Academy of Technological Sciences and Engineering in 2014 suggests that Australia needs a long-term policy and vision to fully capitalize on the growth of Asia's middle class (ASTE Report, 2014). The report also suggests an increasing focus on research and development and technological innovation, which would allow researchers to address the problems constraining agricultural development and could play a significant role and make an important contribution to agriculture in Australia and in the region.

Similarly, a recent report by the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) has suggested that public investment in research and development is the key for unlocking agricultural producers' potential in Australia and for meeting the growing food demand in the global markets. The report, entitled 'Public investment in agricultural R&D and extension: an analysis of the static and dynamic effects on Australian broadacre productivity', has also recommended increasing investment in public agricultural R&D because of its large benefits, with an average return as high as 28 per cent per annum (Gray *et al*., 2011). This suggests that achieving higher productivity growth in agriculture continues to be an important policy objective of producers and Australian governments.

In Australia, agricultural research has been largely supported by public investments through different sectoral funding (Department of Agriculture, Australian Government) and public research agencies (Mullen, 2007). Until recently, agricultural research in Australia has been carried out mostly in the public sector. Statistics show that generally more than 90 per cent of total agricultural R&D is funded by the public sector. The Grains Research and Development Corporation (GRDC) is one of the world's leading grain R&D organizations supported by the combined research investment of grain growers and the federal government. Since 1990, it has been playing an important role in helping grain growers to ensure the greatest return on their investments and shaping the future of the grain industry in Australia.

Similarly, research and development corporations (RDCs) are the main funding bodies of the Australian government for rural research and development (R&D) in Australia. Covering a broad spectrum of Australia's agricultural, fishing and forestry industries, RDCs invest in R&D and innovation to strengthen the competitiveness and profitability of these industries by improving the productivity and quality of products. Managing targeted investment in research, innovation, knowledge creation and extension, RDCs also support the sustainability of primary production and the natural resource base (Department of Agriculture, 2014). In addition to the RDCs, the Australian government has created industry research centres known as 'cooperative research centres' (CRCs) aimed at working on priority scientific issues from both the public and private sectors (Core, 2009).

Additionally, each state has an established department of agriculture and food for its own research programme. Moreover, the Australian federal government has developed and implemented a national approach for rural research, development and extension (RD&E) in Australia working together with the state and territory governments, departments of some public universities and the Commonwealth Scientific and Industrial Research Organization (CSIRO), which operates research programmes in agriculture.

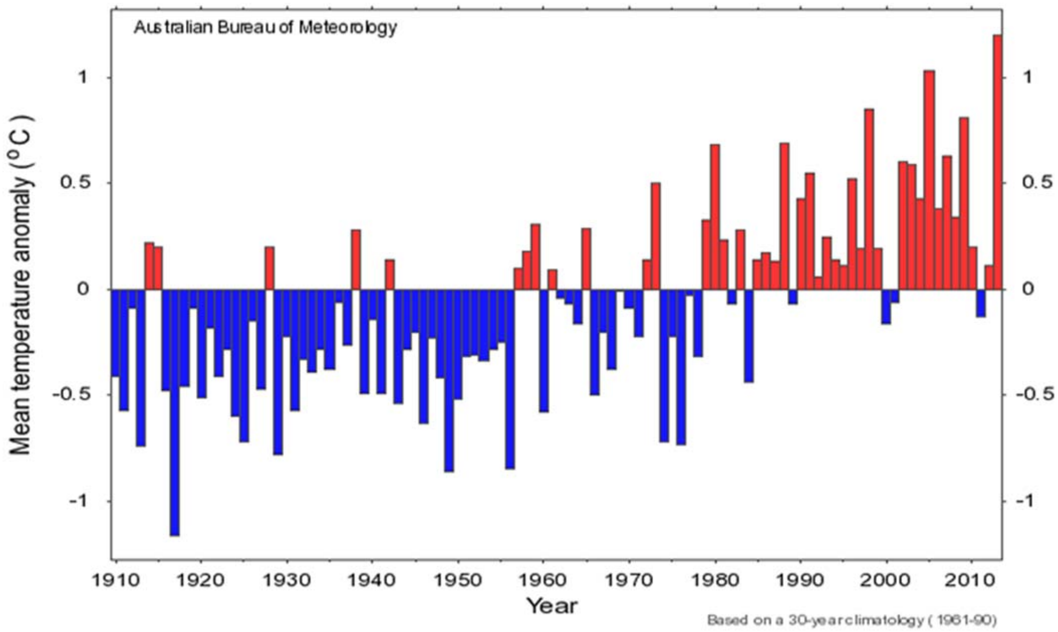
Further, there are some international agriculture research partnerships, which involve many of Australia's key institutions, including the CSIRO, universities and the state departments of agriculture in their various forms, which contribute in regional and global agriculture. Many of these partnerships have been supported by the Australian Centre for International Agricultural Research (ACIAR) since 1982. ACIAR is an Australian government agency, which manages research partnerships between Australian institutions, research partners in developing countries and other groups.

## 2.7 Climate Change and Agriculture in Australia

Changes in climate are evident both in Australia and globally in terms of measures of temperature, rainfall, sea level, and ocean acidification and salinity. The trends of these measures over the past century give a picture of how climate has changed over time. The possible causes behind these changes come from both natural and human-induced influences on natural resources (Solomon *et al*., 2007). According to Australian Bureau of Meteorology records, the average annual daily maximum temperatures are reported to have increased by 0.75 °C since 1910. There has been an increasing warming over decades since the 1950s (Figure 2.13). Australia has experienced a series of warm years since 1980, showing higher temperatures than average. In particular, over the last 100 years, 2013 was recorded as the warmest year in Australia. Moreover, Australia has also experienced an increased number of hot days (maximum temperature greater than 35 °C) and nights (minimum temperature greater than 20 °C) in recent decades.

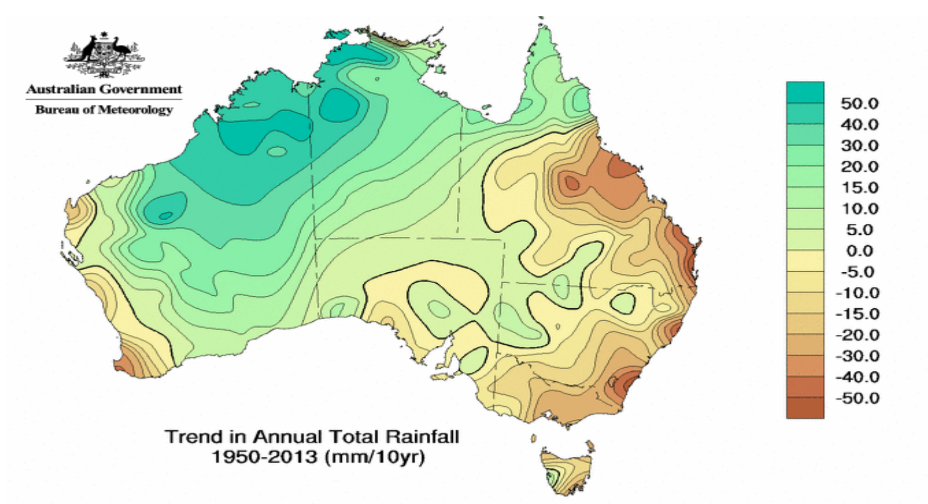
In addition, Australia has become drier since 1950, particularly in most of eastern and south-western Australia (Figure 2.14). The recent rainfall patterns across New South Wales and Queensland reflect an unusually dry period around the 2000s. A decreased number of wet days (at least 1 mm/day) and heavy rainfall events (over 30 mm/day) also have been observed in the south of Australia, with increasing events to the north (BoM, 2007). During recent decades, monsoonal rainfall has generally increased in spring and summer across north-western Australia. In contrast, there has been a reduced rainfall trend in late autumn and winter across Australia's south.

**Figure 2.13: Annual temperature anomaly – Australia (1910–2013)**




Source: Australian Bureau of Meteorology

**Figure 2.14: Map of trends in annual total rainfall 1950–2013**




Source: Australian Bureau of Meteorology

Climate change and its possible effects are likely to present a significant economic and environmental risk to Australian agricultural and resource industries (Garnaut, 2010). In particular, it poses challenges for water and food security, ecosystems, forestry, buildings, transport, energy, health and ecotourism. The changes in climatic conditions, for example the observed higher-than-average temperatures and lower-than-average rainfall, have affected many agricultural products (Nossal and Gooday, 2009). Besides, under most current projections, Australia's agriculture producers are more likely to be affected by the changes in climate than most other nations because Australia has probably been living with climates that are more variable and less predictable. According to the IPCC report, Australian agriculture and its associated natural base are significantly exposed to the projected climate change in terms of the changes in temperature and rainfall over the next 100 years (Hennessy *et al*., 2007).

### *2.7.1 Adaptation to Climate Change*

An urgent need for adaptation responses to growing risks associated with the climate changes is recognised by the concerned national and international agencies (IPCC, 2014). The importance of finding ways to adapt to the climate change has been recognized globally by governments, donors and international research institutions. To deal effectively with climate change it is important to improve the country's ability to develop effective strategies to adapt to climate change, which can be ensured by providing the necessary scientific knowledge. To ensure long-term sustainable production in agriculture it is imperative to adapt all primary industries to changes in temperature, rainfall, droughts and other extreme events. Moreover, the rising public awareness about climate change and its potential effects on vulnerable rural communities creates a need for an increasing investment in research that prioritizes the capacity for adaptation responses (Nelson *et al*., 2010).

The effects of climate change along with other recent concerns in agriculture, including the recent productivity slowdown, create a substantial challenge for Australian agriculture. In particular, they add pressure to the existing food security issue amidst the country's commitment to an environmentally friendly agriculture system with reduced greenhouse gas emissions and conserved biodiversity and the natural resource base in the future. To face such challenges Australia needs to find and implement ways of focusing more on improving productivity growth.

Climate change and its likely impact on Australian agriculture make two things increasingly apparent. Firstly, being prepared in advance to adopt an adaptation strategy is essential and the approach needs to be supported by good scientific methods and innovative ideas. This requires a strong research, development and extension base with adequate funding to support the efforts of adaptation more effectively and scientifically. Secondly, all stakeholders need to have access to quality information to successfully face the challenges of climate change. Availability of information on practical scales of time and space could help policymakers design the best policy adaptation decisions and develop practical solutions.

## 2.8 Contribution of Australia's Agriculture Policy Reforms to R&D

There is widespread consensus among policymakers that agricultural and economy-wide policy settings are the important factors contributing to agricultural productivity. Agricultural policy incentives affect innovation in agriculture by shaping farmers' motivations and capacity to increase agricultural productivity. In Australia, agricultural development was a public policy priority in the decades after World War II up until the early 1990s. A number of agricultural institutions and R&D efforts grew considerably during this period (Williams, 1998). In addition, agricultural extension services in state and territorial governments expanded significantly from the late 1960s through to the late 1980s (Hunt *et al*., 2014). These efforts at innovations and extension practices emerged not simply for production improvements but with a broader objective of resolving socio-economic issues within rural industries in Australia.

Historically, to support and smooth farmers' returns in Australia, governments undertook various agricultural policy measures, such as price support, input subsidy and quota systems. However, such interventions were poorly assessed because of inefficiencies resulting from the distortions in resource allocation within agriculture and inability to find better ways of managing risk and improving productivity (Gray *et al*., 2014). Understanding these limitations, the Australian federal government as well as state and territorial governments largely reformed these market interventions under the significant microeconomic and structural reforms during the 1980s and 1990s. These market reforms, particularly opening the economy to competition and the deregulation of industries and institutions, contributed to achieving productivity gains in Australian agriculture (Parham, 2004). Despite its contribution to agricultural productivity growth through reducing inefficiencies of resource use disparities across farms and improving farmers' incentives for innovation, these agricultural reforms moved the Australian agriculture sector to one of the least supported farming sectors around the world (Botterill, 2003). These past reforms were largely to make farmers more responsive in decision-making to market forces and to convince them to begin to invest in their own R&D rather than relying solely on states or federal governments.

In the early 1990s, the Australian government created agricultural institutions, such as 'research and development corporations' (RDCs) and 'cooperative research centres' (CRCs), aimed at delivering outcomes to industry and the nation. These government initiatives indirectly created a situation for state governments to redirect their focus from undertaking production-orientated RD&E services to agriculture (Core, 2009). As a result, public investment in agricultural RD&E has remained static for around two decades or has been falling in the recent period in Australia. These declining trends in R&D investments may cause a decline in the rate of agricultural productivity, which has begun to be seen in recent years (Hughes *et al*., 2011; Mullen, 2010; Sheng *et al*., 2010).

## 2.9 Conclusion

Australian agriculture plays a crucial role in the domestic and the regional economy. The production of this sector has been increasingly dependent on productivity growth. Over the past few decades, Australian broadacre agriculture has performed better than the agricultural sectors in most other countries. Despite its variable climate and fragile environment, the public investment in research and development has contributed significantly to realizing this remarkable agricultural productivity growth. However, the recent trend of slowing productivity growth in agriculture is clearly a matter of interest in the country and what causes this slower productivity rate remains an important question in Australian agriculture. There is some anecdotal evidence that this productivity decline may be the result of reduced public investments in research and development, which have been slowing in Australia since the 1970s. Other possible causes of the productivity declines are presumed to be the effects of ongoing droughts as well as climate variations. Yet there is a clear lack of solid empirical evidence regarding what causes productivity declines and how close the relationship between productivity growth and R&D investment is in agriculture for Australia.

Overall, Australian agriculture is now facing challenges brought about by seasonal variations and climate change, government policies and international competition in the export markets. Along with these challenges, some opportunities are also presented for Australian agriculture in terms of sharing the growing food demand in the Asia-Pacific region. Under these emerging challenges and opportunities, a revitalized attention to lifting productivity growth is essential for Australian agriculture to play a pivotal role in the future success of the economy. This research is aimed at exploring the effects of changes in R&D investments on agricultural performance and the possible ways in which the country needs to respond to address these challenges effectively and adapt to opportunities presented. Using standard and novel econometric approaches, the subsequent chapters explore the issues empirically with up-to-date methodology.

# CHAPTER THREE

## Nonparametric Estimates of Productivity and Efficiency Change in Australian Broadacre Agriculture

**Summary:** This chapter computes and decomposes Färe-Primont indexes of total factor productivity of Australian broadacre agriculture by estimating distance functions. Using state-level data from 1990 to 2011, the empirical results show that total factor productivity (TFP) grew at an average rate of 1.36 per cent per annum in the broadacre agriculture over the period 1990-2011. There are variations of TFP growth across states and fluctuations over time within each state. However, overall there is a clear movement towards slower TFP growth across the sample period. Further decomposition of TFP growth shows that it is declining growth in technical possibilities (technological progress) that is the main driver of the declining trend in productivity growth in broadacre agriculture in Australia.

### 3.1 Introduction

Over the last few decades, efficiency and productivity growth analysis in agriculture has attracted attention of economic researchers and policymakers in both developed and developing countries (Battese and Coelli, 1995; Bravo-Ureta *et al*., 2007; O'Donnell, 2012b; Samarajeewa *et al*., 2011; Van Beveren, 2012). It is not easy for a country to advance prosperity without attaining a considerable growth in productivity. Recently, in the global context agricultural productivity growth has been falling, particularly in developed economies. This also has implications for food security in developing countries, where growing populations will continue to raise demand for food in the coming decades (Pardey *et al*., 2006).

There is limited empirical evidence concerning the drivers of total factor productivity (hereafter, TFP) growth and its components in Australian broadacre agriculture. Previous empirical studies of Australian broadacre agriculture make limited use of decomposition analysis to find the components of productivity and efficiency changes. They are mainly concerned with estimating the growth of total factor productivity and technical efficiency change. Productivity researchers have also recognized the importance of measuring different types of efficiency change in both the agriculture and manufacturing sectors.

Using aggregate data O'Donnell (2010) computes TFP indexes and the components of TFP change in Australian agriculture during the period from 1970 to 2001. One of the major limitations in this study is the use of the Hicks-Moorsteen TFP index that fails the transitivity test and is thus unsuitable for multi-lateral and multi-temporal comparisons (O'Donnell, 2012b). O'Donnell (2014) also provides argument that the Färe-Primont index is preferred to the Hicks-Moorsteen index in estimating productivity changes and its components.

Other previous studies in Australian agriculture mainly focus on aggregate (Mullen and Cox, 1996) or regional and industry-specific (Fraser and Hone, 2001) productivity growth. However, state-level productivity analysis in the agricultural sector is reported in studies conducted in other countries (Ball *et al*., 2004; and Laurenceson and O'Donnell, 2011; O'Donnell, 2012b; Rahman and Salim, 2013). These studies suggest that analysis of state-level data can provide useful insights into the drivers of productivity growth.

The main objective of this chapter is to estimate total factor productivity changes in Australian broadacre agriculture and to decompose these changes into measures of technical change and technical efficiency[4] change. This is done using the Färe-Primont index of total factor productivity, which satisfies all axioms of index number theory, including the identity and transitivity axioms. Further, this study uses a new linear programming methodology developed by O'Donnell (2014) for exhaustively decomposing TFP change into measures of technical change and technical efficiency change. Finally, by exploring the different components of productivity growth this chapter contributes information for policy formulation, as different policies generally affect different components of productivity change.

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[4] Technical efficiency reflects the ability of a farm to produce maximum possible output using a given set of inputs and technology, regardless of market information (Kalirajan and Obwona, 1994). A firm is technically efficient if it operates on the production frontier – i.e. obtains maximum output from a given set of inputs and technology.

The rest of the chapter proceeds as follows. The next section reviews theoretical issues and previous empirical studies. Section 3.3 outlines the empirical methodology to be used, followed by a discussion on data sources in Section 3.4. Section 3.5 presents the empirical estimates and an analysis of results. Finally, Section 3.6 concludes the chapter.

## 3.2 Review of Theoretical and Empirical Literature

### *3.2.1 Theoretical Issues: Total Factor Productivity Index*

The change in the level of TFP can be measured as the ratio of an aggregate output quantity index to an aggregate input quantity index. There are several formulas available for constructing such indexes in the productivity literature. The Tornqvist index, the Fisher index, and the Malmquist index of Caves, Christensen and Diewert (1982) are some of the widely used indexes in empirical research in agriculture.

Both the Tornqvist index and the Fisher index satisfy the identity axiom, which says that if two firms produce the same outputs using the same inputs the relative index value is one. However, neither of these two indexes satisfies the circularity (transitivity) axiom, which requires that both a direct comparison and an indirect comparison of two firms/periods through an intermediate firm/period will yield the same estimate of productivity change. Intransitivity makes indexes inappropriate to be used to make multi-lateral or multi-temporal comparisons (O'Donnell, 2012b, 2014).

Malmquist productivity indexes are one of the standard approaches in the productivity literature (Lovell, 2003), that can be decomposed exhaustively (Färe *et al*., 1994), especially in nonparametric specifications and for translog technologies (Bjurek, 1996). However, the DEA (data envelopment analysis) estimates of Malmquist indexes are incomplete measures of productivity change as they fail to capture productivity changes associated with changes in scale (Grifell-Tatje and Lovell, 1995; O'Donnell, 2012b). In fact, the Malmquist index is not a productivity index rather it is only a measure of technical change and technical efficiency change (Färe *et al*., 1994). Except in special cases, the Malmquist TFP index may not reliably measure TFP change and its decompositions. It generally yields biased estimates of technical change and efficiency change (O'Donnell, 2012a).

Recently, two other indexes, namely the Hicks-Moorsteen TFP index proposed by Bjurek (1996) and the Färe-Primont index proposed by O'Donnell (2014) have been used in constructing productivity indexes. They can be broken into recognizable components without requiring data on prices or any restrictive assumptions concerning statistical noise. However, between the two indexes O'Donnell (2014) argues that the Färe-Primont index is more reliable than the Hicks-Moorsteen index, as the former can be used to make reliable multi-lateral and multi-temporal comparisons. The Hicks-Moorsteen index can validly only be used to make a single binary comparison, as it fails the transitivity test.

Apart from choosing an index formula, decomposing TFP indexes into measures of technical change and other measures of efficiency change involves estimating the production frontier. A range of approaches has been proposed in the literature on how to estimate the production technology. The two competing approaches to obtain potential or frontier output are stochastic frontier analysis (SFA) and data envelopment analysis (DEA).

The SFA approach is a stochastic parametric approach, which parameterises the production frontier under some distributional assumptions of random error terms. This approach uses a two-component error term - a stochastic random error component and a technical inefficiency component (Aigner *et al.*, 1977; Meeusen and Broeck, 1977). The main weaknesses of this approach are that results may be sensitive to the choice of functional form of the unknown production frontier and assumptions concerning the distributions of error terms, and the estimates of unknown parameters may be statistically unreliable if sample sizes are small (O'Donnell, 2014). The issue of endogeneity is also likely to be associated with estimating multiple-input and multiple-output production technologies in the SFA model (Mutter *et al.*, 2013; O'Donnell, 2014). Besides, the SFA approach has difficulties in identifying some components of TFP change, such as pure scale efficiency change and pure mix efficiency change.

DEA is a nonparametric deterministic approach popularly employed to estimate the production frontier. This approach primarily involves mathematical programming and requires no assumption about the error term and the distributions of the parameters (e.g., means and variances) (Farrell, 1957). Moreover, it does not require any explicit assumptions regarding the functional form of the production frontier or any structure to compute relative efficiency scores (Banker, 1993). However, a limitation of assuming away the statistical noise is that it leads to an intrinsic bias with all deviations from the estimated frontier attributed to inefficiency (Coelli *et al*., 2005). If there is substantial statistical noise in the data, then the use of DEA becomes problematic and stochastic frontier analysis remains the only choice as it allows statistical noise (Simar and Wilson, 2000). Nonetheless, this chapter uses a nonparametric DEA to estimate a production frontier and then to compute and decompose the TFP index. This allows more direct comparison to most other studies that have applied index number approaches to measuring productivity in Australian agriculture.

### *3.2.2 Empirical Studies: Productivity Growth in Agriculture*

A substantial body of literature has emerged over the past few decades on efficiency and productivity measurement in Australian agriculture. At the economy-wide level, Males *et al*. (1990) measure productivity growth of broadacre agriculture and find that TFP growth averaged 2.2 per cent per annum over the period 1978 to 1989. They also disaggregate the sample size into different enterprise-types and find that productivity growth rates vary across enterprise types. Particularly, they report 5.5 per cent productivity growth per annum for specialist crops. Knopke *et al*. (1995) extend a similar dataset to 1994 and find the productivity growth of the specialist crop slowed to 4.6 per cent per annum, while productivity growth in broadacre agriculture was at 2.7 per cent per annum for the period 1978 to 1994. Dividing the farms into three groups, they also find that scale matters significantly in productivity growth.

Using a farm-level dataset covering the period from 1953 to 1994, Mullen and Cox (1996) find an average rate of productivity growth of 2.5 per cent per annum in Australian broadacre agriculture. They compare alternative measures of productivity growth including traditional index number approaches, a scale-adjusted Christensen and Jorgenson index, nonparametric measures and an econometric estimate of a translog cost function. They find a small variation in average TFP growth from 2.4 per cent to 2.6 per cent over the different estimation approaches. These robust results from parametric and nonparametric methodologies suggest confidence for traditional index number approaches, such as the Fisher index. However, when they disaggregate the study periods into three sub-periods, they find that productivity growth in Australian broadacre agriculture declined from 2.0 per cent to 1.8 per cent between the sub-periods 1953–1968 and 1969–1984.

Recently, using country-level agriculture data for 88 countries over the period 1970–2001, O'Donnell (2010) computes indexes of TFP change and decomposes them into economically meaningful components. Particularly in Australia, O'Donnell shows that over the period agriculture experienced a 15 per cent decline in productivity and he explains that increases in net returns to agriculture are associated with falls in productivity. However, this study uses the Hicks-Moorsteen TFP index, which is only valid for binary comparisons. Moreover, it uses only two outputs and is for overall country-level agriculture data which fails to capture regional variations in agricultural productivity.

One major drawback of the previous studies of productivity for Australian broadacre farms is that it is difficult to disentangle changes in technical efficiency and scale-mix efficiency from the contribution of technical change to productivity growth. Studies that use the conventional measures of productivity do not take the multiple sources of the productivity growth into account. For example, the previous studies of Australian broadacre farms cannot properly assess whether the productivity change is sourced from improving the rate of technical progress or from improving levels of either technical or scale and mix efficiency. Further, most of the previous studies use imputed prices for the broadacre outputs or inputs to construct the indexes, which may bias the estimates due to measurement error.

## 3.3 Empirical Methodology

### *3.3.1 Total Factor Productivity Indexes*

This chapter uses the Färe-Primont index to compute and decompose TFP growth into a measure of technical change and several finer measures of efficiency change for Australian broadacre agriculture. Index number approaches to measuring total factor productivity as a ratio of aggregate outputs over aggregate inputs can be traced back to Jorgenson and Grilliches (1967), Nadiri (1970) and Good *et al*. (1996). However, these early studies rely on market prices to form aggregates in case of multiple outputs and multiple inputs farms.

Recently, O'Donnell (2012b) defines TFP, without the use of prices, as the ratio of an aggregate output to an aggregate input where the aggregator functions are non-negative, non-decreasing and linearly homogeneous. These properties of the aggregator functions are crucial to construct a TFP index that satisfies basic axioms from index theory. Let $q_{it} \in \Re_{+}^{J}$ and $x_{it} \in \Re_{+}^{K}$ denote vectors of output and input quantities for firm $i$ in period $t$. Following O'Donnell (2012b), TFP is defined as $TFP_{it} = Q_{it}/X_{it}$ where $TFP_{it}$ indicates the *TFP* of firm $i$ in period $t$, and $Q_{it} = Q(q_{it})$ and $X_{it} = X(x_{it})$ are aggregate output and aggregate input, respectively.

Using this TFP definition, the productivity index that compares the TFP of firm $i$ in period $t$ with the TFP of firm $h$ in period $s$ is (O'Donnell, 2014):

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \frac{Q_{it}/X_{it}}{Q_{hs}/X_{hs}} = \frac{Q_{it}/Q_{hs}}{X_{it}/X_{hs}} = \frac{Q_{hs,it}}{X_{hs,it}} \qquad (3.1)$$

where $Q_{hs,it}$ *and* $X_{hs,it}$ are the output quantity index and input quantity index, respectively, which compare the output and input of firm $i$ in period $t$ with the output and input of firm $h$ in period $s$. Equation 3.1 shows that TFP change can be obtained by dividing an index of output growth by an index of input growth. The index number formed in this way as a measure of relative productivity is said to be multiplicatively complete (O'Donnell, 2012a).

The Färe-Primont index is a member of a class of "multiplicatively complete" productivity indexes that uses the following non-negative, non-decreasing and linearly homogenous aggregator functions: $Q(q) = D_{\mathrm{O}}(\mathrm{x}_0, q, t_0)$ and $X(x) = D_I(x, q_0, t_0)$, where $D_{\mathrm{O}}(\mathrm{x}_0, q, t_0)$ and $D_{\mathrm{I}}(x, q_0, t_0)$ are the Shephard output and input distance functions, respectively, representing the production technology available in period $t_0$. Here, $q_0$ and $\mathrm{x}_0$ are arbitrary vectors of representative outputs and inputs. O'Donnell (2011, 2014) shows that the Färe-Primont index that measures the TFP of firm *i* in period *t* relative to the TFP of firm *h* in period *s* is:

$$TFP_{hs,it} = \frac{D_O(\mathrm{x}_0, \mathrm{q}_{\mathrm{it}}, t_0)}{D_O(\mathrm{x}_0, \mathrm{q}_{\mathrm{hs}}, t_0)} \frac{D_I(\mathrm{x}_{hs}, \mathrm{q}_0, t_0)}{D_I(\mathrm{x}_{\mathrm{it}}, \mathrm{q}_0, t_0)} \tag{3.2}$$

Production technologies represented as Shephard output and input distance functions maintain the following basic regularity properties:

For the output distance function-

O.1 non-increasing in inputs: $D_{\mathrm{o}}(\mathrm{x}_1, q, t_0) \leq D_{\mathrm{o}}(\mathrm{x}_0, q, t_0)$ for $\mathrm{x}_1 \geq \mathrm{x}_0$,

O.2 non-decreasing in outputs: $D_{\mathrm{o}}(\mathrm{x}, q_1, t_0) \geq D_{\mathrm{o}}(\mathrm{x}, q_0, t_0)$ for $\mathrm{q}_1 \geq \mathrm{q}_0$,

O.3 linearly homogenous in outputs: $D_{\mathrm{o}}(\mathrm{x}, \lambda q, t) = \lambda D_{\mathrm{o}}(\mathrm{x}, q, t)$ for $\lambda > 0$.

For the input distance function-

I.1 non-decreasing in inputs: $D_{\mathrm{I}}(\mathrm{x}_1, q, t_0) \geq D_{\mathrm{I}}(\mathrm{x}_0, q, t_0)$ for $\mathrm{x}_1 \geq \mathrm{x}_0$,

I.2 non-increasing in outputs: $D_{\mathrm{I}}(\mathrm{x}, q_1, t_0) \leq D_{\mathrm{I}}(\mathrm{x}, q_0, t_0)$ for $\mathrm{q}_1 \geq \mathrm{q}_0$,

I.3 linearly homogenous in inputs: $D_{\mathrm{I}}(\lambda \mathrm{x}, q, t) = \lambda D_{\mathrm{I}}(\mathrm{x}, q, t)$ for $\lambda > 0$.[5]

[5] O.2 and I.1 properties hold under the assumptions of strong disposability.

### *3.3.2 Measures of Efficiency*

Following O'Donnell (2012a), several measures of efficiency are defined as:

Output-oriented technical efficiency, $OTE_{it} = \frac{Q_{it}}{\bar{Q}_{it}}$ (3.3.a)

Output-oriented scale efficiency, $OSE_{it} = \frac{\bar{Q}_{it}/X_{it}}{\tilde{Q}_{it}/\tilde{X}_{it}}$ (3.3.b)

Output-oriented mix efficiency, $OME_{it}=\frac{\bar{Q}_{it}}{\hat{Q}_{it}}$ (3.3.c)

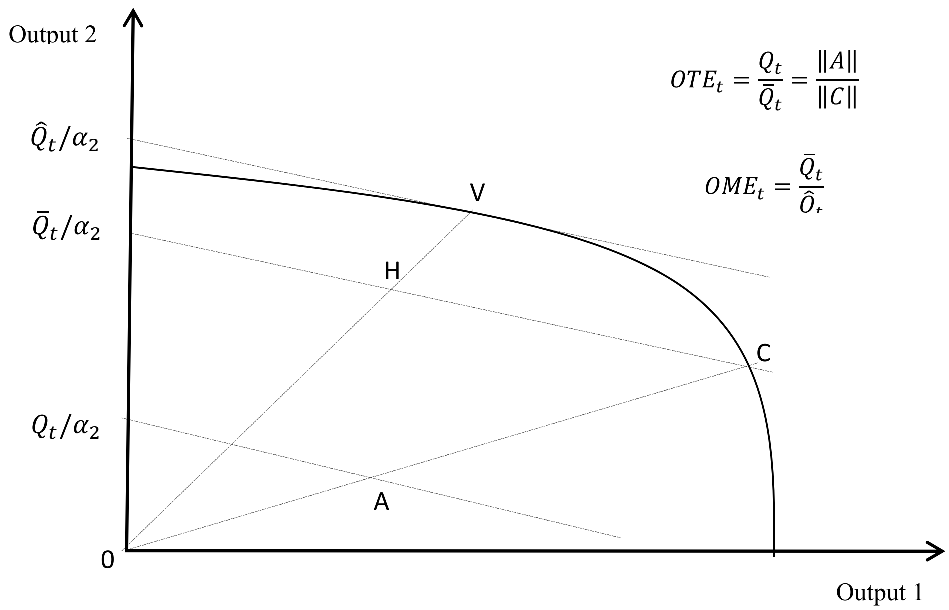
Residual output-oriented scale efficiency, $ROSE_{it}=\frac{\hat{Q}_{it}/X_{it}}{Q^*_{it}/X^*_{it}}$ (3.3.d)

Residual mix efficiency, $RME_{it} = \frac{\tilde{Q}_{it}/\tilde{X}_{it}}{Q^*_{it}/X^*_{it}}$ (3.3.e)

where, $\bar{Q}_{it}$ is the maximum aggregate output that is technically feasible to produce a scalar multiple of $q_{it}$ using $x_{it}$; $\hat{Q}_{it}$ is the maximum possible aggregate output using $x_{it}$ to produce any output vector; $\tilde{Q}_{it}$ and $\tilde{X}_{it}$ denote the aggregate output and input quantities at the point where *TFP* is maximised subject to the constraint that the output and input vectors are scalar multiples of $q_{it}$ and $x_{it}$ respectively; and $Q^*_{it}$ and $X^*_{it}$ denote the aggregate output and input quantities at the point of maximum productivity.

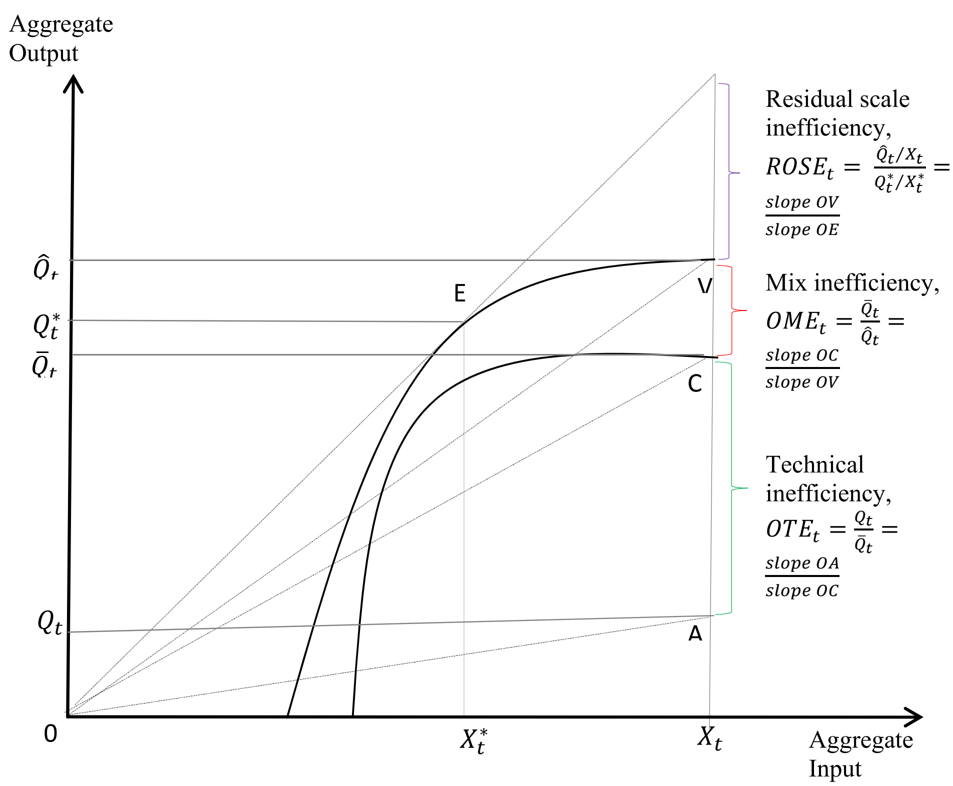
These efficiency measures are also illustrated using three simple diagrams. Figure 3.1 illustrates technical efficiency measurement in the two-output case. The curve passing through point *C* and *V* is a familiar production possibility frontier representing all technically efficient output combinations that can be produced using a given level of input $x_{it}$. The dashed line passing through point *A* is an iso-output line that represents all output combinations that have the same level of aggregate output as at point *A*. O'Donnell (2010) further provides an alternative graphical representation in the multiple-output multiple-input case, which is drawn in Figure 3.2 to illustrate the relationships between measures of efficiency. In Figure 3.2, the curve passing through point *C* represents a mix-restricted (output mix) frontier as the input and output vectors are scalar multiples of $x_{it}$ and $q_{it}$.

**Figure 3.1: Output-oriented technical and mix efficiency for a two-output firm**




Source: Modified from O'Donnell, 2010

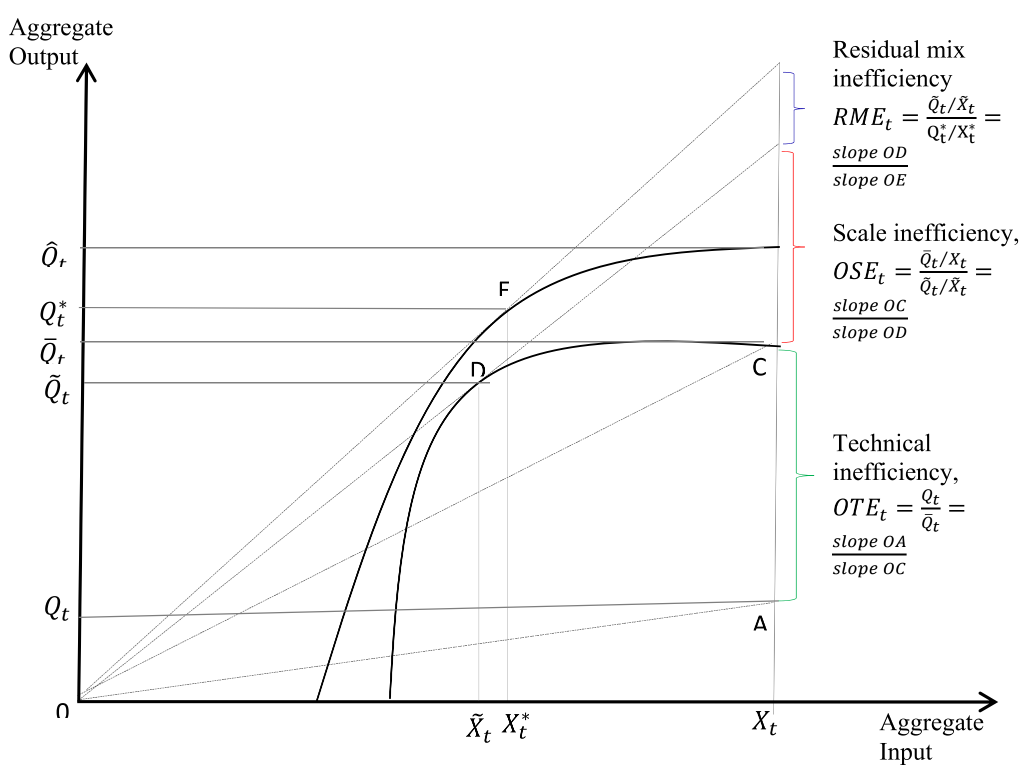
**Figure 3.2: Output-oriented measures of efficiency**




Source: Modified from O'Donnell, 2010

If the output mix and input vector are held fixed, then the ratio of the distances 0A and 0C in Figure 3.1 is the measure of OTE proposed by Farrell (1957), which measures movements towards or away from the frontier. Similarly, in Figure 3.2 the measure OTE represents the proportionate increase in TFP when the firm moves from point A to point C on the restricted frontier. If restrictions on the output mix are relaxed, the firm can further increase aggregate output by moving to point V in Figure 3.1, which corresponds to a vertical movement from point C to point V in Figure 3.2. This potential change in productivity is termed as the OME which can be defined as the ratio of the distance 0H to the distance 0V in Figure 3.1. Thus, the measure OME shows the increase in TFP while holding inputs fixed and relaxing restrictions on the output mix. However, improvements in technical and mix efficiency do not maximise productivity of a firm. The firm can maximise productivity by moving around the unrestricted frontier from point V to point E in Figure 3.2. The point E is referred as the point of maximum productivity. O'Donnell termed this potential productivity gain as ROSE (residual output-oriented scale efficiency) that can be achieved through economies of scale.

**Figure 3.3: Output-oriented alternative measures of efficiency**




Source: Modified from O'Donnell, 2010

Further, O'Donnell (2011) presents two more output-oriented measures of efficiency OSE (output-oriented scale efficiency) and RME (residual mix efficiency), which are depicted in Figure 3.3. If the input and output mixes are kept unchanged, the firm can maximise its productivity by moving to point D from point C in Figure 3.3. Point D is the point of *mix-invariant optimal scale* (MIOS). The measure of OSE is a measure of the proportionate increase in productivity that occurs as the firm moves from a technically efficient point C to a MIOS point D. The measure of RME is the ratio of productivity at a MIOS point to productivity at a point of maximum productivity. In Figure 3.3, RME is the ratio of productivity at point D on the mix-restricted frontier to productivity at point E on the unrestricted frontier.

**TFP Efficiency (TFPE)**

As an overall measure of firm performance, O'Donnell (2011) measures TFP efficiency (TFPE) as the ratio of observed TFP to the maximum TFP given the available technology. Mathematically, TFP efficiency of firm *i* in period *t* is

$$TFPE_{it} = \frac{TFP_{it}}{TFP_t^*} = \frac{Q_{it}/X_{it}}{Q_{it}^*/X_{it}^*} \quad (3.4.a)$$

where $TFP_t^*$ indicates maximum TFP possible given the technology in period *t* and $Q_t^*$ and $X_t^*$ are the TFP-maximizing aggregate output and aggregate input, respectively. This measure is shown both in Figure 3.2 and in Figure 3.3 that provide two of many meaningful decompositions of TFP efficiency as the firm moves all the way from point A to point E:

$$TFPE_{it} = \frac{TFP_{it}}{TFP_t^*} = \frac{slope0A}{slope0E} = \frac{slope0A}{slope0C} \times \frac{slope0C}{slope0V} \times \frac{slope0V}{slope0E} = (OTE_{it} \times OME_{it} \times ROSE_{it})$$
(3.4.b)

$$TFPE_{it} = \frac{TFP_{it}}{TFP_t^*} = \frac{slope0A}{slope0E} = \frac{slope0A}{slope0C} \times \frac{slope0C}{slope0D} \times \frac{slope0D}{slope0E} = (OTE_{it} \times OSE_{it} \times RME_{it})$$
(3.4.c)

Rewriting Equations 3.4.b and 3.4.c, the output-oriented TFP index can be decomposed into following meaningful components proposed by O'Donnell (2012b):

$$TFP_{it} = TFP_t^* \times (OTE_{it} \times OME_{it} \times ROSE_{it}) = TFP_t^* \times (OTE_{it} \times OSE_{it} \times RME_{it}) \quad (3.5)$$

A similar decomposition holds for firm $h$ in period $s$.

Using the above decompositions, the relative TFP index comparing TFP of firm $i$ in period $t$ with the TFP of firm $h$ in period $s$ can be decomposed exhaustively in either of the two following ways:

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{OTE_{it}}{OTE_{hs}} \times \frac{OME_{it}}{OME_{hs}} \times \frac{ROSE_{it}}{ROSE_{hs}}\right) \tag{3.6.a}$$

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{OTE_{it}}{OTE_{hs}} \times \frac{OSE_{it}}{OSE_{hs}} \times \frac{RME_{it}}{RME_{hs}}\right) \tag{3.6.b}$$

The first term in parentheses on the right-hand side of each of the above equations is a measure of technical change, which compares the maximum TFP possible in period $t$ with the maximum TFP possible in period $s$. The other terms on the right-hand sides of the equations are the different output-oriented measures of relative efficiency, including relative technical efficiency, relative mix efficiency, and relative residual scale efficiency. The other two alternative components are output-oriented relative scale efficiency and relative residual mix efficiency.

Further, Equations 3.6.a or 3.6.b can be written as

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{OTE_{it}}{OTE_{hs}}\right)\left(\frac{OSME_{it}}{OSME_{hs}}\right) \tag{3.6.c}$$

where $OSME_{it} = OME_{it} \times ROSE_{it} = OSE_{it} \times RME_{it}$ is the measure of scale-mix efficiency defined by O’Donnell (2012b), which is a combined measure of scale and mix efficiency. The output-oriented scale-mix efficiency, OSME, measures the increase in TFP between a technically efficient point with the observed scale and input mix to the point of maximum productivity.

### *3.3.3 Estimation Using the DEA Approach*

The Färe-Primont index is a distance-based index which can be estimated relatively straightforwardly by DEA methodology, which assumes the frontier of a firm takes the linear form in the neighbourhood of the technically efficient point (O’Donnell, 2011). The distance function representing the production technology is also locally linear. Then, according to O'Donnell, (2011) the (local) output distance function holds only in the neighbourhood of the (technically efficient) point $(x_{it}, q_{it} / OTE_{it})$ and takes the form:

$$D_O(x_{it}, q_{it}, t) = (q_{it}^{'}\alpha)/(\gamma + x_{it}^{'}\beta) \quad (3.7.a)$$

The standard output-oriented DEA problem involves finding the solutions for the unknown parameters in Equation 3.7.a in order to minimize technical efficiency: $OTE_{it} = D_O(x_{it}, q_{it}, t)$. If $\alpha$ and $\beta$ are non-negative, then the only constraint that needs to be satisfied is $D_O(x_{it}, q_{it}, t) \leq 1$. Setting an additional constraint $q_{it}^{'}\alpha = 1$ the DEA problem takes the following form of linear programming (LP):

$$D_O(x_{it}, q_{it}, t)^{-1} = OTE_{it}^{-1} = \min_{\alpha,\gamma,\beta}\{\gamma + x_{it}^{'}\beta : \gamma\tau + X'\beta \geq Q'\alpha; q_{it}^{'}\alpha = 1; \alpha \geq 0; \beta \geq 0\} \quad (3.7.b)$$

where $Q$ is a vector of observed outputs, $X$ is a vector of observed inputs, and $\tau$ is a unit vector (for details, see O'Donnell, 2011).

Similarly, in the input-oriented case, the inputs distance function takes the form:

$$D_I(x_{it}, q_{it}, t) = (x_{it}^{'}\eta)/(q_{it}^{'}\phi - \delta) \quad (3.8.a)$$

The corresponding input-oriented DEA problem is

$$D_I(x_{it}, q_{it}, t)^{-1} = ITE_{it} = \min_{\phi,\delta,\eta}\{q_{it}^{'}\phi - \delta : Q'\phi \leq \delta\tau + X'\beta; x_{it}^{'}\eta = 1; \phi \geq 0; \eta \geq 0\} \quad (3.8.b)$$

To compute the Färe-Primont aggregates, the following variants of LPs (3.7.b) and (3.8.b) need to be solved:

$$D_O(x_0, q_0, t_0)^{-1} = \min_{\alpha,\gamma,\beta}\{\gamma + x_0^{'}\beta : \gamma\tau + X'\beta \geq Q'\alpha; q_0^{'}\alpha = 1; \alpha \geq 0; \beta \geq 0\} \quad (3.9.a)$$

$$D_I(x_0, q_0, t_0)^{-1} = \min_{\phi,\delta,\eta}\{q_0^{'}\phi - \delta : Q'\phi \leq \delta\tau + X'\beta; x_0^{'}\eta = 1; \phi \geq 0; \eta \geq 0\} \quad (3.9.b)$$

Estimates of aggregate outputs, $Q_{it}$ and aggregate inputs, $X_{it}$ for all *i* and *t* are then estimated as:

$$Q_{it} = (q_{it}^{'}\alpha_0)/(\gamma_0 + x_0^{'}\beta_0) \quad (3.10)$$

$$X_{it} = (x_{it}^{'}\eta_0)/(q_0^{'}\phi_0 - \delta_0) \quad (3.11)$$

where $\alpha_0$, $\beta_0$, $\gamma_0$, $\phi_0$, $\delta_0$ and $\eta_0$ solve Equations 3.9.a and 3.9.b. The computer software DPIN 3.0 further uses a linear programming technique to decompose productivity into various efficiency indexes. [6] It is also noteworthy to mention that the first-order partial derivatives of the aggregate output (equation 3.10) and aggregate input (equation 3.11) functions with respect to outputs and inputs can be represented as revenue- and cost-deflated output and input shadow prices, which also yield an estimator of the Färe-Primont TFP index (for more details see O'Donnell, 2011).

## 3.4 Data Sources and Variables

This chapter makes use of a state-level panel dataset from the AgSurf data of the Department of Agriculture, Australian Government, covering the period 1990-2011. The data in AgSurf are sourced from the annual farm surveys of ABARES (Australian Bureau of Agricultural and Resource Economics and Sciences). The dataset consists of observations on quantities of agricultural inputs, outputs and corresponding values in each state in each year. This study uses six major inputs: land, labour, capital, fertilizer, materials and services and rainfall, and four outputs: crops, livestock, wool and other output variables. In the case of the other output variable, farm's total receipt is used as there are no quantity data available for this variable.  Rainfall data are collected from the Australian Bureau of Meteorology. This study includes the rainfall variable as an important input of broadacre agriculture production, assuming that seasonal conditions may have influence on broadacre agriculture in Australia. The period for measuring rainfall is chosen to match the growing season in each state.

[6] DPIN 3.0 is computer software provided by the Centre for Efficiency and Productivity Analysis, University of Queensland, Australia.

### *3.4.1 Variable Construction*

In this study, the following six major input and four output variables are constructed from detailed input and output data by using a weighted aggregative method:

**Crop output (q1)**: It is a weighted aggregate quantity of all crops, where weights are given based on revenue shares of individual crops to total receipts of crops. The ABARES farm surveys contain data on the value and quantity for different crops. The varieties of crops included in the Crop output are Wheat, Barley, Oats, Sorghum, Rice, Oilseeds and Grain Legumes (includes lupins, field peas and others).

**Livestock (q2)**: Livestock is generated as a weighted aggregate of the number of Beef Cattle and Sheep (including lambs) during the survey period using revenue share as a weight.

**Wool (q3)**: Total Wool produced during the survey period (kg).

**Other Output (q4)**: Farm's total receipts from off-farm contracts, off-farm share farming and other farm income ($).

**Land (x1)**: Land includes all land areas operated on 30 June (ha) by the farm business whether owned or rented by the business but shared farm land on another farm is excluded.

**Labour used (x2)**: Labour used is the total number of weeks worked by all farm workers including hired labour.

**Capital (x3)**: This is the average of total closing value of capital on 30 June and opening value of capital on the prior 1 July. Capital includes the value of all assets used on the farm, including leased equipment but excluding machinery and equipment either hired or used by contractors. ABARE uses market value of fixed improvements and livestock/crop inventories and replacement value less depreciation for plant and machinery.

**Fertilizer (x4)**: The implicit quantity of fertilizer is calculated by dividing expenditure on fertilisers and soil conditioners during the survey year by the price index of fertiliser paid by farmers in Australia.

**Materials and Services (x5)**: Most of the materials and services data collected by ABARE are in value terms. Therefore, this variable is constructed by summing a wide range of input costs including materials, such as fodder, seed, fuel, crop chemicals; and services, such as contract services, rates and taxes and administrative services.

**Rainfall (x6)**: Growing season rainfall (April to October) is used for WA, SA, TAS and VIC, but annual rainfall is used for both NSW and QLD as April to October is not appropriate for them. QLD has summer dominant rainfall and NSW has both summer and winter rainfall. They are collected from the Australian Bureau of Meteorology (BoM).

## 3.5 Analysis of Empirical Results

Table 3.1 presents the Färe-Primont estimates of actual TFP, maximum TFP and TFPE along with their relative changes between 1990 and 2011. The Färe-Primont indexes are estimated assuming that the production technology exhibits variable returns to scale (VRS). The production possibilities set also allows both technical progress and technical regress. All the indexes reported in this table are meaningfully comparable in performance, both spatially and inter-temporally, as the indexes are transitive.

The estimates of actual TFP relative to the DEA maximum in the first column show that WA (Western Australia) was the most productive state and QLD (Queensland) was the least productive state in 1990. The difference in productivity between the two states was 72 per cent ($TFP_{WA}/TFP_{QLD} = 0.69/0.40 = 1.72$), so that WA was 72 per cent more productive than QLD in 1990. The TFP estimates in the second column also show that in 2011 WA and QLD remained the most productive state and the least productive state, respectively. The productivity difference between the highest and the least productive states remained almost the same, 70 per cent ($TFP_{WA}/TFP_{QLD} = 0.97/0.57 = 1.70$).

The third column of Table 3.1 reveals that productivity increased in all states over the sample period. Among them, SA (South Australia) experienced the largest increase in productivity, which was 46 per cent between the period 1990 and 2011. The last row of the table shows average estimates for Australia. It shows that, on average, Australian broadacre agriculture experienced a 33 per cent productivity increase between the periods 1990 and 2011.

The maximum TFP (TFP*) estimates are obtained under the assumption that in any given period all states experience the same set of production possibilities, which can be observed in the first and second column of TFP* estimates in Table 3.1. The third column of TFP* estimates reveals that over the period between 1990 and 2011 technical possibilities improved by 41 per cent or 1.62 per cent per annum [ln(1.41)/(2011-1990) = 0.0162 or 1.62 per cent)].

**Table 3.1: TFP index and its components: 1990–2011**

| | TFP | | | TFP* | | | TFPE | | |
|---|---|---|---|---|---|---|---|---|---|
| States | 1990 | 2011 | change | 1990 | 2011 | change | 1990 | 2011 | change |
| NSW | 0.63 | 0.73 | 1.14 | 0.69 | 0.97 | 1.41 | 0.92 | 0.75 | 0.81 |
| VIC | 0.53 | 0.72 | 1.38 | 0.69 | 0.97 | 1.41 | 0.76 | 0.75 | 0.98 |
| QLD | 0.40 | 0.57 | 1.43 | 0.69 | 0.97 | 1.41 | 0.58 | 0.59 | 1.02 |
| SA | 0.59 | 0.86 | 1.46 | 0.69 | 0.97 | 1.41 | 0.85 | 0.89 | 1.04 |
| WA | 0.69 | 0.97 | 1.41 | 0.69 | 0.97 | 1.41 | 1.00 | 1.00 | 1.00 |
| TAS | 0.50 | 0.61 | 1.20 | 0.69 | 0.97 | 1.41 | 0.73 | 0.62 | 0.86 |
| AUS | 0.56 | 0.74 | 1.33 | 0.69 | 0.97 | 1.41 | 0.81 | 0.77 | 0.95 |

Note: Other output-oriented measures, namely OTE, OSE, OME, ROSE and RME are not reported here to conserve space. For the details of the estimates, see appendix A.3.2 and A.3.3. Source: Author's own calculations

The TFP change is a combined effect of the maximum technically feasible change and efficiency change (dTFP = dTFP* x dTFPE). The maximum technically feasible TFP in a particular year is the TFP achieved by the most productive state. For example, Table 3.1 shows both in 1990 and 2011 WA is the most productive state, and its achieved TFP is considered as TFP*. The third column of TFPE estimates reveals that efficiency has improved over the period in SA, and QLD, but fell for NSW (New South Wales), TAS (Tasmania) and, less so, for VIC (Victoria). In WA, TFPE equals one in both 1990 and 2011 as it defines the frontier. Estimates shown in Table 3.1 suggest that, in spite of a fall in efficiency in a few states, all states experienced TFP improvement due to the more powerful common improvement in technology. In QLD, SA, and WA both technical possibilities and efficiency increased, resulting in large TFP increases.

When TFPE is further decomposed into OTE and OSME, the estimates indicate that OTE is almost always equal to 1.0 and, in particular, equals 1.0 for all states in both 1990 and 2011. Other studies that have calculated OTE also find most values are equal to 1.0 or at least very close, suggesting that pure technical efficiency is commonly achieved (see, for example, O'Donnell, 2010 and 2012b). This implies that the shortfall in TFP efficiency is due solely to scale and mix efficiency, rather than pure technical efficiency, with TFPE = OSME in each state for both time periods. The individual year and state values of these components are reported in the appendix Table A.3.2.

Table 3.2 reports estimated annual growth in TFP, maximum TFP and TFPE of broadacre agriculture in Australian states for three cumulative periods of 1990-2000, 1990-2007, and 1990–2011 and also for two recent sub-periods of 2000–2007 and 2007–2011.[7] The choices of these sub-periods are made based on studies by ABARES in Australia and to facilitate comparison with them (e.g., Sheng *et al.*, 2011). The entries in the table can be interpreted as the average rate of growth for the indicated periods. For example, in the 1990s WA experienced the highest average rate of TFP growth, which was estimated to be 3.78 per cent per annum ($\ln(TFP_{2000}/TFP_{1990})/(2000–1990) = \ln(1.006/0.689)/10 = 0.0378$). During this sub-period, broadacre agriculture experienced a 3.78 per cent annual average rate of technological progress.

The last row of Table 3.2 presents estimates of the average annual rate of growth of broadacre agriculture in Australia, which shows that on average broadacre agriculture in Australia experienced an annual productivity growth rate of 1.36 per

[7] These categorizations are used to make the results comparable with other relevant studies.

cent during the study period of 1990 to 2011. In spite of a 0.26 per cent per annum fall in overall efficiency, the main driver of this productivity growth was a 1.62 per cent per annum technical progress over the entire period of study. Importantly, there has been a generally falling average rate of TFP growth over the sub-periods. For example, average TFP growth was estimated to be 2.40 per cent per annum in the 1990–2000 sub-period, 1.65 per cent per annum in 2000–2007 and –1.74 per cent per annum in the latest sub-period of 2007–2011.

The slowdown of total factor productivity growth in broadacre agriculture has been largely driven by a slowing technical change during the past two decades. Table 3.2 shows that technical change in broadacre agriculture fell from 3.78 per cent per annum in 1990–2000 to 1.55 per cent per annum in 2000–2007. In the latest sub-period, 2007–2011, it dropped as low as -3.64 per cent, implying technical regress. Like Coelli and Rao (2005) and O'Donnell (2010; 2012b), this study allows technical regress as a proxy for the adverse effects of external shocks omitted from the model. The term technical change is viewed in a broad sense - the same way that Solow expressed it, namely "any kind of shift in the production function" (Solow, 1957, p.312). It is the measure of the change in the production possibilities set, which might be caused by any changes in external environmental factors, including weather and climatic variations (O'Donnell, 2010). A drought may cause production possibilities to contract (the same inputs can no longer produce as much output). However, as this research includes rainfall as an input to production, the estimated recent technical regress in broadacre agriculture is not believed to be due to the major drought over most of Australia in recent period. Rather, relevant is the adjustment of farmers to changes in the terms of trade, with the rise in prices since 2000 associated with more extensive and intensive production, suggesting an unmeasured average decline in the quality of land farmed as output expands, and a resulting drop in measured TFP as the ratio of output to input.[8] Also, it could be due to the measurement errors or other sources of statistical noise, as DEA makes no allowance for them (O'Donnell, 2010).

[8] O'Donnell (2010) notes a negative impact of a rising terms of trade on TFP in Australian agriculture in the period 1970 to 2001.

**Table 3.2: Average annual rates of growth in TFP and efficiency (%)**

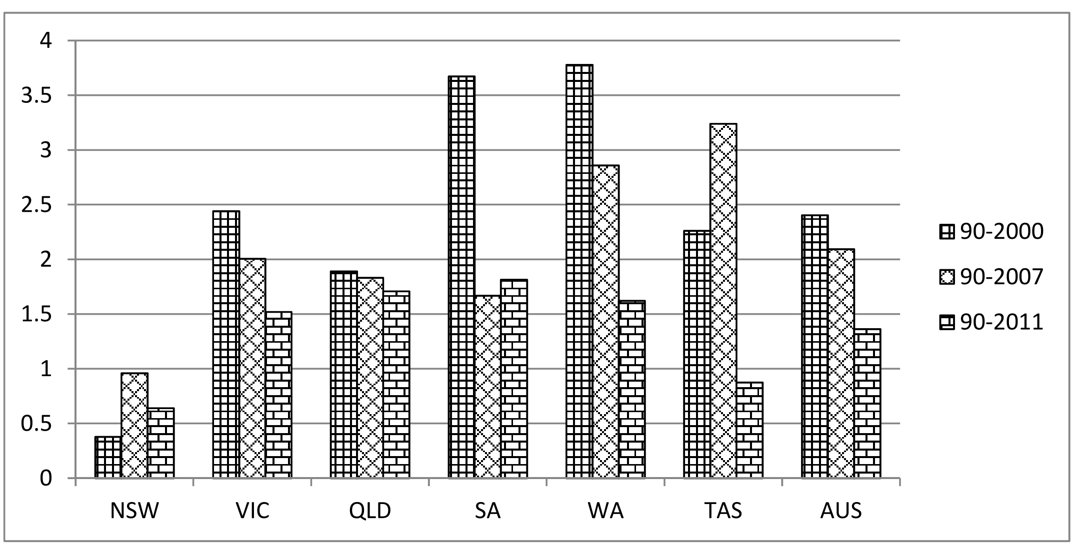
| | 1990–2000 | | | 1990–2007 | | | 1990–2011 | | | 2000–2007 | | | 2007–2011 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| States | TFP | TFP* | TFPE | TFP | TFP* | TFPE | TFP | TFP* | TFPE | TFP | TFP* | TFPE | TFP | TFP* | TFPE |
| NSW | 0.38 | 3.78 | -3.40 | 0.96 | 2.86 | -1.90 | 0.64 | 1.62 | -0.98 | 1.79 | 1.55 | 0.24 | -0.71 | -3.64 | 2.93 |
| VIC | 2.44 | 3.78 | -1.34 | 2.01 | 2.86 | -0.85 | 1.52 | 1.62 | -0.10 | 1.38 | 1.55 | -0.16 | -0.54 | -3.64 | 3.10 |
| QLD | 1.89 | 3.78 | -1.89 | 1.83 | 2.86 | -1.03 | 1.71 | 1.62 | 0.09 | 1.75 | 1.55 | 0.20 | 1.18 | -3.64 | 4.82 |
| SA | 3.67 | 3.78 | -0.10 | 1.67 | 2.86 | -1.19 | 1.82 | 1.62 | 0.19 | -1.20 | 1.55 | -2.74 | 2.44 | -3.64 | 6.08 |
| WA | 3.78 | 3.78 | 0.00 | 2.86 | 2.86 | 0.00 | 1.62 | 1.62 | 0.00 | 1.55 | 1.55 | 0.00 | -3.64 | -3.64 | 0.00 |
| TAS | 2.26 | 3.78 | -1.52 | 3.24 | 2.86 | 0.38 | 0.88 | 1.62 | -0.75 | 4.64 | 1.55 | 3.09 | -9.17 | -3.64 | -5.54 |
| AUS | 2.40 | 3.78 | -1.37 | 2.09 | 2.86 | -0.76 | 1.36 | 1.62 | -0.26 | 1.65 | 1.55 | 0.11 | -1.74 | -3.64 | 1.90 |

Note: Annual TFP indexes for each state are reported in Table A.1. Source: Author’s own calculations

These findings are consistent with a few recent studies indicating slowing broadacre agricultural productivity growth in recent years. The ABARES research report by Sheng *et al*. (2011), reports that productivity growth declined from 2.2 per cent to 0.4 per cent per annum between the two sub-periods 1953–1994 and 1994–2007. Similarly, assembling a productivity dataset for 1953 to 2007 using ABARE farm survey data, Mullen (2010) finds a strong variability in MFP (multi factor productivity) growth in Australian broadacre agriculture including a negative productivity growth rate, – 1.4 per cent per annum over 1998–2007.

Further insight into the performance of broadacre farms can be explored by examining productivity trends across periods and states. For example, the state-level estimated annual rate of productivity growth over the cumulative periods of 1990 to 2000, 1990 to 2007 and 1990 to 2011 are presented in Figure 3.4, which depicts data from Table 3.2. The slowdown of average productivity growth is obvious in broadacre agriculture in Australia. Long-term productivity growth in most of the states (VIC, SA and WA) was substantially higher in the period between 1990 and 2000 than in the period between 1990 and 2011. In the figure, the national average annual rates of productivity growth are shown to be 2.40 per cent in 1990 to 2000, 2.09 per cent in 1990 to 2007 and 1.36 per cent in 1990 to 2011. NSW and TAS had the highest productivity growth over the 1990 to 2007 period, while productivity growth in QLD was only slowly decreasing over the successive cumulative periods.

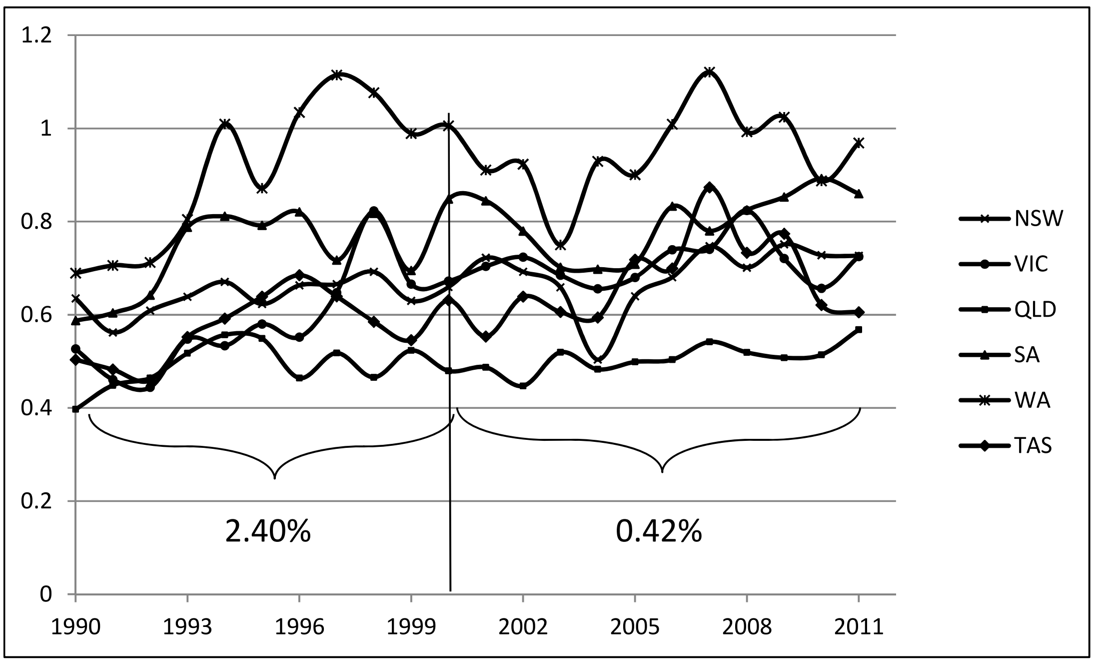
**Figure 3.4: Changes in broadacre productivity growth**




Source: Table 3.2

Figure 3.5 presents Färe-Primont annual estimates of state-level TFP for the sample period. It shows that productivity levels in broadacre agriculture have fluctuated considerably across the states and over the sample period. An overall pattern of rising productivity is shown from 1990 to 1996, productivity then declines until 2004. Since 2005, productivity increases for a couple of years then starts to fall again. TFP went up by an average annual rate of 2.40 per cent in the 1990s and then this productivity growth went down to an average 0.42 per cent annually in period 2000 to 2011. Since 2007 the pattern across states has been mixed. WA and TAS show falling TFP levels, while SA shows generally rising TFP, and NSW, VIC and QLD exhibit fluctuations in TFP without a clear trend.

**Figure 3.5: Productivity levels in Australian states: 1990–2011**




Source: Author's own calculations

Figure 3.5 also shows substantial interstate disparities in TFP levels. Over the study period, WA leads other states as it maintains the maximum TFP among the states (TFP=TFP*). Given the same technology is assumed for each state at each period, the observed disparities in TFP levels imply variations in efficiency levels across states in a given period. These differences may indicate the possibility of enhancing productivity and reducing interstate productivity gaps through improving efficiency.

## 3.6 Conclusions and Policy Implications

This chapter estimates TFP for broadacre agriculture in each of the six Australian states for each year between 1990 and 2011 using Färe-Primont indexes. The empirical results show that TFP has increased by 33 per cent or an average national annual rate of growth of 1.36 per cent over the full period. Decomposing the indexes shows that this productivity growth is mainly due to the effect of a 1.62 per cent annual rate of increase in production possibilities (technical progress) and a 0.26 per cent annual decrease in overall efficiency (TFPE) during this period.

There has been a generally declining trend in productivity growth in Australian broadacre agriculture over the study period. In the 1990s, broadacre agriculture experienced an average annual rate of productivity growth of 2.40 per cent, which decreased to 1.65 per cent in 2000–2007 and culminated in a productivity decline of 1.74 per cent per annum in 2007–2011. The estimates of the maximum TFP over all states (TFP*) show that the production possibilities changes are primarily responsible for the declining trend in TFP. In the earlier periods, broadacre agriculture experienced higher technical progress (a rate of 3.78 per cent per annum over 1990–2000), which has slowed in recent periods and turned negative in 2007–2011 (a rate of -3.64 per cent per annum).

The pattern of productivity growth over time is consistent with earlier empirical studies. In particular, O'Donnell (2010) uses Hicks-Moorsteen index numbers for calculating TFP for the aggregate agriculture sectors of 88 countries over the period 1970–2001 and shows a rise of 6 per cent in TFP in aggregate Australian agriculture over the period 1990–2000, which is driven by technical progress and offset by declining technical efficiency. Using gross value measures, Mullen (2010) reports that productivity in Australian broadacre agriculture declined at an average rate of 1.4 per cent per annum over 1998–2007. Similarly, Sheng, *et al.* (2011) finds broadacre productivity declined at an average annual rate of 1.7 per cent over 2000–2007.

O'Donnell (2010) suggests that the terms of trade for agriculture are inversely related to TFP performance and attributes a substantial drop in TFP in Australian agriculture in the 1970s to a substantial rise in agricultural output prices relative to input prices.

The parallel in current study period is from 2000 to 2011, when rising agriculture prices have been associated with sluggish or negative growth in TFP. A further contributor to slowing could be low research and development (R&D) expenditure. Salim and Islam (2010) find evidence that R&D expenditure is directly linked to TFP change in WA broadacre agriculture, supporting earlier findings of Mullen and Cox (1995) for aggregate Australian agriculture.

The decline in TFP* in the results reflects the TFP experience of the most productive state, Western Australia. WA has consistently had the highest TFP level of any state so that its experience defines the frontier of production possibilities over all states. However, the performance of WA has been slipping in recent years relative to other states. In particular, average TFP efficiency (TFPE) has increased by 1.90 per cent per annum over the 2007–2011 period in which TFP* declined by 3.64 per cent per annum. Indeed, South Australia and Queensland managed to achieve overall TFP growth of 2.44 per cent and 1.18 per cent per annum, respectively, over the 2007–2011 period. The relative performance of different states may reflect different levels of support for R&D or different environmental conditions (growing conditions in the WA wheat belt were generally poor in 2007–2011, even after controlling for state rainfall differences in the TFP index calculation), or different experience in terms of trade for the different input and output mixes of each state. Thus, in order to fully exploit the economies of scope, coordinated agricultural policies which facilitate innovations in production and support the free movement of production factors across states are crucial. In the current chapter, the slower technical change is identified as the main driver of the declining productivity growth. Therefore, this thesis explores the nexus between research and development expenditure and productivity growth in the next chapter to shed light on future policies in enhancing productivity growth.

# CHAPTER FOUR

## The Public R&D and Productivity in Australia's Broadacre Agriculture

**Summary:** This chapter investigates the nexus between research and development (R&D) expenditure and productivity growth in Australian broadacre agriculture using country-level time-series data for the period 1953 to 2009. Standard time-series data are analysed to examine the dynamic relationships between expenditure R&D and total factor productivity (TFP) growth. The findings here provide econometric evidence of a cointegrating relationship between R&D and productivity growth and a unidirectional causality from R&D to TFP growth. Using the dynamic properties of the model adopted here, data from outside the sample period are analysed by employing variance decomposition and the impulse response function. The findings suggest that R&D can be readily linked to the variation in productivity growth beyond the sample period. Furthermore, the forecasting results suggest a significant out-of-sample relationship exists between the public R&D and productivity in broadacre agriculture. A novel method called modified internal rate of return (MIRR) is employed to obtain a credible estimate of returns on public research investment. The results indicate an MIRR of 12.74 per cent per year for the reinvestment rate of 5 per cent per year. Finally, results establishing a long-run relationship between productivity and R&D in Australian agriculture inform decision making for future policies in R&D investments in Australia.

### 4.1 Introduction

The previous chapter provides evidence of slowing productivity growth and that declining technical possibility is its main driver in the short sample period of time. This chapter has as its motivation examining the nexus between research and development expenditure and productivity growth in the long run, following studies that indicate R&D as one of the contributors to declining TFP growth in agriculture in some developed countries. Moreover, the finding of a long-run relationship has an implication on future policies, for example, a positive relationship would support government policy of devoting more resources for knowledge production in agriculture to raise long-run productivity growth. Therefore, the primary objective of this chapter is to investigate the long-run relationship between R&D expenditure and TFP growth in Australian broadacre agriculture.

There is broad consensus among economists and researchers that the growth in agricultural productivity has been playing a leading role in meeting the growing global food demand (Alston and Pardey, 2014; Fuglie and Toole, 2014; Pardey *et al*., 2013). Rising productivity has also been the crucial factor in achieving economic prosperity and development over the last few centuries. In turn, investment in agricultural research and development (hereafter, R&D) has been identified as a leading factor that fuels productivity improvements in agriculture by producing new knowledge and achieving technological breakthroughs. A number of studies examining the effects of R&D on total factor productivity (hereafter, TFP) in the agricultural sector suggest that R&D, both domestic and foreign, is one of the main sources of productivity growth (Alene, 2010; Coe and Helpman, 1995; Griliches, 1988; Mullen *et al*., 2008).

Some recent studies have shown a close correlation between investment in public R&D and TFP in agriculture. Wang *et al*. (2013), using US agriculture data, show that R&D affects agricultural productivity only over the long term. Using data from Greece's agriculture, Voutsinas and Tsamadies (2014) analyse the contribution of R&D expenditure to farm productivity growth. They find that R&D expenditure improves the rate of innovation achievement, which is an important driver of long-run productivity growth. Similarly, a study in Bangladesh shows that R&D investment is one of the significant aspects that favourably affect TFP growth, and it advocates for policy promoting investment in R&D (Rahman and Salim, 2013).

In recent decades, there has been concern that productivity in agriculture is declining throughout most of the developed world, including Australia, the United Kingdom and the United States (Ball *et al*., 2013; Khan *et al*., 2014; Piesse and Thirtle, 2010). A few studies have examined the possible causes of the recent declines in agricultural productivity growth, and they have found the falling public R&D investment in agriculture over the past decades to be one of the possible causes. For example, Piesse and Thirtle (2010) mention a slowdown and retargeting of public R&D as one of the key factors that caused a slowdown in TFP growth in the United Kingdom. Studies also provide empirical evidence of a long-run relationship between research expenditure and agricultural productivity growth in developed countries, such as the UK (Schimmelfenning and Thirtle, 1994; Thirtle *et al*., 2008) and the US (Alston *et al*., 2011; Wang *et al*., 2013). Similar evidence from recent studies reveals a slowdown in productivity growth in Australian agriculture over the last decade compared with earlier periods (Khan *et al*., 2014; Nossal and Sheng, 2010; Sheng, Gray and Mullen, 2011).

This decline in agricultural productivity has renewed interest in productivity analysis, particularly in the estimation and explanation of the effects of R&D in agriculture. Economists and policymakers identify this decline as one of the current challenges for Australian agriculture. There is some anecdotal as well as empirical evidence suggesting that the declines in productivity growth can be attributed to the lagged impact of the public investment in agricultural research, which is said to have stagnated since 1970s. Mullen and various co-authors have conducted a series of econometric research studies into agricultural R&D and productivity in Australia where they have found R&D to be a major source of productivity in Australian agriculture (Mullen, 2007). Furthermore, some previous studies have estimated the rates of return to R&D expenditure in Australian broadacre agriculture and indicate that public investment in agricultural R&D is contributing to TFP growth.

Previous studies on Australian broadacre agriculture have estimated the growth of TFP over recent decades, but there is apparently very little empirical evidence about what determines the slowing TFP growth. Many of the reported studies have emphasised returns to agricultural research and, thus, ignore the existence of a stable long-term cointegrating relationship between research and productivity growth. To date, there have been very few studies that examine the long-run relationship between R&D and productivity growth in Australian broadacre agriculture. One study conducted by Salim and Islam (2010) has explored the long-run relationship between R&D and agricultural productivity in broadacre agriculture in Australia. Although they have applied standard time-series techniques to investigate the long-term and causal relationship between R&D and TFP, their results are only for

Western Australian broadacre agriculture and are not based on a very long time-series dataset.

This study, therefore, aims to fill this empirical gap by examining the relationship between public R&D spending and productivity growth in Australian broadacre agriculture with more than a data series spanning more than 50 years. To achieve this objective, this study applies cointegration and Granger causality in order to investigate the relationship between R&D and TFP and the direction of causality running between them. It also applies variance decomposition, an impulse response function and a forecasting exercise to explore the dynamic properties of the relationship beyond the sample period. Moreover, a relatively novel approach, the modified internal rate of return (MIRR), is used to obtain a credible estimate of returns to public research investment. This method is regarded as conceptually superior to the conventional internal rate of return (IRR).

The rest of this chapter proceeds as follows. The next section provides a brief overview of public R&D and agricultural productivity in Australia. A discussion on data sources and variable selection is in Section 4.3. Section 4.4 discusses the time-series econometrics and empirical results. The benefits of the research are detailed in Section 4.5, and Section 4.6 provides a conclusion to this study.

## 4.2 Public R&D and Broadacre Agricultural Productivity in Australia

Australian agriculture is primarily based on extensive cropping and livestock farming activity, which is generally termed ‘broadacre’ agriculture. Broadacre agriculture is a significant contributor to the country’s agricultural and economic growth. It generates more than 85 per cent of the country’s gross value of agricultural production. The economic prosperity of the rural community depends upon the growth of the country’s agriculture. Moreover, Australia exports approximately 60 per cent of its agricultural production, which represents 10.9 per cent of the total export earnings in 2010–2011.

The public sector plays a dominant role in R&D investment in Australian agriculture, generally accounting for more than 90 per cent of total agricultural R&D. This statistic strongly contrasts with those of other OECD countries, where the share of private R&D is more than half the total investment in agricultural R&D (Sheng *et al.*, 2011). Thus, the level of public investment in agricultural R&D and its impact on agricultural productivity have been important factors in terms of public policy issues in Australia. However, the concern is that R&D spending has been falling since 1994. Some recent studies indicate that the sluggishness in public R&D since the mid-1970s may have contributed to the slowdown in agricultural productivity growth in recent periods (Mullen, 2010; Sheng *et al.*, 2011). Before 1994, broadacre farming experienced approximately 2.2 per cent growth in productivity per year, but it has faced a slowdown since then, declining by 0.4 per cent a year.

## 4.3 Data and Variable Selection

The economic theory and the existing empirical studies regarding the short-run and the long-run dynamic relationships between TFP and R&D provide limited guidance in modelling the relationship between research expenditures and total factor productivity in broadacre agriculture. To identify the relationships, this chapter adopts a modelling strategy based upon the information provided by the time-series data. Using four variables namely total factor productivity, domestic public investments in R&D, foreign public investment in R&D and farmers' level of education, this chapter applies an unrestricted VAR approach that allows data to speak to the possible links and directions between these variables.

In the previous chapter I have estimated TFP using the Färe-Primont productivity index formula that satisfies all axioms of index number theory and provides reliable and theoretically plausible estimates for the period 1990 to 2011. As standard time-series techniques are not suitable for such short series, this chapter uses a longer series, assuming that a longer history of R&D expenditures improves the quality of the estimates of the effects of R&D and helps comparing findings with prior studies.

This chapter uses country-level time-series data for the period 1953 to 2009. The broadacre TFP index (*TFP*) is measured by the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) and is estimated as the ratio of a Fisher quantity index of total output to a Fisher quantity index of total input. Empirically, TFP growth is measured as the part of farm output growth that is not contributed by growth of the factor inputs under the control of farmers. TFP, therefore, includes the effects of advances in knowledge or technological progress along with other factors affecting it (Jorgenson and Griliches, 1967). A complete description of how ABARES constructs the TFP index for the broadacre industries can be found in Gray *et al.* (2011).

The domestic public investment in R&D (*RD*) in broadacre agriculture series builds on data calculated by Mullen (2010) and data from the Australian Bureau of Statistics (ABS) biannual Australian Research and Experimental Development Survey. Mullen assembles the data from various public sources, including the Australian Bureau of Statistics (ABS) R&D data and a previous dataset from Mullen *et al.* (1996). The real public R&D expenditure is measured in 2009 dollars, based on the GDP deflator. These data consider investments in plants and animals and exclude investments in fisheries, forestry, environment and processing. Finally, based on broadacre agriculture's share of the total value of production in agriculture, the R&D in broadacre alone is derived from the R&D investment in agriculture.

This chapter uses R&D expenditure in US agriculture, collected from the US Department of Agriculture (USDA), as a proxy for the foreign R&D expenditure (*FRD*). The US plays a significant role in global agricultural R&D in relation to its investment and in terms of research spillover (Alston, 2002; Sheng *et al.*, 2011). In addition, Australia maintains a considerable economic and trade relationship with the US. Moreover, it is often assumed that the transfer of knowledge and technology between countries depends on a trade channel, which facilitates access to the outputs of foreign R&D, thereby enhancing productivity (Ang and Madsen, 2013). Therefore, assuming that the effects of foreign R&D usually depend on how the country is exposed to foreign trade, an import-share-weighted US R&D variable is constructed for the model following Coe and Helpman (1995). These data are weighted by the percentage of agricultural imports to the agricultural gross value of farm production (GVP) in Australia. The agricultural GVP is obtained from ABARES, and imports of agricultural crops and livestock products are obtained from FAO statistics. This series is extrapolated backwards for the period 1953 to 1960 using actual data from 1961 to 2009.

Another variable is farmers' education, which is used as a proxy for the unobserved human capital of broadacre farmers. It is likely that farmers' ability and adoption of new technologies are influenced by his level of education attainment. The inclusion of human capital is natural in the TFP regressions because education makes people more effective in organizing work, communicating, and in becoming more innovative, all of which contribute to a higher productivity level. Following Mullen and Cox (1995) and Sheng et al. (2010), this variable is proxied by the proportion of primary school-age students in the total population enrolled in primary schools in Australia using the World Development Indicators database. This series is also extrapolated backwards for the period 1953 to 1970 using the actual data.

Although farmers level of education is expected to have lagged effect on productivity, like previous studies this chapter does not consider a lag treatment for education variable at least for two practical reasons. First, the school enrolment data has limited fluctuations suggesting perhaps no change in the lag effects and, secondly, the availability of long-series farmers' education data is another constraint against treating the lag.

**Construction of R&D Knowledge Stocks**

A credible estimate of the effects of R&D on subsequent productivity relies on specifying the lag structure as it is widely accepted in the literature that there is a lag relationship between R&D and productivity growth (Griliches, 1998). In the studies, the lag used in estimating the impacts of R&D expenditure on productivity varies from 10 to 50 years to approximate the right lag relationship. A simple way commonly used in empirical studies of accommodating the lag structure is specifying TFP as a function of knowledge stocks (Griliches, 1979; Thirtle *et al*., 2008). Knowledge stock variables are derived as a weighted value of current and past R&D expenditures, where weights are assigned based on specific distributions.

To estimate the effects of R&D, three alternative R&D variables are constructed following the previous time-series studies (e.g., Mullen and Cox, 1995; Sheng et al, 2010; Thirtle et al., 2008). First, a single lagged value of R&D expenditure is used. Like Thirtle *et al*. (2008), this chapter finds a 12-years R&D lag ($RD_{t-12}$) as the strongest influence on TFP. The strongest R&D lag is determined by using the

Ramsey RESET specification test, and different model selection criteria reported in the appendix, Table A.4.1.[9]

Second, I construct a simple R&D knowledge stock variable ($RDS^{PIM}$) following the perpetual inventory method (PIM), which is commonly used to construct stocks for physical capital flows. The following equation is used to define R&D knowledge stocks:

$$K_t = R\&D_t + (1-\delta)K_{t-1} \qquad (4.1)$$

where $K_t$ is the R&D knowledge stock at time t, $R\&D_t$ is the agricultural R&D expenditure at the time t and $\delta$ is the depreciation rate for the R&D knowledge stock. The initial stock is calculated as:

$$K_0 = \frac{R\&D_0}{g+\delta}$$

where $R\&D_0$ is the R&D expenditure in the first year available, and $g$ is the average annual logarithmic growth of R&D expenditure over the period of analysis.

Finally, another R&D knowledge stock ($FRD^{gamma}$) is constructed using the gamma distribution function. In the literature, there are different lag structures and lag lengths used to approximate the lag effects of R&D with a gamma distribution, but there is hardly any consensus among the researchers regarding the common lag selection. For example, in U.S. agriculture a recent study by Huffman and Evenson (2006) uses a 35-year lag profile. Some other studies use a 30-year lag in the case of U.S. agriculture. Alston *et al*. (2011) and Andersen and Song (2013) use a 50-year profile in their studies of U.S. agriculture. On the other hand, studies in UK and Australian agriculture largely use 16 to 35 years for the lag. For example, Cox *et al*. (1997) use 30-year lag specifications of the research impacts on productivity in Australian broadacre agriculture.

[9]The ordinary least-squares regression is fitted to determine strongest R&D lag by using following log-linear relationship:

$$LnTFP_t = \beta_0 + \beta_1 LnRD_{t-i} + \beta_2 LnFRD_t + \beta_3 LnEDU_t + \varepsilon_t$$

The preliminary investigation mentioned above finds the strongest lag suggests 12 (or 15) year as the strongest lag, implying a maximum lag of 24 to 30 years for the gamma distribution. In addition, the number of observations on R&D and the degrees of freedom available for identifying relationships are also a concern for this study. Given the data limitations and considering the relatively applied nature of public agricultural R&D in Australia, this research uses 30 years for the maximum lag of the research impact on productivity, which is consistent with previous studies in Australian broadacre agriculture, e.g., Cox *et al.* (1997). Following Alston *et al.* (2011), the parameters of the gamma lag distribution are assigned values of $\lambda$= 0.70 and $\delta$ = 0.90.

Similarly, this chapter follows the same alternative lag structures for the foreign R&D (*FRD*) variable, assuming that both domestic public R&D and foreign R&D follow the same lag profiles.

## 4.4 Time Series Econometrics and Empirical Results

### *4.4.1 Unit Root Test: Testing for the Order of Integration of the Variables*

To test the presence of unit roots, two well-tried methods presented in recent literature are used, namely, the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. The three different forms of simple relationships allowing various possibilities in economic time series are the random walk, random walk with a drift and trend stationary processes. The equation that nests all three models is

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + u_t \qquad (4.2.a)$$

Equation 4.2a is used for the Dickey-Fuller unit root test where the null hypothesis is that $\delta = 0$, i.e., there is a unit root, and thus, the time series $Y_t$ is non-stationary. If $\delta$ is significantly different from zero, there will be no unit root, and $Y_t$ will be stationary in the levels or integrated of order zero, *I(0)*. If $Y_t$ is non-stationary in the levels but it becomes stationary at first differences, then the series is to be integrated of order one, *I(1)*. However, if $Y_t$ is not a first-order autoregressive process, then more lagged values of the dependent variable need to be added to ensure that the error term is white noise. By adding *m* lagged values of the dependent variable, the equation for the augmented Dickey-Fuller (ADF) test is

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta Y_{t-i} + u_t \qquad (4.2.b)$$

The time-series properties of the variables are investigated using some widely and recently used unit root tests: the Augmented Dickey-Fuller (ADF), the GLS-detrended Dickey-Fuller test (DF-GLS), the Philips-Peron tests, and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test. The ADF test is a modification of the simple Dickey-Fuller test when the assumption of white noise disturbances is violated for the higher order correlated autoregressive lags. The ADF test adjusts a higher order autoregressive process by adding lagged difference terms of the dependent variable in the parametric test regression. DF-GLS is a simple modification of the ADF test proposed by Elliott, Rothenberg, and Stock (1996), where the time series is transformed via a generalized least squares (GLS) regression before performing the test, and this is considered to be better in terms of the statistical power of the test (Apergis, 2014).

Phillips and Perron (1988) have developed more comprehensive tests of unit root non-stationarity. Their tests are similar to the ADF test, but they address the issue of autocorrelation by incorporating an automatic correction to the Dickey-Fuller t-test statistic. Both the Philips-Peron and the KPSS tests apply nonparametric methods for controlling serial correlation in testing for the unit root. The KPSS test differs from the other unit root tests, such as the ADF, DF-GLS and PP, in that it assumes stationarity of the series under the null hypothesis.

Table 4.1 reports the test statistics for the time-series data covering the period 1953-2009 in their natural form. The results show that all variables of TFP, public agricultural R&D expenditures, farmer education and foreign R&D expenditures are non-stationary in their levels, but they are stationary in their first differences, i.e., they are each integrated of order one, *I(1)*. The same integration order is found for all variables across all unit root tests.[10]

**Table 4.1: Unit root tests: ADF; DF-GLS; Phillips-Perron; and KPSS tests**

| Variables | ADF Test | | DF-GLS | | Phillips-Perron Test | | KPSS test statistic | |
|---|---|---|---|---|---|---|---|---|
| | P-value | Constant, Constant and Linear Trend | P-value | Constant, Constant and Linear Trend | P-value | Constant, Constant and Linear Trend | Constant | Constant and Linear Trend |
| TFP | 0.75 | Constant | 0.84 | Constant | 0.67 | Constant | 0.89 | 0.23 |
| ΔTFP | 0.00 | Both+ | 0.00 | Both | 0.00 | Both | 0.24* | 0.18* |
| RD | 0.36 | Both | 0.78 | Both | 0.99 | Both | 0.87 | 0.23 |
| ΔRD | 0.00 | Both | 0.00 | Both | 0.00 | Both | 0.70* | 0.14* |
| FRD | 0.42 | Constant | 0.30 | Constant | 0.08 | Both | 0.88 | 0.12* |
| ΔFRD | 0.00 | Both | 0.00 | Both | 0.00 | Both | 0.07* | 0.07* |
| EDU | 0.20 | Constant | 0.42 | Constant | 0.54 | Both | 0.64 | 0.05* |
| ΔEDU | 0.01 | Both | 0.0 | Both | 0.01 | Both | 0.06* | 0.05* |

Note: KPSS critical values for 1%, 5%, 10% level are 0.21, 0.14, 0.12 respectively for constant, linear trend, and 0.74, 0.46, 0.35 for constant. * Null of stationarity cannot be rejected at 5% level. + Both represents constant and linear trend.

It should be noted, however, that the standard unit root tests may not be appropriate if the concerned series contain any structural breaks (Bloch *et al.*, 2012; Shahiduzzaman and Alam, 2012). The results of ADF or PP tests might indicate a non-stationary series as being stationary because of disallowing breakpoints in the series, if any. Considering the possibility of a structural break in the data series, this test can be treated as a cross check of the other usual unit root tests. Table 4.2 shows the results from the Zivot-Andrews (Z-A) tests (Zivot and Andrews, 1992) considering structural breaks in the series, if any. Similar to the Dickey-Fuller test, the Z-A test also maintains the null hypothesis of a unit root in the process, i.e., non-stationary series. The Z-A test suggests rejecting the null of *I(1)* for all variables except EDU, as the t-statistics are larger than the critical values, which substantiates

[10] I also test unit roots for the alternative R&D variables: $RD_{t-12}$; $RD^{PIM}$ and $RD^{gamma}$ knowledge stock variables, for both domestic and foreign R&D expenditures. The results indicate that all variables have a unit root in the level across all the tests. However, two variables. $RD^{gamma}$ and $FRD^{gamma}$, are not integrated in first their differences according to the PP and KPSS tests.

the unit root results of stationarity in first difference found in Table 4.1. However, for the TFP and EDU variables, cannot be rejected the null of *I(0)*, which suggests they are integrated in the levels when the structural break is considered in the series.

Table 4.2: Zivot-Andrews unit root tests

| Series | Level | Break at | First diff. | Break at | Lag length |
|---|---|---|---|---|---|
| TFP | -7.985*** | 1999 | -7.935*** | 2001 | 1 |
| RD | -4.173 | 1980 | -5.497** | 1984 | 1 |
| FRD | -3.018 | 1983 | -12.082*** | 1979 | 1 |
| EDU | -6.110*** | 1975 | -4.739 | 1981 | 1 |

Critical values: 1%: -5.57 and 5%: -5.08; *** significant at 1% level, ** significant at 5% level.

Note: Breaks are considered both in intercept and in trend. All variables are in logarithm form.

### *4.4.2 Cointegration and the VEC Model*

**Cointegration test: Johansen approach based on VAR**

For the purposes of this research, economic theory regarding the short-run and long-term dynamic relationships between TFP and R&D has been set aside in favour of adopting a modelling strategy based upon the information provided by the time-series data. Hence, an unrestricted VAR (vector autoregression) model is used that allows the data to speak to the possible links and directions among the variables of interest. The VAR-based cointegration test proposed by Johansen (1995) uses the maximum likelihood estimation methodology to test for the cointegration rank *r,* which represents the number of independent cointegrating vectors. It is more generally applicable than the traditional Engle–Granger two-step methodology for exploring a single cointegrating relationship. The VAR approach models every endogenous variable within the system. The following mathematical formula gives the VAR of order $p$ in standard form:

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + \varepsilon_t \qquad (4.3)$$

Here, $y_t$ is a $k$ vector of endogenous variables that are integrated of order one, *I(1)*, $A_1$ … $A_p$ are ($k$ $x$ $k$) matrices of coefficients to be estimated, and $\varepsilon_t$ is a vector of disturbances that are serially uncorrelated with all the right-hand-side variables. The issue of simultaneity does not arise in this specification, as all explanatory variables of Equation 4.3 are only predetermined lagged variables. Hence, each equation in the system can be estimated using the *OLS* technique, which gives consistent and asymptotically efficient estimates.

To use the Johansen test, the VAR model is reparameterized into a vector error correction model (VECM) of the following form:

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t \qquad (4.4)$$

where $\Pi = \sum_{i=1}^{p} \mathrm{A}_i - \mathrm{I}$ and $\Gamma_i = -\sum_{j=i+1}^{p} A_j$ .

The Johansen test examines the coefficient matrix $\Pi$, as the key interest is the rank of the matrix. According to Engle and Granger (1987), if all variables of the vector $y_t$ are integrated of order one, *I(1)*, the coefficient matrix $\Pi$ has rank $0 \leq r < k$, where r is the number of linearly independent cointegrating vectors. If rank ($\Pi$) = 0, there is no cointegrating vector. However, if $1 \leq r < k$, there is a single cointegrating vector or multiple cointegrating vectors in the system. If all variables of the vector $y_t$ are integrated of order one, the coefficient matrix has reduced rank $r < k$.

The number of cointegrating vectors is the number of significant characteristic roots $\lambda$ of the coefficient matrix $\Pi$, as the rank of a matrix, is equal to the number of its characteristics roots. Johansen proposes two types of likelihood ratio tests, the trace test and maximum eigenvalue test, for the number of characteristic roots using the following two statistics:

$$\lambda_{trace} = -T \sum_{i=r+1}^{k} \ln(1 - \hat{\lambda}_i) \qquad (4.5)$$

$$\lambda_{\max} = -T \ln(1 - \hat{\lambda}_{r+1}) \qquad (4.6)$$

where $\hat{\lambda}$ is equal to the estimated values of the characteristic roots (also called eigenvalues) obtained from the $\Pi$ matrix, and $T$ is the number of usable observations. The null hypothesis for the trace test is $r$ cointegrating vectors, and the alternative is $k$ cointegrating vectors. The maximum eigenvalue tests the null hypothesis of $r$ cointegrating vectors against $r+1$ cointegrating vectors.

To test for cointegration using the Johansen approach, first the number of lags must be specified to include in the VAR model with *I(1)* variables. Table 4.3 presents the statistical results for determining the optimal lag length. Because there is no explicit theory to guide optimal lag lengths, the choice is based on different statistical techniques commonly applied to the literature in selecting the optimal lag for the VAR model. The results reported in Table 4.3 show that according to the sequential modified likelihood ratio (LR) test and Akaike's information criterion (AIC), the number of optimal lags is three, although two other tests, Schwarz information criterion (SC) and Hannan Quinn information criterion (HQ), favour two lags.

**Table 4.3: Selection of the number of VAR lags**

| *Endogenous variables: LnTFP LnRD LnFRD LnEDU* | | | | |
|---|---|---|---|---|
| Lag | LR | AIC | SC | HQ |
| 0 | NA | -4.693 | -4.636 | -4.544 |
| 1 | 523.26 | -13.962 | -13.676 | -13.218 |
| 2 | 279.19 | -18.626 | -18.112* | -17.288* |
| 3 | 39.546* | -18.768* | -18.025 | -16.835 |
| 4 | 17.821 | -18.501 | -17.529 | -15.973 |

* indicates lag order selected by the criterion at 5% level

Determining the common integration properties of all the variables in the model as well as selecting the number of optimal lags, it can be proceed to test the presence of the cointegrating vector. However, because all the variables are stationary in the first difference, i.e., *I(1)*, there may be a cointegrating relationship in the model. To test the existence of this relationship, I use the multivariate maximum likelihood approach of Johansen and Juselius (1990), which allows the estimation of multiple cointegrating relationships. The results for the trace test and the eigenvalue test are presented in Table 4.4.a. The results suggest rejecting the null hypothesis of no cointegrating vectors, but they cannot reject the hypothesis of, at most, one cointegrating equation according to the tests statistics. Both the trace test and the max-eigenvalue test indicate one cointegrating equation at the 5 per cent significance level.[11]

**Table 4.4.a: Cointegration tests: Johansen and Juselius approach**

| Series Tested: *LnTFP LnRD LnFRD LnEDU* | | | | |
|---|---|---|---|---|
| Hypothesized No. of CE(s) | Eigenvalue | Statistic | 5% Critical Value | Prob.** |
| | | *Trace Test* | | |
| None | 0.445 | 52.426 | 47.85613 | 0.0175* |
| At most 1 | 0.217 | 20.632 | 29.79707 | 0.3810 |
| At most 2 | 0.0894 | 7.407 | 15.49471 | 0.5308 |
| At most 3 | 0.0425 | 2.348 | 3.841466 | 0.1255 |
| | | *Max-Eigenvalue Test* | | |
| None | 0.445 | 31.795 | 27.58434 | 0.0135* |
| At most 1 | 0.217 | 13.225 | 21.13162 | 0.4318 |
| At most 2 | 0.0894 | 5.059 | 14.26460 | 0.7343 |
| At most 3 | 0.0425 | 2.348 | 3.841466 | 0.1255 |

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis p-values

**Cointegration test with unknown structural break: Gregory and Hansen test**

According to the Johansen and Juselius standard cointegration test, a cointegration relationship is found among the variables. However, this result does not consider any regime shifts in the model. In the unit root section, the Zivot and Andrews (1992) unit root test, which allows structural breaks in the series, suggests that all series except EDU are integrated of order one after allowing breaks. Therefore, to check the sensitivity of the cointegration results, the Gregory and Hansen (1996) cointegration test is performed allowing an unknown date of break in the system. Gregory and Hansen propose cointegration tests accommodating a single endogenous structural break in an underlying cointegrating relationship.

[11] Cointegration test is conducted using the original R&D variables.

**Table 4.4.b: Gregory-Hansen test for cointegration with regime shifts**

| | Test Statistic | Date | Asymptotic Critical Values | | |
|---|---|---|---|---|---|
| | | | 1% | 5% | 10% |
| Change in Level | | | | | |
| *ADF* | -7.69 | 1994 | -5.77 | -5.28 | -5.02 |
| *Zt* | -7.76 | 1994 | -5.77 | -5.28 | -5.02 |
| *Za* | -59.28 | 1994 | -63.64 | -53.58 | -48.65 |
| Change in Level and Trend | | | | | |
| *ADF* | -7.55 | 2000 | -6.05 | -5.57 | -5.33 |
| *Zt* | -7.62 | 2000 | -6.05 | -5.57 | -5.33 |
| *Za* | -57.98 | 2000 | -70.27 | -59.76 | -54.94 |
| Change in Regime | | | | | |
| *ADF* | -8.70 | 1981 | -6.51 | -6.00 | -5.75 |
| *Zt* | -8.78 | 1981 | -6.51 | -6.00 | -5.75 |
| *Za* | -66.92 | 1981 | -80.15 | -68.94 | -63.42 |
| Change in Regime and Trend | | | | | |
| *ADF* | -8.76 | 1996 | -6.89 | -6.32 | -6.16 |
| *Zt* | -8.84 | 1996 | -6.89 | -6.32 | -6.16 |
| *Za* | -66.42 | 1996 | -90.84 | -78.87 | -72.75 |

Table 4.4.b reports the test statistics allowing four possible specifications of structural breaks: level shift; level shift with trend; regime shift with change, both in intercept and slope coefficients; and regime shift with change in intercept, slope coefficients and trend. Based on the critical values for the *ADF* and *Zt* tests (residual based unit root test for the presence of cointegration in multiple time series proposed by Phillips (1987)) estimated by Gregory and Hansen (1996) for the different regime shifts, the results suggest rejecting the null of no cointegration against the alternative of cointegration with possible regime shifts at the 1 per cent level of significance. Reflecting on the *Za* test statistics (unit root test suggested by Phillips (1987), which has superior power properties in large sample), the null is rejected at either the 5 per cent or 10 per cent level, except in the case of breaks in regime and trend. These results, therefore, support the previous finding of a cointegration relationship based on standard cointegration tests.

### Vector Error Correction Model: Johansen and Juselius method

The evidence of cointegration only suggests the existence of a long-term, or equilibrium relationship between the time series variables under consideration. It does not consider the short-term dynamics of the model explicitly.[12] However, the presence of cointegration among variables does not necessarily rule out a short-term disequilibrium among them. The Granger representation theorem states that a cointegrated system of variables can be expressed as an error correction model (ECM) (Engle and Granger, 1987). The ECM reconciles the short-run behaviour of variables with its long-run behaviour using the error term of the cointegrating equation, which is also termed, 'equilibrium error'.

Having established cointegration, Johansen-Juselius vector error correction (VEC) method is used to test the short-run dynamic relationship between variables. The error correction model is shown as follows:

$$\Delta TFP_t = \beta_1 + \sum_{i=1}^{m}\beta_{11i}\Delta TFP_{t-i} + \sum_{i=1}^{n}\beta_{12i}\Delta RD_{t-i} + \sum_{i=1}^{n}\beta_{13i}\Delta FRD_{t-i} + \sum_{i=1}^{r}\beta_{14i}\Delta EDU_{t-i} + \alpha_1 ECT_{t-1} + \varepsilon_{1t} \quad (4.7)$$

$$\Delta RD_t = \beta_2 + \sum_{i=1}^{m}\beta_{21i}\Delta TFP_{t-i} + \sum_{i=1}^{n}\beta_{22i}\Delta RD_{t-i} + \sum_{i=1}^{n}\beta_{23i}\Delta FRD_{t-i} + \sum_{i=1}^{r}\beta_{24i}\Delta EDU_{t-i} + \alpha_2 ECT_{t-1} + \varepsilon_{2t} \quad (4.8)$$

$$\Delta FRD_t = \beta_3 + \sum_{i=1}^{m}\beta_{31i}\Delta TFP_{t-i} + \sum_{i=1}^{n}\beta_{32i}\Delta RD_{t-i} + \sum_{i=1}^{n}\beta_{33i}\Delta FRD_{t-i} + \sum_{i=1}^{r}\beta_{34i}\Delta EDU_{t-i} + \alpha_3 ECT_{t-1} + \varepsilon_{3t} \quad (4.9)$$

$$\Delta EDU_t = \beta_4 + \sum_{i=1}^{m}\beta_{41i}\Delta TFP_{t-i} + \sum_{i=1}^{n}\beta_{42i}\Delta RD_{t-i} + \sum_{i=1}^{n}\beta_{43i}\Delta FRD_{t-i} + \sum_{i=1}^{r}\beta_{44i}\Delta EDU_{t-i} + \alpha_4 ECT_{t-1} + \varepsilon_{4t} \quad (4.10)$$

where $\Delta$ denotes the difference operator; *TFP*, *RD*, *FRD* and *EDU* are the endogenous variables that are integrated of order one; and $\varepsilon_t$ is a random error term that is independently and identically distributed. The inclusion of lags of the dependent variable as the explanatory variables in the regression is necessary, as the dependent variable itself may be correlated with its lags. The error correction term, *ECT*, is the one-period lagged value of the error term from the cointegrating equation.

[12] The long-term relationship measures at the level form of the variables, while short-run dynamics use the first-differences of the variables.

*ECT* equals zero in the long-run equilibrium relationship. However, if it is non-zero, the variables are adjusted in the short run to correct the equilibrium error to obtain model equilibrium. In the short run, the error correction term is non-zero, and each variable adjusts to restore the equilibrium. The coefficients, $\alpha_1$, $\alpha_2$, $\alpha_3$ and $\alpha_4$, are the adjustment parameters and they represent the speed of adjustment in the error correction mechanism. The ECM has both a long-run property, which is built into the error correction term, $ECT_{t-1}$, and a short-term property, which is captured by the error correction coefficient, $\alpha$.

Table 4.5 presents the test results for error correction by using the Johansen-Juselius vector error correction method with different lag specifications of R&D discussed in Section 4.3. In Table 4.5, *Panel A* shows results for 12 years of lag values of both R&D and foreign R&D. This type of lag structure has been applied in other studies, including Piesse and Thirtle (2010), Salim and Islam (2010), Schimmelpfennig and Thirtle (1994) and Thirtle *et al.* (2008). The statistically significant and non-zero equilibrium error term provides evidence of the adjustment of the short-run disequilibrium condition towards the long-run equilibrium for the model in the case of the 12-year lagged R&D. For the ΔTFP equation, the coefficient of -0.924 suggests a 92.4% adjustment towards the long-run equilibrium in each year.

*Panel B* and *Panel C* report results based on R&D stocks constructed by the two alternative specifications of R&D lag structure: the perpetual inventory method (PIM) and gamma distribution, respectively. In *Panel B,* under the PIM method, R&D stocks are calculated assuming a depreciation rate fixed at 5 per cent. The result shows that in the ΔTFP equation, the coefficient associated with the error correction term is statistically significant and non-zero. The negative value of this adjustment coefficient indicates that the change in TFP is opposite to the error, suggesting a move towards long-run equilibrium.

In *Panel C*, R&D stocks are calculated assuming a gamma distribution with a 30-year research lag length. The result shows that in the case of the R&D stock using gamma distribution, the error correction term is not statistically significant, suggesting no error correction adjustment towards long-run equilibrium.

**Table 4.5: Unrestricted VECM Results: Dependent variable ΔlnTFP**

| Variable | Estimated Coefficients (Std. Err.) | | |
|---|---|---|---|
| | *Panel A.* 12-year Lag R&D | *Panel B.* R&D Stocks (PIM) | *Panel C.* R&D Stocks (Gamma distribution) |
| $ECT_{t-1}$ | -0.923683*** | -0.936533*** | -0.092051 |
| | (0.19762) | (0.17652) | (0.07773) |
| $\Delta \ln TFP_{t-1}$ | 0.001114 | 0.074174 | -0.390205*** |
| | (0.15312) | (0.13713) | (0.13236) |
| $\Delta \ln RD_{t-13}$ | -0.134035 | | |
| | (0.17817) | | |
| $\Delta \ln FRD_{t-13}$ | -0.094480 | | |
| | (0.08011) | | |
| $\Delta \ln RDS_{t-1}^{PIM}$ | | 1.271427*** | |
| | | (0.44833) | |
| $\Delta \ln FRDS_{t-1}^{PIM}$ | | 1.755252*** | |
| | | (0.56797) | |
| $\Delta \ln RDS_{t-1}^{gamma}$ | | | -1.019522 |
| | | | (0.79853) |
| $\Delta \ln FRDS_{t-1}^{gamma}$ | | | 0.906417 |
| | | | (0.96645) |
| $\Delta \ln EDU_{t-1}$ | -0.698104 | -1.273997 | -2.231255 |
| | (1.69180) | (1.62469) | (1.96767) |
| Constant | 0.036015 | -0.184527 | 1.96767 |
| | (0.02139) | (0.04707) | (0.05170) |
| Adj. R-squared | 0.453231 | 0.459173 | 0.229158 |
| S.E. equation | 0.094154 | 0.087366 | 0.109495 |
| F-statistic | 7.962980 | 10.16943 | 2.913379 |

*** denotes rejection of the null hypothesis at the 0.01 level

Note: The details of results are given in the appendix Table A.4.2.

The coefficients on the first-difference terms reported in Table 4.5 represent short-run elasticities as all variables are in natural logarithms. In *Panel A* and *Panel B*, the result shows that the dependent variable adjusts positively in the short run to its long-run position, although they are not statistically significant. The short-run adjustment parameters of the explanatory variables R&D stock and foreign R&D stock under the PIM method are positive and significant indicating that they adjust to deviations from the equilibrium but other short run parameters are not significant. [13]

The long-run parameters of the cointegrating equations estimated from the ECM are reported in the following equations. The estimated parameters are exactly identified, and the model fits well.[14] The results of the normalized cointegrating coefficients are presented in the following relationship for different specifications of the R&D variable where "***" and "**" denote that the associated long-run parameters are statistically significant at the 0.01 and 0.05 levels, respectively:

$$LnTFP = 6.158 + 0.1279 LnRD_{t-12}^{***} + 0.0945 LnFRD_{t-12} - 0.6074 LnEDU_t^{***} \quad (4.11)$$

$$LnTFP = 12.863 + 0.3146 LnRDS_t^{PIM\,***} - 0.1861 LnFRDS_t^{PIM} - 2.343 LnEDU_t^{**} \quad (4.12)$$

$$LnTFP = 15.583 + 0.2488 LnRDS_t^{gamma} - 1.440 LnFRDS_t^{gamma***} - 3.778 LnEDU_t \quad (4.13)$$

The normalized cointegrating Equation 4.11 considers 12 years of R&D lag for both domestic and foreign research expenditure. Equations 4.12 and 4.13 are specified with research stocks (*RDS*) based on the PIM and the gamma distribution, respectively. In the case of both 12-year lagged R&D and research stock based on the PIM specifications, the beta coefficients for R&D are positive and statistically significant. This beta coefficient indicating a positive relationship between lagged R&D and TFP can be considered as a long-term marginal effect on TFP. Because a double logarithmic functional form is used, the beta coefficient can be interpreted as a long-term elasticity. The long-run elasticities of TFP with respect to the 12-year

[13] The ECM results for the other variables are reported in the appendix Table A.4.2, where none of the equations contains a statistically significant error correction term.

[14] P>chi2=0.00 in the case of the cointegrating equations. Overall model fits statistics report P>chi2=0.00; the coefficients on cointegrating equations are largely statistically significant, as are the adjustment parameters.

peak R&D lag and research stock based on the PIM are 0.128 and 0.315, respectively, suggesting a good support for the public investments in agricultural R&D in Australia.

Further results in 4.11 show that foreign R&D is positively related to TFP in the case of 12-year R&D lag, although the coefficient is not statistically significant and that the long-run coefficient of school enrolment variable (*EDU*) is negative and significant. The ratio of primary school enrolment is a crude proxy for the farmers' level of education. However, this research includes this variable following other studies (e.g., Mullen and Cox, 1995 and Sheng et al., 2010) without considering the possibility of its lagged effects on productivity due to limitations on data availability.

Like the error correction term, the long-run coefficient of R&D in 4.13 is not statistically significant in the case of R&D stock based on gamma distribution. Limited data availability might be one possible reason for this inconsistent result. The actual data series used for foreign R&D variable is for the period from 1961 to 2009. To construct the 30-years lagged R&D stock based on gamma distribution the series is extrapolated backward to 1924. To avoid using the early data based on extrapolation, an alternative model is tested considering R&D stock based on gamma distribution only for the domestic R&D but not for the foreign R&D variable. This alternative specification gives an expected and consistent result.[15] Nevertheless, to be consistent with treating both domestic and foreign R&D variables, the same lag structure for both domestic and foreign R&D variables is assumed.

In this research, the likelihood ratio (LR) test for linear restrictions is used to see whether the long-run (beta) coefficients are significant in the cointegrating relationship. Table 4.6 reports the $\chi^2$ (chi-squared) test statistics for zero restrictions (coefficient restricted to zero) tests to see whether each of the variables can be excluded from the cointegrating relationship. The results suggest that TFP and R&D (both 12-year lagged R&D and research stock based on the PIM) contribute significantly to the cointegrating relationship because each restriction is rejected at

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15 $LnTFP = 16.2565 + 0.3144 LnRDS_t^{gamma***} + 0.109 LnFRD_t - 2.933 LnEDU_t^{**}$

the 5 per cent level.[16] The result also suggests that the foreign R&D and enrolment can be excluded from the cointegrating relationship as restrictions cannot be rejected at the 5 per cent significance level. Overall, this test supports the evidence of the existence of a long-run equilibrium relationship between the TFP and the public R&D in Australian broadcare agriculture.

**Table 4.6: LR test for exclusion of variables from cointegrating relationship (zero restriction)**

| Variable | 12-Years R&D Lag | | R&D Stocks based on PIM | |
|---|---|---|---|---|
| | $\chi^2$ | p-value | $\chi^2$ | p-value |
| $LnTFP_t$ | 4.963 | 0.026 | 11.98 | 0.001 |
| LnRD | 4.612 | 0.032 | 8.524 | 0.004 |
| $LnFRD_t$ | 0.246 | 0.620 | 1.181 | 0.277 |
| $LnEDU_t$ | 0.140 | 0.707 | 3.44 | 0.064 |

**Specification testing**

A series of diagnostic tests are performed to check the specifications of the model and to ensure the validity of the estimated coefficients and inferences. The eigenvalue statistics for checking the stability condition of the VAR estimates are reported in Table 4.7.a. The results show that all the eigenvalues lie inside the unit circle, which suggests that the VAR estimates satisfy the stability condition. Similarly, Table 4.7.b reports results for checking the stability condition of the VECM estimates. The results suggest that the number of cointegrating equations has been correctly specified, as $K - r$ ($K$ endogenous variables and $r$ cointegrating equations) unit moduli are found in the stability tests, and the remaining moduli are all less than one. An LM test for autocorrelation in the residuals is also performed. The results reported in Table 4.7.c suggest that the null hypothesis cannot be rejected that there is no autocorrelation in the residuals at either lag order one or two. Thus, the test indicates no evidence of autocorrelation in the model.

[16] Results for the R&D stock based on the gamma distribution aren't included as the model with this R&D stock does not suggest statistical evidence of error correction adjustment.

**Table 4.7.a: Eigenvalue stability condition: VAR model**

| Eigenvalue | | Modulus |
|---|---|---|
| 0.969643 | | 0.969643 |
| 0.962198 | + 0.09522078i | 0.966899 |
| 0.962198 | – 0.09522078i | 0.966899 |
| 0.597254 | + 0.2451709i | 0.645617 |
| 0.597254 | – 0.2451709i | 0.645617 |
| -0.384441 | | 0.384441 |
| 0.025591 | + 0.282619i | 0.283775 |
| 0.025591 | – 0.282619i | 0.283775 |

**Table 4.7.b: Eigenvalue stability condition: VEC model**

| Eigenvalue | | Modulus |
|---|---|---|
| 1 | | 1 |
| 1 | | 1 |
| 1 | | 1 |
| 0.7354733 | | 0.735473 |
| -0.4575463 | | 0.457546 |
| 0.3426255 | + 0.1186199i | 0.362578 |
| 0.3426255 | – 0.1186199i | 0.362578 |
| -0.1185675 | | 0.118567 |

The VECM specification imposes 3 unit moduli.

**Table 4.7.c: Lagrange-Multiplier test**

| Lag | $\chi^2$ | Df | Prob > $\chi^2$ |
|---|---|---|---|
| 1 | 17.55 | 16 | 0.35034 |
| 2 | 20.21 | 16 | 0.21081 |

H0: no autocorrelation at lag order

### *4.4.3 Granger Causality Tests*

Granger causality tests are used to shed light on the direction of possible causality between variables. According to the Granger representation theorem, there is Granger causality from at least one direction if two variables integrated of order one, *I(1),* are cointegrated. The Granger causality test is applied to explore the direction of the causality among the variables in the cointegrated vector. The presence of one cointegrating vector implies that there should be Granger causality in at least one direction. Granger causality can be examined using the following VAR framework of order-*p*:

$$TFP_t = \beta_1 + \sum_{i=1}^{p} \beta_{11i} TFP_{t-i} + \sum_{i=1}^{p} \beta_{12i} RD_{t-i} + \sum_{i=1}^{p} \beta_{13i} FRD_{t-i} + \sum_{i=1}^{p} \beta_{14i} EDU_{t-i} + \varepsilon_{1t} \quad (4.14.a)$$

$$RD_t = \beta_2 + \sum_{i=1}^{p} \beta_{21i} TFP_{t-i} + \sum_{i=1}^{p} \beta_{22i} RD_{t-i} + \sum_{i=1}^{p} \beta_{23i} FRD_{t-i} + \sum_{i=1}^{p} \beta_{24i} EDU_{t-i} + \varepsilon_{2t} \quad (4.14.b)$$

$$FRD_t = \beta_3 + \sum_{i=1}^{p} \beta_{31i} TFP_{t-i} + \sum_{i=1}^{p} \beta_{32i} RD_{t-i} + \sum_{i=1}^{p} \beta_{33i} FRD_{t-i} + \sum_{i=1}^{p} \beta_{34i} EDU_{t-i} + \varepsilon_{3t} \quad (4.14.c)$$

$$EDU_t = \beta_4 + \sum_{i=1}^{p} \beta_{41i} TFP_{t-i} + \sum_{i=1}^{p} \beta_{42i} RD_{t-i} + \sum_{i=1}^{p} \beta_{43i} FRD_{t-i} + \sum_{i=1}^{p} \beta_{44i} EDU_{t-i} + \varepsilon_{4t} \quad (4.14.d)$$

Equation 4.14.a models *TFP* as a linear function of its own lagged values plus the lagged values of all other variables treated as excluded. If the lagged values of all excluded variables have non-zero effects on *TFP*, then these variables Granger cause *TFP* in a manner conditional on the effects of its own lags accounted for. In a simple case, say, for two variables, *TFP* and *RD*, Granger causality tests whether past values of *RD* help predict *TFP* conditional on taking the effects of past values of TFP into account in the model. If they do, then *RD* is presumed to "Granger cause" *TFP*. Granger causality testing sets the null hypothesis that *RD* does not Granger cause *TFP*.

$$H_0 : \beta_{121} = ... = \beta_{12p} = 0.$$

This joint hypothesis can be tested using a standard Wald *F* or $\chi^2$ test because each individual set of restricted parameters is drawn from only one equation. Similarly, in Equation 4.14.b, the null hypothesis that *TFP* does not Granger cause *RD* can be expressed as

$$H_0 : \beta_{211} = ... = \beta_{21p} = 0.$$

If *RD* causes *TFP*, lags of *RD* should be significant in the equation for *TFP*. If RD does cause TFP and not vice versa, the results indicate unidirectional causality from RD to TFP.

Table 4.8.a presents the Granger causality Wald test based on vector autoregressions to establish the direction of causality of the cointegrated vector.[17] The $\chi^2$ statistics in the first row tests whether *RD* (R&D), *FRD* (foreign R&D) and *EDU* (school enrolment) are Granger-prior to TFP, the dependent variable in this case. The probabilities in the next row show that both R&D and EDU are Granger-prior to TFP, and this is also true for all excluded variables together, which is an expected outcome. A similar test is also run for each of the remaining dependent variables such as *RD*, *FRD*, and *EDU* to determine whether they are Granger-caused by any variables. The results suggest no evidence of any feedbacks in the opposite direction, which establishes the presence of unidirectional Granger causality running from R&D and EDU to TFP.

**Table 4.8.a: Granger causality Wald tests – Vector Autoregressions**

| | Dependent Variable | Excluded Variables | | | | |
|---|---|---|---|---|---|---|
| | | TFP | RD | FRD | EDU | All |
| $\chi^2$ | TFP | | 14.620 | 5.421 | 6.935 | 32.785 |
| Prob > $\chi^2$ | | | 0.001* | 0.067 | 0.031* | 0.000* |
| $\chi^2$ | RD | 0.057 | | 0.154 | 0.167 | 0.554 |
| Prob > $\chi^2$ | | 0.972 | | 0.926 | 0.920 | 0.997 |
| $\chi^2$ | FRD | 0.323 | 0.180 | | 2.739 | 5.634 |
| Prob > $\chi^2$ | | 0.851 | 0.914 | | 0.254 | 0.465 |
| $\chi^2$ | EDU | 1.569 | 0.160 | 1.189 | | 6.502 |
| Prob > $\chi^2$ | | 0.456 | 0.923 | 0.552 | | 0.369 |

* denotes rejection of the null hypothesis at the 0.05 level

[17] Granger causality test is performed using the original R&D variables.

This study also follows the Toda-Yamamoto (TY) procedure to test for Granger causality for sensitivity, i.e., to ensure that the causality testing is performed properly. Toda and Yamamoto (1995) indicate that economic series are likely to be either integrated of the different orders or non-integrated or both. Hence, the usual Wald test statistic does not follow its usual asymptotic distribution, which could lead to a flawed inference. Toda and Yamamoto (1995) therefore develop an alternative augmented Granger causality test that is useful when series are not even integrated in the same order. Table 4.8.b reports the results of the TY-augmented Granger Non Causality test. The test's results support the view that R&D Granger-causes the TFP, and there is no evidence of feedback in the opposite direction. In the case of the dependent variable TFP, the result suggests that rejecting the null hypothesis of Granger non-causality implies the presence of Granger causality running from R&D to TFP. When R&D is considered a dependent variable, the result does not suggest rejecting the null, and there is no Granger causality of TFP to R&D. This implies that the Toda-Yamamoto procedure also suggests that the R&D Granger causes TFP. However, this test also suggests that the domestic R&D Granger-causes the foreign R&D (FRD). This empirical result is, in fact, unlikely as Australian agricultural R&D expenditure logically does not cause foreign (US) R&D expenditure.

**Table 4.8.b: Toda-Yamamoto Granger non-causality Test**

| Dependent Variable | Excluded Variables | | | |
|---|---|---|---|---|
| | TFP | RD | FRD | EDU | All |
| TFP | | 16.970*** | 5.079** | 0.961 | 35.161*** |
| RD | 0.583 | | 0.121 | 0.019 | 0.945 |
| FRD | 1.153 | 8.190*** | | 3.591* | 11.878** |
| EDU | 0.924 | 0.965 | 3.722* | | 7.727 |

"***", "**" and "*" denote rejection of the hypothesis at the 0.01, 0.05 and 0.10 level, respectively.

### *4.4.4 Variance Decomposition and Impulse-Response Function*

The variance decomposition and impulse response functions provide more information on the dynamic properties of the model and allow prediction of the relative importance of the variables beyond the sample period (Salim and Islam, 2010). Variance decomposition measures the proportion of variation in the dependent variable that is induced by its own shocks or shocks emanating from other variables. Table 4.9 presents the variable decomposition estimates for TFP for 30 years of the time horizon. The result shows that in the case of the TFP, approximately 80 per cent of the forecast error variance at the fifth-year horizon is accounted for by its own shock, and the R&D, foreign R&D, and enrolment contribute the remaining 20 per cent of shocks.[18] R&D explains approximately 8.7 per cent and 17.4 per cent in the $10^{th}$ and $20^{th}$ years, respectively, remaining nearly persistent over the future period. The results indicate that the future variability of TFP largely originates from its own shocks, which thus appear to be exogenous. In 30 years, 62.1 per cent of future variation in TFP is due to its own innovations, and the R&D explains approximately 21.6 per cent. The remaining two other variables, FRD and EDU explain around 5 per cent and 11 per cent of shocks in TFP, respectively, and they remain considerably stable over the time period.

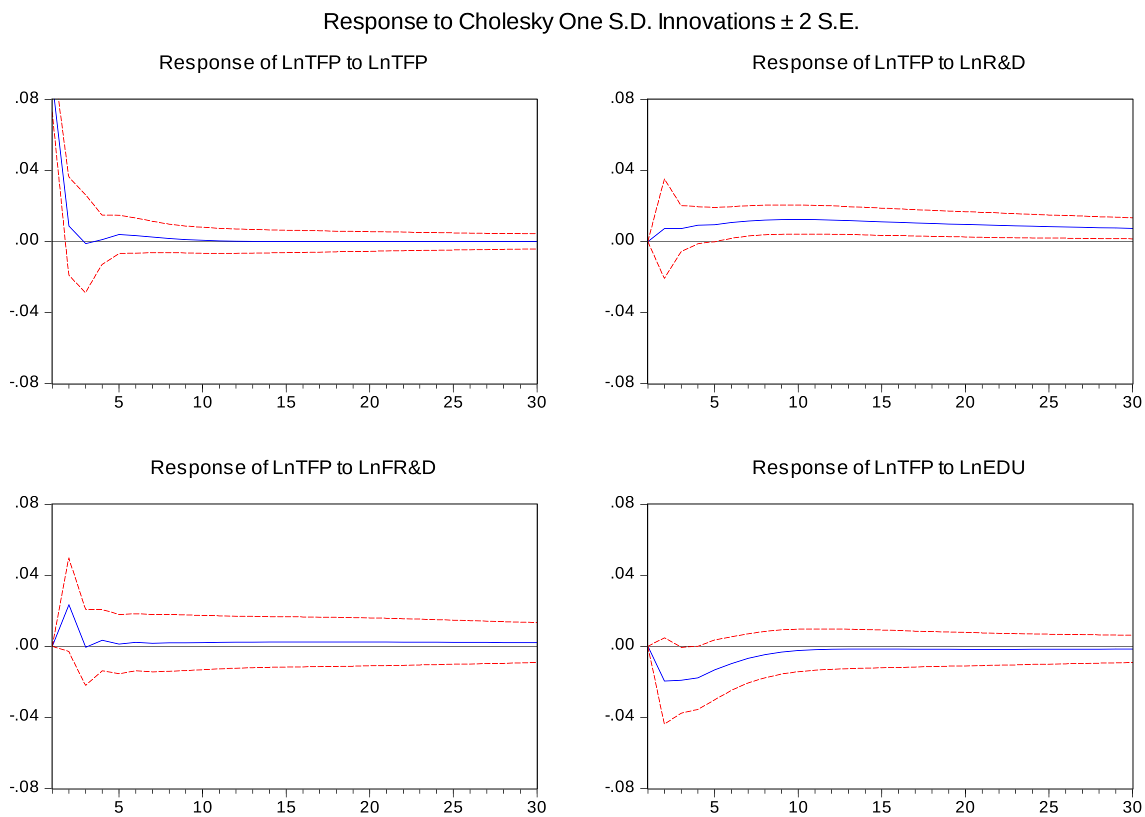
**Table 4.9: Variance decomposition of TFP**

| Period | S.E. | LnTFP | LnRD | LnFRD | LnEDU |
|---|---|---|---|---|---|
| 1 | 0.090 | 100 | 0 | 0 | 0 |
| | | (0.000) | (0.000) | (0.000) | (0.000) |
| 5 | 0.102 | 79.864 | 2.695 | 5.446 | 11.995 |
| | | (9.124) | (4.875) | (6.139) | (6.424) |
| 10 | 0.106 | 73.533 | 8.689 | 5.177 | 12.602 |
| | | (10.797) | (6.821) | (8.060) | (8.033) |
| 15 | 0.109 | 69.074 | 13.890 | 5.093 | 11.942 |
| | | (12.094) | (8.182) | (10.463) | (8.332) |
| 20 | 0.112 | 65.979 | 17.400 | 5.111 | 11.511 |
| | | (13.228) | (9.320) | (12.429) | (8.627) |
| 25 | 0.114 | 63.771 | 19.842 | 5.154 | 11.232 |
| | | (14.263) | (10.281) | (14.294) | (9.037) |
| 30 | 0.115 | 62.151 | 21.614 | 5.196 | 11.039 |
| | | (15.182) | (11.025) | (16.007) | (9.407) |

[18] Both the domestic R&D and the foreign R&D are used in the original form, not as lagged or stocks form.

Note. Cholesky Ordering: LnTFP LnRD LnFRD LnEDU. Standard Errors based on Monte Carlo simulations (100 repetitions) are reported in the parentheses. The results for each period are reported in the appendix Table A.4.3.

**Figure 4.1: Generalized Impulse Response Functions in the TFP equation.**

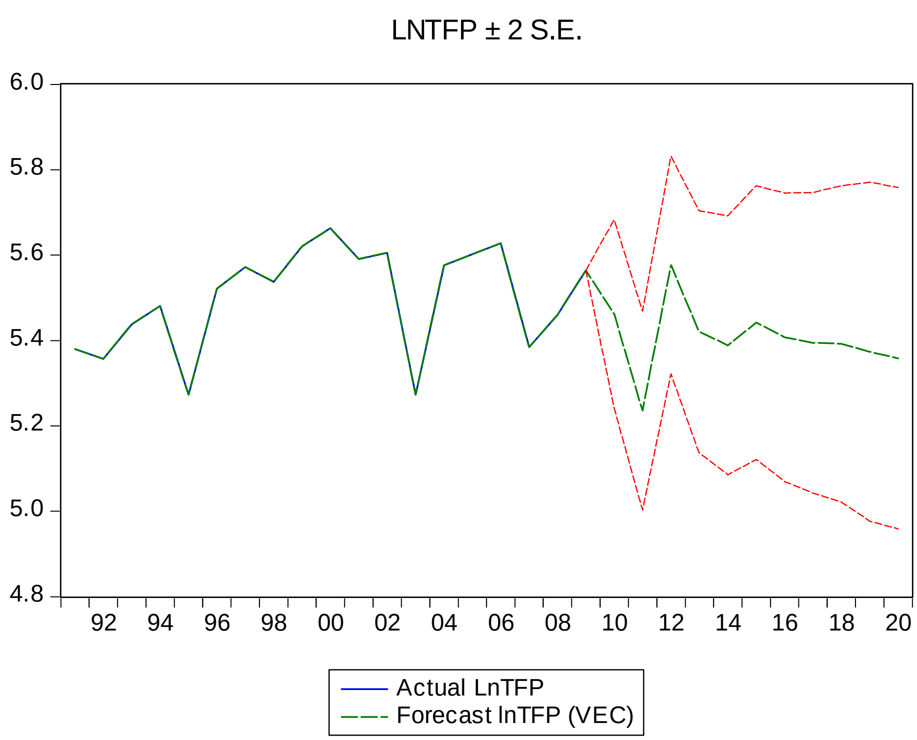



This study, furthermore, uses Cholesky one standard deviation impulse response functions as part of the robustness checks of the cointegration findings beyond the sample period. The impulse response functions provide the response of the dependent variables to the shocks to each of the variables in the VEC model. Figure 4.1 shows the impulse response functions based upon the VAR estimates. Because the main interest of this study is to examine the responses of TFP, it is only presented the effects of shocks in all variables to the variable TFP. The impulse response functions for the rest of the variables are presented in the appendix, Figure A.4.1. Figure 4.1 shows that the response of productivity growth to a one standard deviation innovation in research and development is positive and persistent. In response to a shock in R&D, the future TFP initially increases and then remains positive and nearly permanent for the future periods. It also shows a negative response of productivity to the shocks both in foreign R&D and in enrolment, which are transitory as the effects die out in the future. In the graph, the broken lines indicate confidence limits around the estimates based on asymptotic standard errors.

### *4.4.5 Forecasting Exercise*

This section presents a forecasting exercise to evaluate whether changes in R&D stocks based on PIM method contain information about future changes in the productivity of Australian broadacre agriculture. This chapter produces forecasts from the estimated VEC model, where both lagged values of TFP and R&D stocks are used for forecasting. The model also includes foreign R&D and enrolment as two exogenous variables. Figure 4.2 shows estimated forecasts of TFP for the forecast period 2010 to 2020 along with confidence error bands. Based on the estimated VEC model, the graph shows that productivity declines over the forecast period. A dynamic forecasting approach is used for this out-of-sample forecasting, which has the forecasted value of the lagged dependent variable. As a result, the confidence error bands widen towards to the end of the forecast sample because the forecasts errors tend to compound over time.

**Figure 4.2: Out-of-sample forecasts of TFP for the period 2010–2020**



To examine the out-of-sample performance of the VEC model, the forecast evaluation estimate is compared to the results with other models. To obtain the out-of-sample forecasting evaluation, part of the sample is reserved by not including it in the estimation sample. The VEC and other models are estimated for the sample period 1953 to 2002 (reserving seven years of actual data for evaluation purposes), and out-of-sample forecasting is performed for the period 2003 to 2020. Following Apergis (2014), the VEC-based TFP forecasts is compared with those of the random walk model (RW) and basic forecasting model (with constant and trends) by using two statistics: root mean squared errors (RMSE) and the Theil coefficients. Table 4.10 reports and compares forecast evaluations across different forecasting models. The results indicate that the VEC model that includes R&D knowledge stocks performs better than the other two models giving smaller RMSE values and Theil coefficients. These results imply that the inclusion of information on R&D knowledge stocks gives better predictive ability of future TFP.

**Table 4.10: Out-of-sample forecasts of TFP for the period 2003–2020**

| | RMSE | Theil Inequality Coefficient |
|---|---|---|
| VEC Model | 0.237512 | 0.021073 |
| RW Model | 0.259072 | 0.023074 |
| Basic | 0.257132 | 0.022905 |

## 4.5 Rates of Return on R&D

This section investigates the economic performance of the public investments in R&D in broadacre agriculture by applying the benefit-cost ratio, IRR, and MIRR measures. The three main ingredients required to calculate these economic performance measures are the elasticity of productivity with respect to a change in the R&D stock, estimates of the real value of agricultural output and estimates of R&D stocks that include a simulated increase in research investments. Following Andersen and Song (2013), the economic performance measures are computed by applying a straightforward method that uses aggregate national-level data and a single estimate of the elasticity of productivity with respect to a change in the R&D stock.

A simulated percentage increase in the R&D stock for period $t$ can be defined as:

$$\Delta \ln \overline{KS}_t = \ln\left(\frac{\overline{KS}_t}{KS_t}\right) \qquad (4.15)$$

where $KS_t$ is the actual knowledge stock and $\overline{KS}_t$ is the simulated knowledge stock after including a hypothetical increase of $1,000 in R&D investment in 1954, the year that represents the present value in the analysis at which $t = 0$.

The present value of benefits from the $1,000 investment in public R&D can be computed as:

$$PVB = \sum_0^N \left(\hat{\beta}_1 \times \Delta ln\overline{KS}_t \times V_t\right) \times e^{-rt} \qquad (4.16)$$

where $V_t$ denotes the real value of the agricultural output in period $t$, $r$ denotes a real interest rate, $N$ is the research lag length and $\hat{\beta}_1$ is the elasticity of productivity with respect to a change in the knowledge stock in Equations 4.11 and 4.12.

Now, the benefit-cost ratio for the $1,000 investment is computed by dividing the present value of benefits, $PVB$, by the present value of cost, $PVC$, which is simply the initial increase in investment of $1,000 in 1954:

$$BCR = \frac{PVB}{PVC} = \frac{\sum_0^N (\hat{\beta}_1 \times \Delta ln\overline{KS}_t \times AV_t) \times e^{-rt}}{\$1{,}000} \qquad (4.17)$$

In addition to the benefit-cost ratio, I compute the IRR, which is the interest rate received for an investment that makes the net present value equal to zero. Next, the future value of benefits after $N$ years is defined as:

$$FVB = e^{(r \times N)} PVB \qquad (4.18)$$

Finally, the modified internal rate of return is defined as:

$$MIRR = \left[\frac{FVB}{PVC}\right]^{\frac{1}{N}} - 1 \qquad (4.19)$$

According to Alston *et al*. (2011) and Andersen and Song (2013), in evaluating the returns to public investments in R&D, an MIRR is superior to a conventional IRR for a conceptual reason. In particular, the conventional IRR implicitly assumes that the flows of benefits that accrue over time can be reinvested in the same initial investment. However, this assumption may be inappropriate for public agricultural R&D, where the benefits that accrue over time go to producers and consumers of farm products by reducing production costs and food prices. The IRR measure is best suited for an investment situation where the investor reaps all the returns. The modified internal rate of return is estimated as an alternative to the conventional IRR. This modified version has an advantage that it allows for alternative reinvestment rates for the stream of benefits.

The estimates of the benefit-cost ratio, the conventional internal rate of return and the modified internal rate of return are reported in Table 4.11. The results show that the benefit-cost ratio measure ranges from 8.14 to 49.32 depending on the assumed maximum lag lengths and discount rates. In the case of a PIM-based R&D stock, the benefit-cost ratio is 21.48 at an assumed real discount rate of 5 per cent per year. The benefit-cost ratios are consistent with other recent studies. For example, in US agriculture, Alston *et al.* (2011) find benefit-cost ratios of 17.5 and 21.9 for 50-year and 35-year research lag lengths, respectively. Similarly, Andersen and Song (2013) find that the estimated benefit-cost ratio for the base model with the preferred estimation procedure is 24.38 for US agriculture.

**Table 4.11: Benefit-cost ratios, IRR and MIRR**

| | 12-Year Research Lag | | | R&D Stock based on PIM | | |
|---|---|---|---|---|---|---|
| Reinvestment rate | Benefit-Cost Ratio | IRR | MIRR | Benefit-Cost Ratio | IRR | MIRR |
| | | % per annum | | | % per annum | |
| 5% | 8.14 | 18.98 | 12.74 | 21.48 | 26.07 | 16.44 |
| 3% | 12.60 | 18.98 | 12.13 | 32.45 | 26.07 | 15.72 |
| 1% | 19.46 | 18.98 | 11.51 | 49.32 | 26.07 | 15.02 |

The conventional IRR is also calculated and reported in columns (3) and (6) in Table 4.11. Although IRR is not the preferred measure, it is common in the literature so it is useful for comparison purposes. The estimated IRR for the 12-year R&D lag and PIM-based R&D stock are, respectively, 18.98 per cent per year and 26.07 per cent per year.

The results in Table 4.11 are consistent with some recent studies in US agriculture, where Alston *et al.* (2011) and Andersen and Song (2013) find the estimated IRR to be approximately 22.7 per cent per year and 21.0 per cent per year, respectively. Similarly, Mullen (2007) finds the real rates of return on public research to be 15 per cent per year in Australian broadacre agriculture. Recently, for all Australian agriculture, Sheng *et al.* (2011) compute an average estimated real rate of return of 28.4 per cent in Australian agriculture. A survey by Alston *et al.* (2009) of the numerous studies over the years shows the estimated rates of return are within the range of approximately 20-80 per cent per year. In addition, in a meta-analysis of 292 studies, Alston *et al.* (2000) report an overall mean internal rate of return of 64.6 per cent using a sample of 1,128 estimates.

A great number of the previous studies reported in contemporary literature use the internal rate of return as a common summary measure of investment performance in agricultural R&D evaluation, despite the methodological criticisms it has received from economists. This chapter computes the modified internal rates of return (MIRR), which addresses the methodological concerns with IRR estimates (Hurley *et al.*, 2014). The MIRR estimates are reported in columns (4) and (7) in Table 4.11 under the assumption of a real reinvestment rate of 1 per cent, 3 per cent and 5 per cent per year. Depending on the maximum research lag length and the assumed reinvestment rate, the results indicate that the MIRR estimates are somewhere in the range of 11.51 per cent per year to 16.44 per cent per year. For a 12-year R&D lag, the estimated MIRR ranges from 11.51 per cent to 12.74 per cent per year for the corresponding reinvestment rates of 1 per cent to 5 per cent per year.

The estimated range of MIRR is consistent with some recent studies in US agriculture. For example, Alston *et al.* (2011) compute an average MIRR of 9.9 per cent per year across the US states. Similarly, Andersen and Song (2013) find that the MIRR is 9.84 per cent per year for public investment in agricultural R&D. The estimated MIRR is also consistent with a recent study by Hurley *et al.* (2014), who re-examine the reported rates of return from 372 separate studies from 1958 to 2011. They find that the median MIRR varies from 9.7 per cent to 10.4 per cent per year for reinvestment rates of benefits ranging from 0 to 50 per cent.

## 4.6 Conclusions

This chapter investigates the long-run relationship between public R&D and the TFP in broadacre agriculture in Australia over a period of five decades. To ensure that cointegration is possible, a set of standard unit root tests is first used, including the Augmented Dickey Fuller, DF-GLS, Phillips Perron and KPSS tests to determine time-series properties of the variables. In addition, following the Zivot-Andrews unit root tests, the standard unit root test results are found consistent even after allowing structural breaks. Then, using the cointegration analysis, econometric evidence is found of a cointegrating relationship between R&D expenditure and productivity growth in Australian broadacre agriculture. For robustness, Gregory and Hansen's cointegration test is applied, allowing unknown structural breaks in the series, and evidence is found of a cointegrating relationship between R&D and productivity. The results also show evidence of a causal relationship between R&D and TFP growth.

With respect to the direction of causality, the empirical evidence indicates a unidirectional causality running from R&D to TFP growth. In other words, R&D expenditure Granger cause total factor productivity, as current and past values of R&D improve TFP predictions compared with using past values alone. This result is robust according to the Toda-Yamamoto Granger non-causality test.

Having established cointegration, an error correction model is constructed that shows that lagged R&D is significant in explaining changes in total factor productivity. This result implies that an increased R&D expenditure leads to better outcomes for productivity in Australian broadacre agriculture. Furthermore, the dynamic properties of the model are explored using variance decomposition and impulse response functions. The result suggests that beyond the sample period, public R&D considerably explains the variation in productivity growth in Australian broadacre agriculture. In addition, TFP responds positively and persistently for the future period because the effect of shock in public R&D does not die out over time. This chapter, therefore, establishes the existence of a long-run unidirectional causal relationship between R&D and productivity growth in a more dynamic fashion. Furthermore, an out-of-sample forecasting exercise also indicates that investment in public R&D in agriculture does matter in forecasting productivity growth. The results show that information on R&D investment improves productivity forecasts significantly.

This chapter also computes and compares different measures of economic performance for public investments in agricultural R&D. The results show that the internal rates of returns are 18.98 per cent and 26.07 per cent, respectively, for two alternative lag specifications, 12-year R&D lag and R&D stock calculated based on the PIM approach. The measures of the conventional internal rates of returns are consistent with some recent studies, e.g., Alston *et al.* (2011) and Andersen and Song (2013). The estimated modified internal rate of return is approximately 11.51–16.44 per cent per year, depending on the research lag length and reinvestment rate of benefits. This estimated modified return to public R&D is lower than the reported conventional IRR and is methodologically more justified and plausible.

These results suggest that research affects agricultural productivity in the long run as an important source of productivity growth. The insight behind the relationship between the public R&D and productivity in broadacre agriculture in Australia is straightforward. An increase in the public expenditure in R&D is likely to lead to higher productivity growth in the long run. Finally, because an increase in R&D expenditure has a positive and sizable rate of return through contributing productivity growth, investments in R&D should attract more public attention in agricultural policy.

The results may, however, be limited by the nature of the R&D data. The model focuses solely on public R&D in broadacre agriculture. Moreover, only the effect of US R&D is represented for the effects of foreign R&D on TFP. Hence, the results may be limited by any effects of the R&D expenditure in private sectors and in other sectors in Australia. Given these practical limitations, the results are still pertinent, as the main interest of this research is to investigate the existence of a long-run relationship as well as causality between the public R&D and TFP rather than the magnitude of that relation. Moreover, the results are consistent with the findings of other relevant studies, such as Cox *et al.* (1997) for Australian broadacre agriculture based on a nonparametric approach, Salim and Islam (2010) for Western Australian broadacre agriculture, Wang *et al.* (2013) and Alston *et al.* (2011) for US agriculture, and Thirtle *et al.* (2008) for UK agriculture.

In this chapter the evidence of cointegrating and causal relationship between R&D and productivity is found using country-level aggregate time series data. However, this finding does not shed any light on the state-level effects of public R&D on productivity. The next chapter, therefore, examines the impact of R&D on the productivity by accommodating non-neutrality in the effects and by capturing the heterogeneities across states.

# CHAPTER FIVE

## The Effects of R&D on Agricultural Productivity of Australian Broadacre Agriculture: A Semiparametric Smooth Coefficient Approach

**Summary:** This research utilizes the semiparametric smooth coefficient model proposed by Hastie and Tibshirani (1993) and Li *et al*. (2002) to investigate the impact of R&D on the productivity of Australia's broadacre farming. A standard production function framework cannot precisely model the relationship between R&D and productivity, as it does not accommodate non-neutrality in the effects of R&D on productivity. The novel semiparametric smooth coefficient approach generalizes the standard production framework, allowing heterogeneities across observations, which captures important differences in the effect of R&D on agricultural output. Moreover, while the conventional approach only captures the direct effects of R&D, this methodology captures both the direct impact of a change in R&D on output and the indirect impact through changes in efficiency of use of factor inputs in the production process. A state-level dataset is utilized here covering the period 1995 to 2007. The findings show that once both the direct and indirect impacts are taken into consideration, R&D investments significantly increase outputs. Moreover, the results show that there are substantial variations in the impact of R&D on output across the states. Such variations need to be taken into account when designing policies for investing public R&D in agriculture.

### 5.1 Introduction

The previous chapter shows the long-run relationship between knowledge stock and productivity growth and estimates different measures of economic performance of the public R&D investments in Australian broadacre agriculture by using country-level aggregate data. The limitation of this country-level time series study is that it does not account state-level heterogeneity and non-neutrality in the effects of R&D on productivity. To make the estimates more justified, this chapter turns to a new measurement of the effects of R&D on productivity growth using a non-parametric method. This chapter applies this sophisticated method in the agriculture sector to estimate properly by explicitly accounting for non-neutral effects of research and development (hereafter, R&D) and recognizing state-level heterogeneities.

In agriculture, the role of public R&D in productivity has been recognized since the early studies of agricultural economics. For example, Schultz (1953) estimates the returns to public R&D and attributes all of the productivity growth in agriculture to public investments in agricultural research. Similarly, Griliches (1964) estimates the Cobb-Douglas type agricultural production function while introducing a research and extension variable along with the conventional input variables.

Recent studies have found that changes in public R&D stocks have a significant impact on agricultural TFP growth. Studies such as Alston *et al*. (2011), Fuglie and Toole (2014) and Wang *et al*. (2013) provide evidence that R&D investments in agricultural research provide new knowledge and technologies that fuel improvements in agricultural productivity in US agriculture. Furthermore, Voutsinas and Tsamadies (2014) have found that R&D expenditure in Greek agriculture improves the rate of technological innovation, which affects long-run productivity growth.

Productivity growth in agriculture has been an essential source of economic prosperity in Australia. The contribution of R&D expenditure to farm productivity growth is also evident in Australian agriculture. According to studies by Mullen (2007, 2010), investments in agricultural R&D and policies that affect agricultural R&D are central to improvements in agricultural productivity growth in Australia. Investments in R&D lead to a more effective use of existing resources and thereby increase productivity levels. Using historical data and standard time series techniques, Salim and Islam (2010) find that R&D affects long-run productivity growth in agriculture in Western Australia.

In recent periods, Australia has been facing slowing productivity growth in at least some sectors of agriculture (Islam *et al*., 2014; Sheng *et al*., 2014). Similar evidence of slowing productivity growth in recent periods has been seen in US agriculture (Ball *et al*., 2013) and in the United Kingdom agriculture (Piesse and Thirtle, 2010).

They mention a slowdown of public R&D as one of the main factors causing this productivity decline. Similarly, other studies also suggest that one of the primary reasons for slowing productivity growth in agriculture is that public investment in R&D has been declining over the past few decades (Bervejillo *et al*., 2012; Mullen, 2010; Pardey *et al*., 2013; Suphannachart and Warr, 2011). These recent phenomena in agriculture have rekindled interest in investigating the relationship between public funding in agricultural R&D and productivity.

The conventional estimation of effects between R&D and productivity generally focuses around country-level or state-specific (i.e., for a particular state) data, but fail to reflect state-level technological heterogeneity. Farms face heterogeneous R&D environments across states, and R&D likely has differential effects on agriculture across different states in Australia. The agricultural structure, physical environment and market circumstances are different from one state to another, which has implications for productivity performance variations across states. Therefore, state-level variations need to be accounted for when estimating the impact of R&D on the productivity in Australian broadacre agriculture. This study aims to fill this empirical research gap in Australian agriculture.

In addition, while it is widely perceived that R&D makes significant contributions to agricultural productivity growth, research has rarely considered non-neutral effects of R&D in the empirical models of agricultural TFP growth. Studies capture the direct effect of R&D expenditure on productivity, but they fail to capture the indirect effects through the efficiency with which factor inputs are used. Therefore, the heterogeneous impact of the R&D on input productivity has largely been neglected in the previous empirical estimations. Furthermore, estimates of the effects of R&D on productivity that have been performed by researchers who apply parametric models are generally based on the assumption that the error term is normally distributed. The non-neutrality of technical change and the non-normality of errors in parametric models may prompt biased estimates of the R&D impacts because they depend on presumptions of the functional form and the distribution of the error term that cannot be known *a priori*.

Against theses backdrops, a number of studies have emerged in the broader economics literature that use semiparametric or nonparametric approaches to address these problems (Mamuneas *et al.*, 2006; Zhang *et al.*, 2012; Zhao *et al.*, 2014). The semiparametric smooth coefficient model is one such empirical approach, and it has potential for the agricultural literature, particularly with regard to gaining a deeper understanding of the relation between R&D and TFP. A popular semiparametric estimator used to estimate the marginal effects of R&D is the kernel density estimator, which avoids the functional forms and distributional assumptions of the parametric models and permits nonlinearity in the model. The main advantage of using this recent methodology is that it permits all sorts of nonlinearities and interactions between the factors without requiring any (preliminary) parametric formulation.

Unlike traditional inputs, such as capital, labour and materials, R&D is one of the environmental factors that characterize the production environment in general. A change in an environmental factor is likely to affect the productivity of the traditional inputs by changing the production environment (Zhang *et al.*, 2012). Following Li *et al.* (2002) and Zhang *et al.* (2012), this study considers R&D as an important environmental variable that may not be capable of producing output directly but is likely to affect the ability of the farm to transform other inputs into outputs more effectively. Although conventional parametric models consider the effects of R&D as a neutral shift variable, the shift of the production function is more likely to be non-neutral. There are some previous studies, for example Swamy (1970) and Kalirajan and Obwona (1995), that apply the varying coefficients regression model to capture the non-neutrality in terms of the observation- and input-specific response coefficients. However, they need restrictive assumptions in estimating their parametric model (Li and Racine, 2007).

Therefore, this study uses the semiparametric smooth coefficient model proposed by Hastie and Tibshirani (1993) and Li *et al*. (2002) to investigate the impact of R&D on the productivity of Australia's broadacre farming in a flexible manner. This novel approach accommodates non-neutrality in the effect of R&D on productivity, allowing for varying effects on input elasticities. At the same time, it allows heterogeneities across observations and provides estimates of the marginal effects of R&D on factor inputs and the output of each firm. Moreover, it estimates both the direct impact of a change in R&D on output and the indirect impact through changes in the efficiency of use of factor inputs in the production process.

The remainder of the chapter is organized as follows. Section 5.2 outlines the econometric methodology, beginning with parametric and Robinson's semiparametric specifications, followed by the semiparametric smooth coefficient model. Section 5.3 describes the data. Section 5.4 analyses the empirical results. Finally, Section 5.5 concludes.

## 5.2 Methodology: A Semiparametric Smooth Coefficient Model

In the standard literature, firm performance is modelled as a linear function of inputs and other firm level attributes. In practice, the Cobb-Douglas production function, *Model 1*, is perhaps the most widely used parametric regression model in applied research. With all variables measured in logarithms, the production relation being estimated to measure firm performance is:

$$y_i = \alpha_0 + x_i'\beta + z_i\varphi + \epsilon_i \qquad (5.1)$$

where $y$ is output, $x$ is a vector of firms inputs, $z$ = R&D is the firm's research and development expenditure, $\beta$ is a vector of unknown parameters, $\varphi$ is the R&D parameter and $\epsilon_i$ is the identically and independently distributed error term. The ordinary least squares method can then be used to estimate the unknown parameters in Equation 5.1.

There are, however, two major shortcomings with the standard Cobb-Douglas production function. First, it is necessary to specify the exact parametric form prior to estimation. Hence, it is likely that the presumed model may not be consistent and the inference may not be valid when the model is not correctly specified. In practice, the true parametric form is hardly ever known. Second, in the model, the $z$ variable affects the productivity of all firms in an identical way and constrains the estimation to give constant marginal effects. It does not capture the effects of R&D on individual firms, even though effects may differ across firms and be variable for each firm.

This study considers nonparametric regression methods to address the concern about incorrect parametric specification in the case of modelling inputs and outputs. The Cobb-Douglas functional form is unable to capture the effects of firm characteristics on TFP through the efficiency with which factor inputs are transformed into output. A natural extension of this model that allows the firm characteristics to have a firm-specific effect on TFP is a semiparametric model. Recently, semiparametric estimation techniques have drawn much attention among econometricians in the study of firm productivity and efficiency.

This study uses Robinson's (1988) semiparametric partial linear model, denoted as *Model 2*, to extend the conventional production function with outputs and inputs measured in logarithms as follows:

$$y_i = \alpha(z_i) + x_i'\beta + \epsilon_i \qquad (5.2)$$

where $x_i$ is a vector of inputs, $\beta$ is a vector of unknown parameters, and $z_i$ is a vector of environmental variables that enter the model nonlinearly. The functional form of $\alpha(\cdot)$ is not specified and constitutes the nonparametric part of the model. Semiparametric models are a compromise between fully nonparametric and fully parametric specifications and, thus, are formed by combining parametric and nonparametric models. The environmental variable, R&D, allows TFP growth to be affected in a flexible way without assuming any particular functional form of $z_i$ variables.

To estimate coefficients in the Robinson model, the basic idea is to first eliminate the unknown function $\alpha(\cdot)$. Taking expectations conditional on $z_i$ for both sides of (5.2),

$$E(y_i|z_i) = \alpha(z_i) + E(x_i|z_i)'\beta + E(\epsilon_i|z_i)$$

Subtracting this expression from (5.2) and assuming $E(\epsilon_i|z_i) = 0$ yields;

$$y_i - E(y_i|z_i) = (x_i - E(x_i|z_i))'\beta + \epsilon_i$$

In shorthand notation,

$$\tilde{y}_i = \tilde{x}_i{}'\beta + \epsilon_i$$

Now, $\beta$ can be estimated by applying the method of least squares:

$$\hat{\beta} = \left[\sum_{i=1}^{n} \tilde{x}_i \tilde{x}_i{}'\right]^{-1} \sum_{1}^{n} \tilde{x}_i \, \tilde{y}_i$$

where $\hat{\beta}$ depends on unknown moments $E(y_i|z_i)$ and $E(x_i|z_i)$ which can be estimated using a nonparametric regression method. Then, replacing them in the above equation yields consistent estimates of $\hat{\beta}$ without modelling $\alpha(z_i)$ explicitly. Finally, $\alpha(z_i)$ can be estimated nonparametrically by regressing $(y_i - x_i'\hat{\beta})$ on $z_i$. Although the Robinson model is widely used in applied settings and tends to be simpler to interpret than fully nonparametric models, it partially relies on parametric assumptions, and thus, the concerns regarding misspecification and inconsistency are as pertinent for this model as they are for parametric models.

Robinson's (1988) semiparametric partial linear model introduces the $z_i$ vector into the regression analysis in a fully flexible manner to explain TFP growth. However, this model only allows the R&D variable to have a neutral effect on the production function, that is, it only shifts the level of the production frontier and does not affect the marginal productivity of inputs. In other words, this semiparametric model does not consider indirect effects of the R&D variable through factor productivity (independent of X variables). Moreover, because it partly depends on parametric assumptions, the issue of misspecification and inconsistency are still relevant.

This study also considers a more general semiparametric regression model, namely, the semiparametric smooth coefficient model proposed by Hastie and Tibshirani (1993) and Li *et al.* (2002). Some studies, such as those of Ahmad *et al.* (2005) and Zhang *et al.* (2012), have applied a similar methodology in their productivity analysis in industrial sectors. The semiparametric smooth coefficient model, *Model 3*, is given by

$$y_i = \alpha(z_i) + x_i'\beta(z_i) + \epsilon_i \qquad (5.3)$$

where both $\alpha(z_i)$ and $\beta(z_i)$ denote vectors of unspecified smooth functions of $z_i$. This is one of the most flexible models, and it nests a linear model and a partially linear model (Robinson's semiparametric model) as special cases. When $\beta(z) = \beta$, this model collapses to the semiparametric partially linear model, and for a given level of an R&D variable (i.e., when $\beta(z) = \beta$ and $\alpha(z) = \alpha_0$), the semiparametric smooth coefficient model reduces to constant coefficient parametric Cobb-Douglas functional form (Hartarska *et al*., 2011; Li and Racine, 2007).

Specifying input coefficients as unknown smooth functions of $z_i$, this semiparametric smooth coefficient model allows indirect effects of the z variable via the input elasticities. For example, if labour and capital are conventional inputs and $z_i$ (R&D expenditures) is an environmental variable, then *Model 3* suggests that the input coefficients of labour and capital may directly vary with firm's R&D. Thus, this model proposes that the marginal productivity of each input, say labour and capital, depends on the firm's $z_i$ variables, such as R&D.

In addition, this generalized model considers the non-neutral impact of R&D on output, capturing the direct effect of $z_i$ variables on TFP and the indirect effects through the efficiency with which factor inputs are used. Furthermore, it provides greater flexibility in the functional form than a parametric linear model or a semiparametric partially linear model. This functional flexibility allows the model to address the non-neutrality in the production function, which has plagued many applied studies in the past (Li and Racine, 2007, 2010). Furthermore, it does not require a sample size as large as that for a nonparametric model. *Model 3* can be expressed more compactly as

$$y_i = \alpha(z_i) + x_i'\beta(z_i) + \epsilon_i = (1, x_i')\begin{pmatrix}\alpha(z_i)\\ \beta(z_i)\end{pmatrix} + \epsilon_i \equiv X_i'\delta(z_i) + \epsilon_i \quad (5.4)$$

Pre-multiplying (5.4) by $X_i$ and taking expectations conditional on $z_i$ yields

$$E(X_i y_i|z_i) = E(X_i X_i'|z_i)\delta(z_i)$$

Assuming $E(X_i\epsilon_i|z_i) = 0$ and following Li *et al*. (2002) and Li and Racine (2010), the kernel method can be employed to estimate the following locally constant least squares estimator for $\delta(z)$ as

$$\hat{\delta}(z) = \left(\sum_{j=1}^{n} X_j X_j' K\left(\frac{z_j - z}{h}\right)\right)^{-1} \times \left\{\sum_{j=1}^{n} X_j y_j K\left(\frac{z_i - z}{h}\right)\right\} \quad (5.5)$$

where $K(\cdot)$ is a kernel function; $h$ is a smoothing parameter or bandwidth, which can be selected via the least squares cross validation method (Li and Racine, 2007); and $z_i$ is the datum at which the kernel function is evaluated. The semiparametric varying coefficient model has the advantage that it allows greater flexibility in functional forms than a parametric linear model or a semiparametric partially linear model. At the same time, it avoids much of the "curse of dimensionality" problem (Ahmad *et al*., 2005).

## 5.3 Data

This chapter uses state-level agricultural input and output data collected from annual farm surveys provided by ABARES (Australian Bureau of Agricultural and Resource Economics and Sciences) for the period 1995-2007. The dataset consists of observations on quantities of agricultural inputs, outputs and values of each state for every year during the period. Four major inputs are used: land, labour, capital, and materials. The aggregate value of agricultural production of broadacre agriculture is the measure of output. Data on public investment in agricultural R&D is obtained from Professor John Mullen, who derives the data from the Australian Bureau of Statistics' (ABS) biannual Australian Research and Innovation surveys.[19] The R&D expenditure in broadacre agriculture alone is calculated based on broadacre agriculture's share in the total value of agricultural production.

All estimates except R&D are state-level per farm averages, and all financial estimates are expressed in 2011–2012 Australian dollars as per data sources from AgSurf.[20] In the dataset, *Land* includes all land areas in hectares operated on 30 June by the farm. *Labour* represents the total number of weeks worked by all farm workers, including hired labour. *Capital* includes the value of all assets used on the

[19] Public agricultural R&D includes expenditure by Australian, state and territory governments as well as research institutions and universities. Funds from research and development corporations (excluding grower levies) and other external funders for agriculture (excluding research in fisheries and forestry) are also included.

[20] AgSurf reports state-level per farm average data from the Australian agricultural and grazing industries survey (AAGIS) and Australian dairy industry survey (ADIS) conducted by ABARES

farm, including leased equipment but excluding machinery and equipment either hired or used by contractors. ABARES uses the market value of livestock/crop inventories and replacement value less depreciation for plants and machinery in calculating the value of capital. *Materials* includes farm expenditures on seeds, crop and pasture chemicals, fuel oil and grease, livestock materials, contracts (cropping and livestock), fertilizer, shearing crutching and other materials and services. The final sample includes 65 observations (5 states over 13 years) with complete records for the variables mentioned above.

Studies suggest that there is a lag relationship between R&D and productivity growth, and a credible estimate of the effects of R&D on subsequent productivity relies on specifying the lag structure (Griliches, 1998). There are various lag structures used in studies in estimating the impacts of R&D expenditure on productivity, which may vary between 10 to 30 years to approximate the right lag structure. However, the short data series restricts us from directly modelling the length and shape of the R&D lag in this study. As one of the simplest ways of accommodating the lag structure in empirical studies, TFP is specified as a function of knowledge stocks, which are determined by current and past R&D expenditures (Griliches, 1979; Thirtle and Schimmelpfennig, 2008). This thesis constructs a simple R&D knowledge stock variable using a perpetual inventory model (PIM). In this method, R&D stocks are calculated from flow of R&D expenditures based on the following equation:

$$K_t = R\&D_t + (1-\delta)K_{t-1} \tag{5.6}$$

where $K_t$ is the R&D knowledge stock at time t, $R\&D_t$ is the agricultural R&D expenditure at the time t and $\delta$ is the depreciation rate for R&D knowledge stock.

The initial stock is calculated as:

$$K_0 = \frac{R\&D_0}{g+\delta}$$

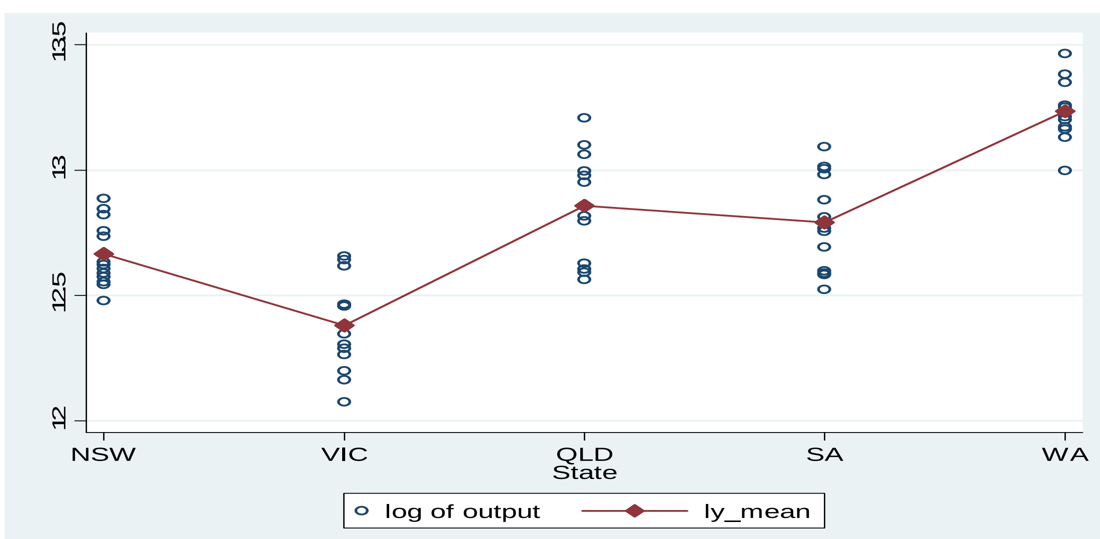
where $R\&D_0$ is the R&D expenditure in the first year available, and $g$ is the average annual logarithmic growth of R&D expenditure for every state over the period of analysis. This PIM method is used as a simple alternative to a complex time-lag structure between current productivity and the flow of past R&D investments.

However, a limitation of the PIM method is the need to choose a depreciation rate, which varies within the range 0.05 to 0.10 across econometric studies in agriculture (Thirtle *et al*., 2008). This research sets a depreciation rate of R&D fixed at 8 per cent. Table 5.1 reports the summary statistics for the natural logarithms of the variables. Figure 5.1 shows state-level heterogeneity in output means. As can be seen from the figure, there are large variations in terms of output across states.

**Table 5.1: Summary statistics**

| Variable | Obs | Mean | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| *ln Output* | 65 | 12.7858 | 0.32580 | 12.07448 | 13.46515 |
| *ln Capital* | 65 | 14.6511 | 0.37637 | 14.05605 | 15.52822 |
| *ln Labour* | 65 | 4.62423 | 0.13361 | 4.35671 | 4.89035 |
| *ln Land* | 65 | 8.34441 | 1.12009 | 6.40853 | 9.60407 |
| *ln Materials* | 65 | 11.0072 | 0.37565 | 10.30189 | 12.08648 |
| *ln R&D* | 65 | 14.4151 | 0.87196 | 12.98421 | 15.68413 |

**Figure 5.1: State-level output variations**



## 5.4 Empirical Results

In this section, results are presented from the different production function specifications mentioned in the methodology section, starting with a simple Cobb-Douglas model and generalizing it stepwise through a semiparametric partial linear model and a semiparametric smooth coefficient model. These models are nested, which means that the semiparametric smooth coefficient model can reduce with appropriate restrictions to the traditional Cobb-Douglas production model with constant elasticities. Hence, the specifications can be tested against each other.

### *5.4.1 Parametric and Semiparametric Regression Coefficients*

Table 5.2 shows the results from Models 1, 2 and 3. Model 1 is a simple Cobb-Douglas production function where (log) output is modelled as a linear function of (log) factor inputs and is extended to include an environmental variable, (log) *R&D* investment. The *R&D* variable is introduced additively and parametrically and the model is estimated using OLS. The estimates of the conventional Cobb-Douglas production specifications are reported in column 2 under the heading *Model 1*. The results show that the estimated coefficients of two major inputs, *capital* and *labour,* are both positive and significant. The estimated coefficient of R&D captures the marginal effect of *R&D* on productivity, which is constrained to be the same across the states. The results do not suggest R&D has a significant influence on productivity growth.

Model 2, which estimates Robinson's semiparametric partial linear model is used to bring flexibility into the specification. It allows the effects of R&D in a flexible manner and captures the state-specific impact of the R&D variable on productivity through TFP.[21] In this model, (log) output is modelled as a linear function of (log) factor inputs as in Model 1, and the R&D variable enters the model nonparametrically by introducing the intercept term as an unknown (flexible) function of the R&D variable. Model 2 captures the non-linearity in the relation

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[21] Model 2 is estimated with *semipar* package of STATA software where the variable R&D enters the model nonlinearly. The Gaussian kernel function is used to estimate the regressions nonparametrically in a local weighted polynomial fit. In addition, in Model 2 intercept term could not be identified separately from the unknown function $\alpha(\cdot)$.

between the output and R&D. The estimates of the semiparametric partially linear model are presented in column 3 in Table 5.2, which shows that the coefficients of the capital and labour inputs are positive and significant, as in Model 1. In addition, it shows a negative but insignificant partial effect of the environmental variable R&D.

**Table 5.2: Parametric and semiparametric regression coefficients: pooled data**

| Variables | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| | OLS | Robinson's Semiparametric | Semiparametric smooth coefficients |
| *Capital* | 0.251** | 0.290*** | 0.3136*** |
| | (0.113) | (0.0790) | (0.1144) |
| *Labor* | 1.254*** | 0.664** | 0.8298** |
| | (0.315) | (0.303) | (0.1477) |
| *Land* | 0.0152 | -0.0849** | 0.0988 |
| | (0.0361) | (0.0368) | (0.0884) |
| *Materials* | 0.119 | -0.0386 | 0.00832 |
| | (0.130) | (0.108) | (0.1267) |
| *R&D* | -0.0696 | -0.1153 | 0.0653* |
| | (0.0443) | (.0717) | (0.0386) |
| *Constant* | 2.879** | | 3.406** |
| | (1.190) | | (0.5530) |
| *Observations* | 65 | 65 | 65 |
| *R-squared* | 0.801 | 0.416 | 0.9303 |

Robust standard errors in parentheses in Model 1 & 2. Model 3 reports bootstrapped standard errors. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

### *5.4.2 Semiparametric Smooth Coefficient Results*

Finally, *Model 3*, which is termed the semiparametric smooth coefficient model, brings more flexibility in the specifications where both intercept and input coefficients are unknown, and it provides a smooth function of the environmental variable R&D. In both *Models 1 and 2*, R&D shifts the production frontier neutrally, i.e., the input elasticities are invariant with respect to R&D, although in *Model 2*, R&D allows TFP growth to be affected in a flexible manner.

In *Model 3*, R&D is allowed to non-neutrally affect the production function, where both the intercept and slope coefficients are modelled as an unknown smooth function of the R&D variable.[22] Thus, in this model, the input coefficients, i.e., the elasticity of output with respect to capital, labour, land, and materials are allowed to vary with respect to R&D. This model is estimated nonparametrically using the semiparametric smooth coefficient model proposed by Li *et al*. (2002) and Li and Racine (2010), where the local constant least squares procedure is applied to estimate these functional coefficients. Table 5.2 reports the mean values for *Model 3*, as it gives rise to observation-specific estimates (detailed results of *Model 3* are reported in Table 5.3).

There are some variations in terms of magnitude, sign and significance across the three different models presented in Table 5.2. The elasticities of output with respect to the capital ($\hat{\beta}_1$) and labour ($\hat{\beta}_2$) inputs are positive and significant across each of the three specifications. The marginal effect of R&D on output is positive and significant only in *Model 3*. The negative effects of R&D in both the Cobb-Douglas parametric model (*Model 1*) and Robinson's semiparametric model (*Model 2*), though insignificant, are inconsistent with conventional expectations.

*Model 3* as a local-linear regression follows the rule-of-thumb that the bandwidth needs to be less than twice the standard deviation ($\sigma_z$) of the continuous variable to enter the model non-linearly.[23] This implies that the R&D variable does not enter the model in the linearly and additively separate fashion assumed in the conventional parametric specification - *Model 1*. These statistical results are economically meaningful and make the semiparametric smooth coefficient model (*Model 3*) more appealing than the corresponding parametric model or Robinson's semiparametric model.

Table 5.3 summarizes the detailed results from the semiparametric smooth coefficient production specification - *Model 3*. Because *Model 3* gives observation-

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[22] *Model 3* is computed using the *np* package of the R software (*version 3.1.0 "Spring Dance"*). The smooth coefficient Kernel Regression *npscoef* functions is used with the bandwidth selection *npscoefbw* function, *bwmethod* = "*cv.ls*" (least squares cross validation), *ckertype* (continuous kernel type) = "gaussian". Semiparametric fits of the estimates are obtained using the bootstrapped standard error.

[23] $2 \times \sigma_z = 1.7438\ and\ Bandwidth\ for\ Z\ variable = 0.2057$.

specific estimates, the summary results are reported at the mean, 1st Quartile (25th percentile), Median (2nd Quartile), and 3rd Quartile (75th percentile), along with minimum and maximum values. The results show a large variation in the marginal impacts of environmental variable R&D on farm performance in the semiparametric smooth coefficient model. This heterogeneity in impact suggests that the traditional Cobb-Douglas production model capturing the average (or mean) impact of the R&D variable is not appropriate. The marginal effects of R&D on the elasticities of the factor inputs at the mean and at each of the three quartile values suggest that impact of R&D on production technology is not input neutral.

The environmental variable, R&D, affects the marginal productivity of inputs in a non-neutral manner, as indicated in Table 5.3. It has both a direct effect through TFP ($\partial\hat{\beta}_0/\partial lnZ$) and an indirect effect via the productivity ($\partial\hat{\beta}_i/\partial lnZ$) with which the inputs are used in the production process. The marginal effect of the environmental variable on overall productivity, $\partial lnY/\partial lnZ$, (here $Z$ is R&D) is given by

$$\frac{\partial lnY}{\partial lnZ} = \overbrace{\frac{\partial\hat{\beta}_0}{\partial lnZ}}^{\boxed{\textit{Direct Effect}}} + \overbrace{\frac{\partial\hat{\beta}_1}{\partial lnZ}k + \frac{\partial\hat{\beta}_2}{\partial lnZ}l + \frac{\partial\hat{\beta}_3}{\partial lnZ}a + \frac{\partial\hat{\beta}_4}{\partial lnZ}m}^{\boxed{\textit{Indirect Effects}}} \qquad (5.7)$$

where $k$ is (log) capital, $l$ is (log) labour, $a$ is (log) land and $m$ is (log) materials.

The seventh column of Table 5.3 reports the marginal productivity of R&D (i.e., the elasticity, $\partial lnY/\partial lnZ$). R&D has a positive and statistically significant effect on output with a mean value of 0.0653, which means that for a 1 per cent increase in R&D investment, the output responds positively by 0.0653 per cent, on average.

The results also show that there is some variation in the marginal effects of R&D on overall productivity, with a range of effects from -0.11 per cent to 0.52 per cent. These marginal effects are the combined effect of both direct and indirect effects of R&D on productivity. The results reported in column 8 show substantial heterogeneity in the direct effects of R&D on TFP ($\partial\hat{\beta}_0/\partial lnZ$).

**Table 5.3: Summary of the results for semiparametric smooth coefficients**

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Variable* | $\hat{\beta}_0$ | $\hat{\beta}_1$ | $\hat{\beta}_2$ | $\hat{\beta}_3$ | $\hat{\beta}_4$ | $\partial lnY/\partial lnZ$ | $\partial\hat{\beta}_0/\partial lnZ$ | $\partial\hat{\beta}_1/\partial lnZ$ | $\partial\hat{\beta}_2/\partial lnZ$ | $\partial\hat{\beta}_3/\partial lnZ$ | $\partial\hat{\beta}_4/\partial lnZ$ |
| *Mean* | 3.406 | 0.3136 | 0.8299 | 0.0988 | 0.0083 | 0.0653 | 5.264 | 0.0136 | 0.0807 | -0.1995 | 0.1555 |
| | (0.5530) | (0.1144) | (0.1477) | (0.0884) | (0.1267) | (0.0386) | (1.2619) | (0.0796) | (0.2752) | (0.1123) | (0.0867) |
| *1st Qu.* | 2.088 | 0.0357 | 0.4866 | -0.052 | -0.262 | 0.0435 | -1.281 | -0.4573 | -0.7503 | -1.1110 | -0.4238 |
| | (0.0528) | (0.0291) | (0.0921) | (0.0382) | (0.0436) | (0.0135) | (0.9957) | (0.0305) | (0.1395) | (0.1030) | (0.0721) |
| *Median* | 3.351 | 0.3566 | 1.1284 | 0.0802 | -0.110 | 0.0521 | 4.543 | 0.1913 | 0.3342 | -0.2201 | -0.1123 |
| | (0.2654) | (0.0613) | (0.1806) | (0.0277) | (0.0621) | (0.0081) | (0.9014) | (0.1330) | (0.2270) | (0.0306) | (0.2020) |
| *3rd Qu.* | 3.809 | 0.5925 | 1.5343 | 0.2994 | 0.2822 | 0.0728 | 11.440 | 0.4328 | 1.1600 | -0.0664 | 0.6140 |
| | (1.2196) | (0.0819) | (0.2573) | (0.0177) | (0.0432) | (0.0115) | (1.1288) | (0.0829) | (0.3990) | (0.1965) | (0.0386) |
| *Min* | -3.077 | -0.188 | -0.891 | -0.169 | -0.406 | -0.1084 | -10.490 | -1.4270 | -6.6310 | -1.4330 | -1.2170 |
| | (0.0537) | (0.0004) | (0.0890) | (0.0169) | (0.0261) | (0.0334) | (1.3571) | (0.2192) | (0.1580) | (0.1375) | (0.4321) |
| *Max.* | 9.738 | 0.7167 | 1.9141 | 0.3811 | 0.6059 | 0.5199 | 27.510 | 0.8374 | 3.4310 | 0.3567 | 1.4320 |
| | (1.0442) | (0.0234) | (0.0992) | (0.0206) | (0.0814) | (0.2429) | (7.870) | (0.1580) | (0.6602) | (0.0066) | (0.2425) |

*Bootstrapped standard errors in parentheses*

This thesis follows the residual based wild bootstrap method to estimate standard errors in the semiparametric smooth coefficient model in the following steps (Sun and Kumbhakar, 2013):

1. Obtain fitted residuals, $\hat{\varepsilon}_i$, from the sample.

2. Generate wild bootstrap disturbance, $\varepsilon_i^*$, such that the distribution of two points is as follows: $\varepsilon_i^* = a\hat{\varepsilon}_i$ with probability $r = (\sqrt{5}+1)/(2\sqrt{5})$ and $\varepsilon_i^* = b\hat{\varepsilon}_i$ with probability $1 - r$, where $a = -(\sqrt{5}-1)/2$ and $b = (\sqrt{5}+1)/2$, as suggested by Mammen (1993).

3. Resample the response variable $y_i^*$ based on the bootstrapped disturbance, $\varepsilon_i^*$.

4. Refit the model using the fictitious response variables.

5. Repeat steps 2 and 4 a statistically significant number of times, say, B=99.

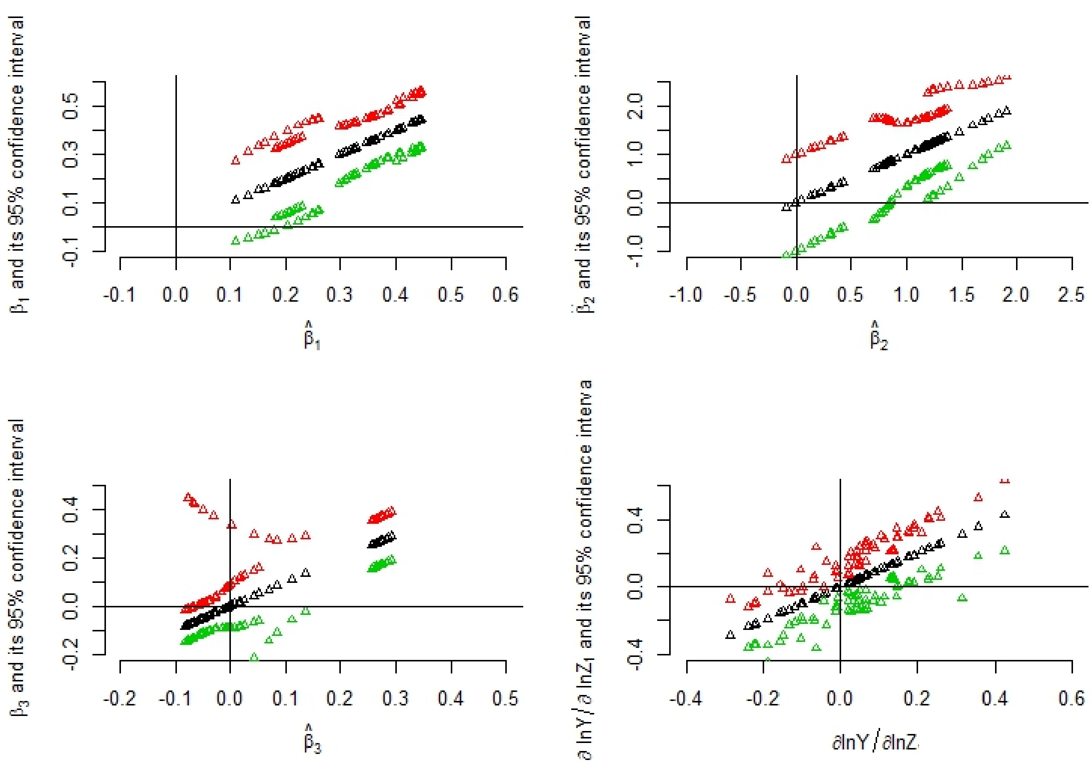
The marginal effects of *R&D* on the factor productivity of inputs vary across the inputs as well as over the observations in the sample. On average, the effects of *R&D* on input productivity are 0.0136 per cent, 0.0807 per cent, -0.1995 per cent and 0.1555 per cent for *capital*, *labour*, *land* and *materials*, respectively. These results indicate that all inputs except *land* have positive contributions of R&D to productivity, and the effect is biased towards the increased productivity of *materials*. The greatest variation is found in the marginal effect of *R&D* on the contribution of *labour* to output ($\partial\hat{\beta}_2/\partial lnZ$), with minimum and maximum values of -6.63 per cent and 3.43 per cent, respectively.

Figure 5.2 plots the partial effects for each observation in the sample ordered by the value of the estimated coefficient, along with bootstrapped confidence bounds for each of the partial effects. The advantage of this type of plot is that it shows statistical significance for the partial effect of each observation.[24] Here the plot

[24] The following procedure is followed to construct these plots. For any given estimate, say, $\hat{\hat{\beta}}_1$, $\hat{\hat{\beta}}_1$ is plotted against $\hat{\hat{\beta}}_1$, which plots $\hat{\hat{\beta}}_1$ along the 45 degree line. Then, to obtain the confidence

shows substantial heterogeneity in the coefficients of the observation-specific partial effects of capital ($\hat{\beta}_1$), labour ($\hat{\beta}_2$), land ($\hat{\beta}_3$) and R&D ($\partial \ln Y/\partial \ln Z$). For most of the observations the lower bounds of the input coefficients, $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$, are greater than zero, indicating positive and statistically significant estimates of output elasticities with respect to capital, labour and land. Turning to the marginal effects of R&D, $\partial \ln Y/\partial \ln Z$ (where Z is R&D), Figure 5.2 also shows a plot of the marginal effects of the R&D. It is found that although R&D has both positive and negative effects on output, the effect at the mean is positive and statistically significant. Therefore, only considering the impact of R&D on the average can be misleading when there is non-neutrality in the effects of R&D investment.

**Figure 5.2: Semiparametric fits: estimates with confidence intervals**




To check the robustness of the estimates, I treat the dataset as a panel (repeated cross section over periods) and use both the fixed effects and the semiparametric smooth

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bounds the standard error is added (subtracted) twice from $\hat{\beta}_1$, which gives the upper (lower) confidence bounds. The upper and lower confidence bounds are plotted against $\hat{\beta}_1$.

coefficient model. These panel specifications control state-level unobserved fixed effects in analysing the data. Table 5.4 presents estimates of the parametric (fixed effects) and semiparametric smooth coefficient models (plot of the marginal effects of R&D based on panel data is reported in appendix Figure A.5.1). Like the OLS model, the fixed effects model shows that the input coefficients for both capital and labour are positive and significant and that the R&D coefficient is negative but insignificant. In turn, the partial effect of R&D is positive and significant for the semiparametric smooth coefficient model with panel data. These results suggest the estimates are robust for panel data as well.

**Table 5.4: Fixed effects and semiparametric smooth coefficients: panel data**

| Variables | Fixed Effects Model | Semiparametric smooth coefficient model |
|---|---|---|
| *Capital* | 0.346* | 0.2889** |
| | (0.162) | (0.0886) |
| *Labor* | 0.856* | 0.8525** |
| | (0.323) | (0.284) |
| *Land* | 0.0457 | 0.1433 |
| | (0.214) | (0.0834) |
| *Materials* | -0.0590 | 0.1154 |
| | (0.176) | (0.0844) |
| *R&D* | -0.140 | 0.1024* |
| | (0.182) | (0.0507) |
| *Constant* | 7.477** | 1.0497 |
| | (2.230) | (1.5153) |
| *Observations* | 65 | 65 |
| *R-squared* | 0.590 | 0.90425 |

*Robust standard errors in parentheses*

**** p<0.01, ** p<0.05, * p<0.1*

[25] The pseudo R-squared is derived as the square of the Pearson product moment correlation coefficient, r. This correlation coefficient is based on the correlation between the predicted values and the actual values in the model, which can range from -1 to 1, and so the square of the correlation then ranges from 0 to 1.

### 5.4.3 Specification Tests

The following model specification tests are applied to formally test for the correct specification.

**Ramsey RESET Model Specification Test**

To test the parametric specification of *Model 1*, the Ramsey RESET model specification test is used. The test using powers of the independent variables produces a significant test statistic $F\ (12,\ 48) = 4.00$ with $Prob > F = 0.0003$ for specification error. This test suggests rejection of the null hypothesis that the model has no omitted variables, and it indicates that the parametric specification is not a correct specification.

**Hardle and Mammen's (1993) Specification Test**

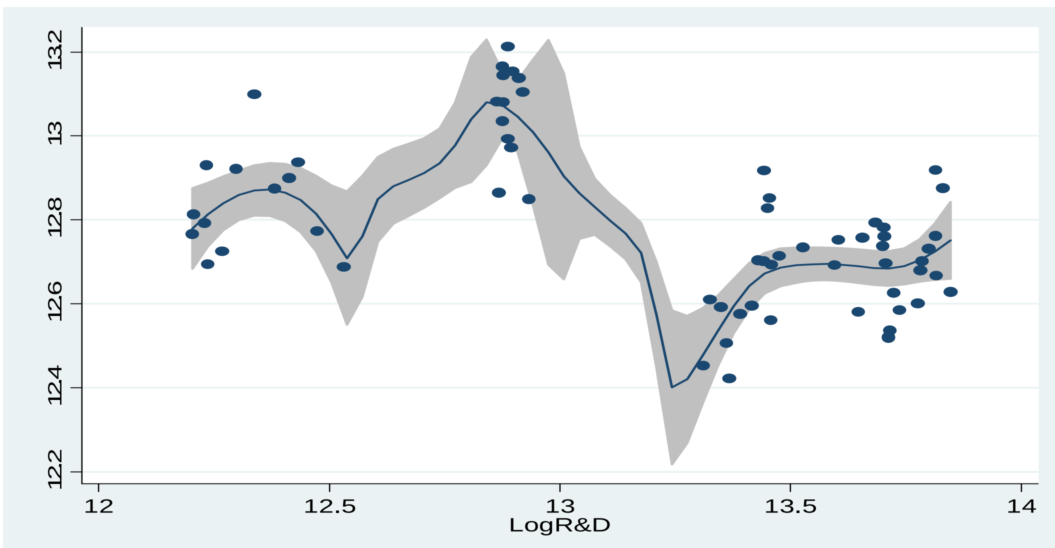
Nonparametric functions may be approximated by a parametric polynomial alternative. To test for the appropriateness of such an approximation, Hardle and Mammen (1993) develop a statistic that compares the nonparametric and parametric regression fits using the squared deviations between them. This specification test is implemented to check whether the nonparametric fit can be approximated by a polynomial fit in any order. Absence of rejection of the null (i.e., "accepting" the parametric model) means that the polynomial adjustment is at least of the degree that has been tested. The test statistics reported in Table 5.5 show that the parametric model could be approximated with a polynomial fit of degree 3 of R&D.

Figure 5.3 shows the relationship between the output and R&D (in logs) in Robinson's partial linear model, which is clearly nonlinear. The shaded areas visualize the confidence interval around the nonparametric fit. This graph shows evidence that the linear specification of the model is not appropriate when the environmental variable, R&D, is incorporated into the model.

**Table 5.5: Hardle and Mammen's (1993) specification test**

| H0: Parametric and nonparametric fits are not different | | |
|---|---|---|
| Polynomial Degree | Approximate P-value | Decision |
| 1 | 0.0 | Linear approximation rejected |
| 2 | 0.07 | Quadratic approximation rejected |
| 3 | 0.21 | Cubic approximation cannot be rejected |

**Figure 5.3: Estimated relationship between the output and R&D (in logs) in Robinson model**




Note: The standard errors of the estimated parameters are calculated with correction for heteroskedastic errors.

### Cai, Fan and Yao Specification Test

To choose the preferred model, I also use the model specification test proposed by Cai *et al.* (2000). This test is used to determine which model best fits the data between the parametric and smooth semiparametric models. This test is based on a comparison of the residual sum of squares (RSS) from both parametric and semiparametric fittings. The test statistic is defined as

$$T_n = \frac{(RSS_{para} - RSS_{semipara})}{RSS_{semipara}} = \frac{RSS_{para}}{RSS_{semipara}} - 1$$

where a large value of $T_n$ suggests rejection of the null hypothesis. A nonparametric bootstrap approach is used to evaluate the p-value of the test. The bootstrapped test statistic $T_n^*$ is calculated from the generated bootstrap residuals from the semiparametric fit. . The p-value of the test is simply the relative frequency of the event $T_n^* \geq T_n$ in the bootstrap samples. The goodness-of-fit test statistics suggest rejecting the null hypothesis that both the parametric and nonparametric fittings are the same with a p-value equal to 0.00. Hence, the semiparametric smooth coefficient model is the preferred specification in this case. This result confirms that the production function is of the variable coefficient type and that the impact of R&D on output is non-neutral and input specific. Therefore, the semiparametric smooth coefficient model is more appealing because of its ability to capture both direct and indirect effects of the environmental variable, R&D.

**Likelihood Ratio Test**

A likelihood ratio test is also performed for adding a time variable to the model. The test gives the likelihood ratio test statistic, a chi-square of 0.53 with one degree of freedom, as well as the associated p-value of 0.4658 (*LR chi2(1) = 0.53; Prob > chi2 = 0.4658*). Thus, according to the data, it cannot be rejected the null hypothesis that the model excludes a time variable. The results show that adding time as a predictor variable does not result in a statistically significant improvement in model fit. Moreover, an F test is performed to see if time-fixed effects are needed when running a fixed effect model. The null is that no time-fixed effects are needed and that all-year dummies are jointly non-significant. In the case of our sample, the test statistic is 1.55 with a p-value 0.3404 (*F (4, 4) = 1.55; Prob > F = 0.3404*). This indicates that the sample data are compatible with the null hypothesis that no time-fixed effects are needed in the model.

These specification tests generally reject the parametric specifications in favour of more flexible counterparts. This result is consistent with studies that apply similar methodologies but perform the tests in the manufacturing sector. For example, Li *et al*. (2002) use the nonparametric kernel method to estimate the semiparametric varying coefficient model with China’s non-metal mineral manufacturing industry data. They find that the semiparametric varying coefficient model is more appropriate than either a parametric linear model or a semiparametric partially linear model. Similarly, using a provincial-level dataset Zhang *et al*. (2012) suggest that the semiparametric model yields outcomes that are more intuitive and have fewer economic violations than the parametric counterpart in China's high technology industry.

## 5.5 Conclusion

This research uses a novel econometric methodology to analyse the effect of R&D on productivity in Australian broadacre farming. The semiparametric smooth coefficient model gives rise to the observation-specific estimates of input coefficients. Using state-level average farm data, estimates are provided of the state-level effect of R&D on productivity and the marginal productivity with which factor inputs are used in the production process. Using this method, it is possible to estimate both the immediate effect of R&D on output growth and the indirect effect through changes in the marginal productivity of factor inputs in the production process.

Econometric investigations ordinarily produce point estimates of the effect of R&D on the productivity of the average unit of analysis. Implicitly, this assumes that environmental variables influence productivity neutrally, through the TFP alone, and the differential effect of R&D on factor inputs is not recognized. As a result, the policy implications for R&D investment turn into a one-size-fits-all sort of strategy. Against this backdrop, this research opens an additional window of information regarding the role of R&D in driving productivity in Australian broadacre farming.

The results suggest that the R&D does not have the same effect on TFP and productivity at the average farm level across states within Australia. By specifying intercept and slope coefficients as a function of the environmental variable, R&D, the model gives rise to significant variation in the state-level effects of R&D. Therefore, this study confirms the non-neutrality in the effects of R&D on productivity. The estimates of the effect of R&D investments on productivity in broadacre farming are more useful than that of parametric estimates in terms of policy implications. First, the results suggest that Australia may enhance its farming productivity by improving investment in public R&D. Second, the large variations in the state-level average farm effects of R&D on productivity imply that initiation of the same R&D policy in different states can have considerably diverse effects on the productivity of inputs.

Furthermore, R&D expenditure is found to have a direct impact on productivity and indirect effects through impacting the marginal productivity of factor inputs such as labour and capital. Importantly, none of these issues come into consideration in the parametric regression specifications of modelling the impact of R&D on productivity. This is the fundamental point of interest of using this novel methodology.

Finally, the results provide evidence that the effect of environmental variables on economic performance needs to be revisited. Specifically, consideration should be given to the variations in the effect of R&D on farms. This chapter has limitations in that it could not consider the effect of private R&D due to data unavailability. However, other studies show that increased spending on public research appears to supplement private research in agriculture (Wang *et al*., 2013). Another limitation is that the within-state variations in the effects of R&D are not estimated, as data are available only at the aggregate state level. Moreover, the possibility of errors of measurement with the state-level public R&D data cannot be ruled out. Nevertheless, this research explores the relationship from a novel methodological point of view and broadly confirms the results of previous studies regarding the average impact of R&D on productivity, and it provides the additional insight that R&D affects productivity non-neutrally and differentially across farms.

# CHAPTER SIX

## Conclusions and Policy Implications

### 6.1 Introduction

Over the last few decades, productivity and efficiency growth analysis in agriculture has attracted considerable attention from researchers and policymakers in both developed and developing countries. Recently, in Australia, there has been increasing concern about the slowing productivity growth in agriculture while gains in the productivity of this sector are important for improving the living standards for the rural community. Since, Australia is one of the major food producing countries, this declining productivity has implications for food security in developing countries where demand for food is continuing to rise for their growing populations. In the face of the widely discussed recent productivity falling scenario, this thesis considers it important to empirically estimate and decompose agricultural productivity growth along with its major determinants in Australian broadacre agriculture using country-level aggregate as well as state-level average farm data.

This thesis makes a significant contribution to understanding the dynamics of productivity in Australian broadacre agriculture. Given the limited empirical evidence concerning the total factor productivity (TFP) change and its components there are the research gaps in the literature in the context of productivity analysis in Australian agriculture. Previous empirical studies hardly use any decomposition analysis to find the components of productivity changes in agriculture, although the importance of measuring different types of productivity change for effective policy measures has been recognized by researchers and policymakers. Moreover, to date, there have been very few studies undertaken in Australia examining the relationship between R&D and productivity growth considering the state-level heterogeneity in the effects.

This thesis empirically makes the following major contributions to the productivity literature: (1) it employs the Färe-Primont index, which satisfies all the axioms of index number theory, including the identity and transitivity axioms, to compute and decompose productivity changes using state-level data for the period 1990 to 2011; (2) it identifies and estimates the main drivers of productivity growth in Australian broadacre agriculture; (3) using standard time-series techniques, the existence of a long-term relationship is examined between productivity changes and public investment in R&D over the period 1953 to 2009; (4) it applies a novel and conceptually superior method than the conventional internal rate of return (IRR) known as the modified internal rate of return (MIRR) to obtain a credible estimate of returns on public research investment; (5) finally, it applies a semiparametric smooth coefficient approach to investigate the effects of R&D on TFP enabling observation of specific heterogeneities and non-neutrality using state-level data covering the period 1995–2007. This is one of the first studies to apply this nonparametric approach in the agriculture context, and it broadens our understanding of the effects of R&D, in particular recognizing and measuring the heterogeneity in its effects.

The findings of this thesis empirically confirm that productivity has been slowing in Australian broadacre agriculture, and further decompositions suggest that a fall in technological progress is the main driver of the slowing productivity growth. This finding along with the evidence of a long-term relationship between R&D and TFP, with the former causing the latter, suggests that investment in public R&D is an important driver in productivity growth in Australian broadacre agriculture. An additional insight is that once both the direct and the indirect impacts are taken into consideration, R&D investments significantly increase output. Results also show that there are substantial variations in the impact of R&D on output across the states, which need to be taken into account while designing policy on investing public R&D in agriculture.

The rest of this chapter proceeds as follows. The following section presents a summary of the key findings of the empirical analysis undertaken in Chapters 3, 4 and 5. Section 6.3 discusses some policy implications of the findings of the thesis. The final section mentions some limitations of this thesis and indicates some future research directions.

## 6.2 Key Findings

This thesis empirically analyses productivity in Australian broadacre agriculture, the relationship between research and development and productivity growth. The main research objectives are empirically analysed in Chapter 3, Chapter 4 and Chapter 5. Chapter 3 measures productivity changes and its decompositions into different meaningful and finer components to analyse the determinants of productivity changes. The relationship between the public R&D and TFP is investigated both in Chapter 4 and Chapter 5 from up-to-date methodological points of view. The findings from these empirical analyses are summarized below.

Chapter 3 estimates total factor productivity changes in Australian broadacre agriculture and decomposes these changes into different meaningful components, such as technical change and technical efficiency change. This is done using the Färe-Primont index of total factor productivity, which estimates and exhaustively decomposes TFP changes into different finer measures of components of the productivity changes. The empirical results show that TFP has grown at an average rate of 1.36 per cent per annum in the broadacre agriculture over the period 1990–2011, with a clear movement towards slower TFP growth over consecutive sub-periods. In the 1990s, broadacre agriculture experienced an average annual rate of productivity growth of 2.40 per cent, but it decreased to 1.65 per cent in 2000–2007. In the period 2007–2011, productivity declined at 1.74 per cent per annum.

This declining pattern of productivity growth over time is consistent with earlier empirical studies. In particular, Mullen (2010) reports that productivity in Australian broadacre agriculture declined at an average rate of 1.4 per cent per annum over 1998–2007. Similarly, Sheng *et al*. (2011) find that productivity declined at an average annual rate of 1.7 per cent over the period 2000–2007 in broadacre agriculture.

Further, the decomposed measures of the productivity changes indicate that the average productivity growth of 1.36 per cent over the period 1990–2011 is mainly due to the combined effects of a 1.62 per cent annual rate of increase in production possibilities (technical progress) and a 0.26 per cent annual decrease in overall efficiency (TFPE). Moreover, decomposition of TFP changes over different sub-periods suggests that broadacre agriculture experienced higher technical progress (a rate of 3.78 per cent per annum over 1990–2000) in the earlier periods, which has slowed in recent periods and even turned negative in 2007–2011 (a rate of -3.64 per cent per annum). This declining growth in technical possibilities (technological progress) appears to be the main driver of the declining trend in productivity growth in broadacre agriculture in Australia.

Chapter 3 also estimates TFP for broadacre agriculture in each of the six Australian states. Variations in total factor productivity (TFP) are observed across states as are fluctuations over time within each state. The results reflect that Western Australia is the most productive state in Australia, and has consistently had the highest TFP level among all states. However, the performance of WA has been slipping in recent years relative to other states. In particular, in the recent sub-period 2007–2011, WA experienced a negative productivity growth of -3.64 per cent per annum, whereas South Australia and Queensland managed to achieve overall TFP growth of 2.44 per cent and 1.18 per cent per annum.

The slowdown of total factor productivity growth, largely driven by slowing technical change during the past two decades, may be associated with falling public investment in R&D in Australian agriculture. Similarly, the differential performances of states may also reflect different levels of support for R&D across the states, or different environmental conditions (for example, growing conditions in the WA wheat belt were generally poor in 2007–2011, even after controlling for state rainfall differences in the TFP index calculation). These issues are empirically investigated in Chapters 4 and 5.

Chapter 4 investigates the nexus between research and development expenditure and productivity growth in Australian broadacre agriculture using country-level time-series data for the period 1953 to 2009. Data are analysed using standard time-series econometrics. A set of standard unit root tests, including the Augmented Dickey Fuller, DF-GLS, the Phillips Perron and the KPSS tests, suggest that all series are integrated of order one. Moreover, the Zivot-Andrews unit root test confirms that the standard unit root test results are consistent even after allowing for structural breaks.

Results in Chapter 4 provide econometric evidence of a cointegrating relationship between R&D and productivity growth. This evidence of a cointegrating relationship between R&D and productivity is robust even with unknown structural breaks, according to the Gregory and Hansen cointegration test. Moreover, the empirical evidence indicates a unidirectional causality running from R&D to TFP growth. In other words, current and past values of research and development expenditure are useful in predicting TFP above and beyond the past values of TFP alone. This result is robust according to the Toda-Yamamoto Granger non-causality test. An error correction model is also constructed, which shows that lagged R&D is significant in explaining changes in total factor productivity.

Findings of variance decomposition and the impulse response function in Chapter 4 further suggest that public R&D can be readily linked to the variation in productivity growth beyond the sample periods. TFP responds positively and persistently for the future period as the effect of shock in the public R&D does not die out over time. Further, the results using an out-of-sample forecasting exercise also indicate that a significant out-of-sample relationship exists between the public R&D and productivity in broadacre agriculture, which implies that investment in public R&D in agriculture does matter in forecasting productivity growth.

Moreover, this chapter also computes and analyses different measures of rates of return on public investments in agricultural R&D. It finds the benefit-cost ratio and the IRR as 32.45 per cent (with 3 per cent reinvestment rate) and 26.07 per cent per annum, respectively. Employing a recently developed method, the MIRR, this study obtains a credible estimate of returns on public research investment showing an MIRR of 15.72 per cent per annum with the reinvestment rate of 3 per cent per annum, which is lower than suggested by the reported benefit-cost ratio and conventional IRR. The MIRR is a methodologically more justified and plausible measure, which ranges from 8.14 to 16.44 per cent per annum depending on the research lag length and reinvestment rate of benefits.

Chapter 5 analyses the impact of R&D on the productivity of Australia's broadacre farming using the semiparametric smooth coefficient model proposed by Hastie and Tibshirani (1993) and Li *et al*. (2002). The novelty of this approach compared to the standard production function model is that it accommodates non-neutrality in the framework and captures heterogeneity across observations. This approach can capture varying effects of R&D investment on input elasticities and allows heterogeneities across observations and provides estimates of marginal effects of R&D on factor inputs and outputs of each firm. Moreover, this model estimates both the direct impact of a change in R&D on output and the indirect impact through changes in efficiency from the use of factor inputs in the production process, while the conventional approach only captures direct effects of R&D.

Utilizing a state-level average farm dataset covering the period 1995 to 2007, the findings in Chapter 5 show that once both the direct and the indirect effects of R&D expenditures are taken into consideration, R&D investments significantly increase outputs. Moreover, by specifying intercepts and slope coefficients as a function of the R&D variable, the estimates give rise to significant variations in the state-level effects of R&D. Importantly, none of these issues come into consideration in the parametric regression specifications for modelling the impact of R&D on productivity. This is the fundamental point of interest of using this model.

## 6.3 Policy Implications

The empirical findings of this thesis suggest several policy implications for Australian broadacre agriculture. Firstly, the observed declining trend in productivity growth in Australian broadacre agriculture over the study period suggests the need for a coordinated agricultural policy to lift the productivity growth. In particular, the declining technical progress generally indicates the need for government policymaking aimed at improving the production environment, which facilitates innovations in production. Moreover, by exploring different components of productivity changes, this thesis provides important information for policy formulation, as different policies generally affect different components of productivity change. State-level variations in scale and mix efficiency suggest that there is scope for improving productivity by taking a differential approach to the efficient use of agricultural resources and to increasing scale and mix efficiency in production in the Australian states. There are several ways the government can possibly undertake policies to change the scale and/or mix efficiency of farming operations. Firstly, the government can offer incentives to farmers approving mergers and acquisitions to improve the scale of their operations. Secondly, the government can improve output-oriented mix efficiency by allowing farmers to grow GM crops, banning live cattle exports to Indonesia or providing output subsidies. Lastly, input-oriented mix efficiency can be gained by changing the mix of inputs through reducing interest rates and initiating appropriate wages policy.

Secondly, in investigating the long-term relationship between public R&D and TFP in broadacre agriculture over a period of five decades, this thesis finds evidence of a long-term cointegrated and causal relationship between productivity and R&D in Australian agriculture. This evidence of a cointegrated relationship along with the direction of causation has an implication for informed decision-making for future policies in R&D investments in Australian agriculture. The causality testing shows that increased R&D expenditure leads to better outcomes for productivity in Australian broadacre agriculture. This implies that information on R&D investment improves productivity forecasts significantly. The insight behind this causal relationship between the public R&D and productivity in broadacre agriculture in Australia is straightforward. An increase in the public expenditure in R&D is likely to lead to higher productivity growth in the long run. Finally, as an increase in R&D expenditure has a positive and sizeable rate of return through contributing to productivity growth, investments in R&D should attract more public attention on agricultural policy.

Thirdly, this research uncovers an additional window of information regarding the role of R&D in driving productivity in Australian broadacre farming. By disaggregating the effects of R&D into direct and indirect effects it enables to isolate and estimate the productive impacts of R&D through input productivity and to estimate the extent of technical change. Taking such variations into account is important when designing policies for investing public R&D in agriculture. As a result of recognizing the differential effects of R&D on farm productivity properly, the estimates possess a better policy basis for R&D investment than the one-size-fits-all sort of policy strategy designed from average parameter estimates, which assume that R&D spending influences productivity neutrally, just through the TFP.

Finally, the results, by showing a strong positive and significant relationship between public R&D investments and productivity growth in broadacre farming, suggest that Australia may enhance its farming productivity by increasing investment in public R&D. As a major contributor to technical change, R&D funding improves long-term productivity growth. Further, the observed variations in the state-level average farm effects of R&D on productivity imply that imposition of the same R&D policy in different states can have very diverse effects on farm productivity. These findings have implications for policymakers in terms of creating opportunities for the development and diffusion of innovations through R&D funding with a state-specific focus. Therefore, the general implication of this thesis is that investment in public R&D is an important policy option for achieving productivity growth in Australian agriculture. Some policy conjectures regarding specific R&D expenditures that the government can undertake to improve productivity in Australian agriculture might be the investments towards improving seed varieties or improving agricultural practices through extending and implementing proper extension services.

## 6.4 Limitations and Focus for Future Research

This thesis is carried out at the state level expecting productivity and efficiency to vary across state boundaries. Although these boundaries are political, the composition of agricultural output, physical environment and market circumstances are different from one state to another, which has implications for productivity performance variations across states. Nevertheless, accessing agro-ecological data (e.g. on AEZs) and preparing a new regionalization of Australia, would be interesting and worthy because of the expected changes in productivity across AEZs.

Moreover, this research does not capture the commodity-level heterogeneities in the analysis and there is also an issue of aggregation. Future research on commodity-specific (such as crops, sheep or livestock) productivity analysis is likely to prove fruitful. Also, livestock data collected by ABARES through the AAGIS farm surveys is deficient in measuring the livestock variable as quality matters in livestock production, particularly with large variations between southern Australia and northern Australia. This study does not adjust the livestock numbers for quality of production.

A further limitation is that this research does not consider the effect of private R&D due to data unavailability. The model focuses solely on public R&D in broadacre agriculture and thus results may be limited by any effects of the R&D expenditure in private sectors and in other sectors in Australia. Another limitation of this study is that it could not be considered the within-state variations in the effects of R&D on TFP, as data are available only for the state-level average farm. Future research incorporating private R&D expenditure and using farm-level data would be interesting in finding the effects of R&D on TFP more broadly.

Despite some practical limitations, the results are still pertinent and provide useful insights into the sources of TFP change in broadacre agriculture. The findings here broadly confirm the results of previous relevant studies, such as Cox *et al*. (1997) for Australian broadacre agriculture, Salim and Islam (2010) for WA broadacre agriculture, Wang *et al*. (2013) and Alston *et al*. (2011) for US agriculture, and Thirtle *et al*. (2008) for UK agriculture. In addition, they provide the additional insight that R&D affects productivity non-neutrally and differentially across states. The research findings and conclusions can be extended to the similar research for broadacre or dryland farming across the world.

# Appendices

# Appendix to Chapter Three

**Table A.3.1: Relative total factor productivity in broadacre agriculture (base: NSW 1990=1)**

| Year | NSW | VIC | QLD | SA | WA | TAS |
|---|---|---|---|---|---|---|
| 1990 | 1 | 0.829 | 0.625 | 0.925 | 1.086 | 0.793 |
| 1991 | 0.885 | 0.726 | 0.706 | 0.951 | 1.112 | 0.760 |
| 1992 | 0.959 | 0.699 | 0.731 | 1.011 | 1.122 | 0.723 |
| 1993 | 1.006 | 0.863 | 0.815 | 1.241 | 1.267 | 0.870 |
| 1994 | 1.056 | 0.840 | 0.877 | 1.278 | 1.589 | 0.932 |
| 1995 | 0.981 | 0.914 | 0.864 | 1.247 | 1.373 | 1.006 |
| 1996 | 1.045 | 0.869 | 0.731 | 1.292 | 1.629 | 1.079 |
| 1997 | 1.048 | 1.019 | 0.816 | 1.129 | 1.756 | 1.007 |
| 1998 | 1.090 | 1.296 | 0.733 | 1.288 | 1.696 | 0.921 |
| 1999 | 0.992 | 1.048 | 0.824 | 1.094 | 1.558 | 0.859 |
| 2000 | 1.039 | 1.059 | 0.755 | 1.336 | 1.584 | 0.994 |
| 2001 | 1.137 | 1.108 | 0.767 | 1.330 | 1.434 | 0.871 |
| 2002 | 1.090 | 1.140 | 0.704 | 1.228 | 1.454 | 1.006 |
| 2003 | 1.038 | 1.079 | 0.818 | 1.106 | 1.182 | 0.954 |
| 2004 | 0.793 | 1.033 | 0.761 | 1.099 | 1.464 | 0.935 |
| 2005 | 1.007 | 1.071 | 0.785 | 1.116 | 1.418 | 1.131 |
| 2006 | 1.072 | 1.164 | 0.793 | 1.312 | 1.589 | 1.102 |
| 2007 | 1.177 | 1.166 | 0.853 | 1.228 | 1.765 | 1.375 |
| 2008 | 1.104 | 1.298 | 0.818 | 1.299 | 1.563 | 1.155 |
| 2009 | 1.183 | 1.135 | 0.800 | 1.343 | 1.613 | 1.219 |
| 2010 | 1.146 | 1.034 | 0.810 | 1.405 | 1.398 | 0.978 |
| 2011 | 1.144 | 1.141 | 0.895 | 1.354 | 1.526 | 0.953 |

**Table A.3.2: Measures of TFP and efficiency**

Levels Computed Using Fare-Primont Aggregator Functions

| obs | State | Period | Q | X | TFP | TFP* | TFPE | OTE | OSE | OME | ROSE | OSME | ITE | ISE | IME | RISE | ISME | RME | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1990 | 0.7058 | 1.1117 | 0.6349 | 0.6892 | 0.9212 | 1 | 1 | 1 | 0.9212 | 0.9212 | 1 | 1 | 1 | 0.9212 | 0.9212 | 0.9212 | |
| 2 | 2 | 1990 | 0.5492 | 1.043 | 0.5266 | 0.6892 | 0.764 | 1 | 1 | 1 | 0.764 | 0.764 | 1 | 1 | 1 | 0.764 | 0.764 | 0.764 | |
| 3 | 3 | 1990 | 0.518 | 1.3053 | 0.3968 | 0.6892 | 0.5757 | 1 | 1 | 1 | 0.5757 | 0.5757 | 1 | 1 | 0.9071 | 0.6347 | 0.5757 | 0.5757 | |
| 4 | 4 | 1990 | 0.7373 | 1.2554 | 0.5873 | 0.6892 | 0.8521 | 1 | 1 | 1 | 0.8521 | 0.8521 | 1 | 1 | 1 | 0.8521 | 0.8521 | 0.8521 | |
| 5 | 5 | 1990 | 0.985 | 1.4292 | 0.6892 | 0.6892 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 6 | 6 | 1990 | 0.6033 | 1.1986 | 0.5034 | 0.6892 | 0.7303 | 1 | 1 | 1 | 0.7303 | 0.7303 | 1 | 1 | 0.9345 | 0.7815 | 0.7303 | 0.7303 | |
| 7 | 1 | 1991 | 0.6024 | 1.0722 | 0.5619 | 0.7058 | 0.7961 | 1 | 1 | 1 | 0.7961 | 0.7961 | 1 | 1 | 1 | 0.7961 | 0.7961 | 0.7961 | |
| 8 | 2 | 1991 | 0.4409 | 0.9573 | 0.4606 | 0.7058 | 0.6526 | 1 | 1 | 1 | 0.6526 | 0.6526 | 1 | 1 | 1 | 0.6526 | 0.6526 | 0.6526 | |
| 9 | 3 | 1991 | 0.5823 | 1.2982 | 0.4485 | 0.7058 | 0.6355 | 1 | 1 | 1 | 0.6355 | 0.6355 | 1 | 1 | 1 | 0.6355 | 0.6355 | 0.6355 | |
| 10 | 4 | 1991 | 0.6798 | 1.1258 | 0.6038 | 0.7058 | 0.8556 | 1 | 1 | 1 | 0.8556 | 0.8556 | 1 | 1 | 1 | 0.8556 | 0.8556 | 0.8556 | |
| 11 | 5 | 1991 | 0.9296 | 1.3171 | 0.7058 | 0.7058 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 12 | 6 | 1991 | 0.5703 | 1.1826 | 0.4823 | 0.7058 | 0.6834 | 1 | 1 | 1 | 0.6834 | 0.6834 | 1 | 1 | 0.9055 | 0.7547 | 0.6834 | 0.6834 | |
| 13 | 1 | 1992 | 0.6629 | 1.0889 | 0.6088 | 0.7121 | 0.8549 | 1 | 1 | 1 | 0.8549 | 0.8549 | 1 | 1 | 1 | 0.8549 | 0.8549 | 0.8549 | |
| 14 | 2 | 1992 | 0.3915 | 0.8816 | 0.4441 | 0.7121 | 0.6236 | 1 | 1 | 1 | 0.6236 | 0.6236 | 1 | 1 | 1 | 0.6236 | 0.6236 | 0.6236 | |
| 15 | 3 | 1992 | 0.5614 | 1.2095 | 0.4641 | 0.7121 | 0.6517 | 1 | 1 | 1 | 0.6517 | 0.6517 | 1 | 1 | 0.8895 | 0.7327 | 0.6517 | 0.6517 | |
| 16 | 4 | 1992 | 0.7419 | 1.1558 | 0.6419 | 0.7121 | 0.9014 | 1 | 1 | 1 | 0.9014 | 0.9014 | 1 | 1 | 1 | 0.9014 | 0.9014 | 0.9014 | |
| 17 | 5 | 1992 | 0.9378 | 1.3169 | 0.7121 | 0.7121 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 18 | 6 | 1992 | 0.5318 | 1.1587 | 0.459 | 0.7121 | 0.6446 | 1 | 1 | 1 | 0.6446 | 0.6446 | 1 | 1 | 0.918 | 0.7021 | 0.6446 | 0.6446 | |
| 19 | 1 | 1993 | 0.6489 | 1.0164 | 0.6385 | 0.8044 | 0.7937 | 1 | 1 | 1 | 0.7937 | 0.7937 | 1 | 1 | 0.9885 | 0.803 | 0.7937 | 0.7937 | |
| 20 | 2 | 1993 | 0.4671 | 0.8531 | 0.5476 | 0.8044 | 0.6808 | 1 | 1 | 1 | 0.6808 | 0.6808 | 1 | 1 | 1 | 0.6808 | 0.6808 | 0.6808 | |
| 21 | 3 | 1993 | 0.6012 | 1.162 | 0.5174 | 0.8044 | 0.6432 | 1 | 1 | 1 | 0.6432 | 0.6432 | 1 | 1 | 0.8713 | 0.7382 | 0.6432 | 0.6432 | |
| 22 | 4 | 1993 | 0.8584 | 1.0898 | 0.7876 | 0.8044 | 0.9792 | 1 | 1 | 1 | 0.9792 | 0.9792 | 1 | 1 | 1 | 0.9792 | 0.9792 | 0.9792 | |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 23 | 5 | 1993 | 1.0618 | 1.32 | 0.8044 | 0.8044 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 24 | 6 | 1993 | 0.5982 | 1.0833 | 0.5522 | 0.8044 | 0.6865 | 1 | 1 | 1 | 0.6865 | 0.6865 | 1 | 1 | 0.9183 | 0.7475 | 0.6865 | 0.6865 | | |
| 25 | 1 | 1994 | 0.6852 | 1.0218 | 0.6706 | 1.0091 | 0.6646 | 1 | 1 | 1 | 0.6646 | 0.6646 | 1 | 1 | 0.9973 | 0.6664 | 0.6646 | 0.6646 | | |
| 26 | 2 | 1994 | 0.4773 | 0.8947 | 0.5335 | 1.0091 | 0.5287 | 1 | 1 | 1 | 0.5287 | 0.5287 | 1 | 1 | 1 | 0.5287 | 0.5287 | 0.5287 | | |
| 27 | 3 | 1994 | 0.6281 | 1.1285 | 0.5566 | 1.0091 | 0.5516 | 1 | 1 | 1 | 0.5516 | 0.5516 | 1 | 1 | 1 | 0.5516 | 0.5516 | 0.5516 | | |
| 28 | 4 | 1994 | 0.8444 | 1.0407 | 0.8114 | 1.0091 | 0.8041 | 1 | 1 | 1 | 0.8041 | 0.8041 | 1 | 1 | 1 | 0.8041 | 0.8041 | 0.8041 | | |
| 29 | 5 | 1994 | 1.3717 | 1.3593 | 1.0091 | 1.0091 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | max |
| 30 | 6 | 1994 | 0.5926 | 1.0018 | 0.5916 | 1.0091 | 0.5862 | 1 | 1 | 1 | 0.5862 | 0.5862 | 1 | 1 | 1 | 0.5862 | 0.5862 | 0.5862 | | |
| 31 | 1 | 1995 | 0.6327 | 1.0156 | 0.6229 | 0.8718 | 0.7145 | 1 | 1 | 1 | 0.7145 | 0.7145 | 1 | 1 | 0.9615 | 0.7431 | 0.7145 | 0.7145 | | |
| 32 | 2 | 1995 | 0.4951 | 0.8536 | 0.58 | 0.8718 | 0.6653 | 1 | 1 | 1 | 0.6653 | 0.6653 | 1 | 1 | 1 | 0.6653 | 0.6653 | 0.6653 | | |
| 33 | 3 | 1995 | 0.6061 | 1.1045 | 0.5488 | 0.8718 | 0.6294 | 1 | 1 | 1 | 0.6294 | 0.6294 | 1 | 1 | 1 | 0.6294 | 0.6294 | 0.6294 | | |
| 34 | 4 | 1995 | 0.7663 | 0.9679 | 0.7917 | 0.8718 | 0.9081 | 1 | 1 | 1 | 0.9081 | 0.9081 | 1 | 1 | 1 | 0.9081 | 0.9081 | 0.9081 | | |
| 35 | 5 | 1995 | 1.2073 | 1.3847 | 0.8718 | 0.8718 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | max |
| 36 | 6 | 1995 | 0.7423 | 1.1622 | 0.6387 | 0.8718 | 0.7326 | 1 | 1 | 1 | 0.7326 | 0.7326 | 1 | 1 | 0.8762 | 0.8362 | 0.7326 | 0.7326 | | |
| 37 | 1 | 1996 | 0.7238 | 1.0914 | 0.6631 | 1.0342 | 0.6412 | 1 | 1 | 1 | 0.6412 | 0.6412 | 1 | 1 | 1 | 0.6412 | 0.6412 | 0.6412 | | |
| 38 | 2 | 1996 | 0.5104 | 0.9247 | 0.552 | 1.0342 | 0.5337 | 1 | 1 | 1 | 0.5337 | 0.5337 | 1 | 1 | 1 | 0.5337 | 0.5337 | 0.5337 | | |
| 39 | 3 | 1996 | 0.5599 | 1.2066 | 0.4641 | 1.0342 | 0.4487 | 1 | 1 | 1 | 0.4487 | 0.4487 | 1 | 1 | 0.8406 | 0.5338 | 0.4487 | 0.4487 | | |
| 40 | 4 | 1996 | 0.8362 | 1.0192 | 0.8204 | 1.0342 | 0.7933 | 1 | 1 | 1 | 0.7933 | 0.7933 | 1 | 1 | 1 | 0.7933 | 0.7933 | 0.7933 | | |
| 41 | 5 | 1996 | 1.3838 | 1.3381 | 1.0342 | 1.0342 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | max |
| 42 | 6 | 1996 | 0.7765 | 1.1337 | 0.6849 | 1.0342 | 0.6623 | 1 | 1 | 1 | 0.6623 | 0.6623 | 1 | 1 | 0.9426 | 0.7026 | 0.6623 | 0.6623 | | |
| 43 | 1 | 1997 | 0.6897 | 1.0362 | 0.6656 | 1.1146 | 0.5972 | 1 | 1 | 1 | 0.5972 | 0.5972 | 1 | 1 | 1 | 0.5972 | 0.5972 | 0.5972 | | |
| 44 | 2 | 1997 | 0.6108 | 0.9438 | 0.6472 | 1.1146 | 0.5807 | 1 | 1 | 1 | 0.5807 | 0.5807 | 1 | 1 | 1 | 0.5807 | 0.5807 | 0.5807 | | |
| 45 | 3 | 1997 | 0.5956 | 1.1502 | 0.5179 | 1.1146 | 0.4646 | 1 | 1 | 1 | 0.4646 | 0.4646 | 1 | 1 | 0.909 | 0.5111 | 0.4646 | 0.4646 | | |
| 46 | 4 | 1997 | 0.7671 | 1.07 | 0.717 | 1.1146 | 0.6433 | 1 | 1 | 1 | 0.6433 | 0.6433 | 1 | 1 | 1 | 0.6433 | 0.6433 | 0.6433 | | |
| 47 | 5 | 1997 | 1.6053 | 1.4403 | 1.1146 | 1.1146 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | max |
| 48 | 6 | 1997 | 0.8456 | 1.3223 | 0.6395 | 1.1146 | 0.5738 | 1 | 1 | 1 | 0.5738 | 0.5738 | 1 | 1 | 1 | 0.5738 | 0.5738 | 0.5738 | | |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 49 | 1 | 1998 | 0.7648 | 1.1051 | 0.6921 | 1.0766 | 0.6428 | 1 | 1 | 0.9416 | 0.6827 | 0.6428 | 1 | 1 | 0.9427 | 0.6819 | 0.6428 | 0.6428 | |
| 50 | 2 | 1998 | 0.7692 | 0.9348 | 0.8228 | 1.0766 | 0.7643 | 1 | 1 | 1 | 0.7643 | 0.7643 | 1 | 1 | 1 | 0.7643 | 0.7643 | 0.7643 | |
| 51 | 3 | 1998 | 0.5658 | 1.2152 | 0.4656 | 1.0766 | 0.4325 | 1 | 1 | 1 | 0.4325 | 0.4325 | 1 | 1 | 0.8496 | 0.5091 | 0.4325 | 0.4325 | |
| 52 | 4 | 1998 | 0.9661 | 1.1819 | 0.8175 | 1.0766 | 0.7593 | 1 | 1 | 1 | 0.7593 | 0.7593 | 1 | 1 | 0.961 | 0.7901 | 0.7593 | 0.7593 | |
| 53 | 5 | 1998 | 1.5085 | 1.4012 | 1.0766 | 1.0766 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 54 | 6 | 1998 | 0.6794 | 1.1615 | 0.5849 | 1.0766 | 0.5433 | 1 | 1 | 0.8606 | 0.6313 | 0.5433 | 1 | 1 | 0.9921 | 0.5476 | 0.5433 | 0.5433 | |
| 55 | 1 | 1999 | 0.6751 | 1.072 | 0.6298 | 0.989 | 0.6369 | 1 | 1 | 0.9478 | 0.6719 | 0.6369 | 1 | 1 | 0.9775 | 0.6515 | 0.6369 | 0.6369 | |
| 56 | 2 | 1999 | 0.6337 | 0.952 | 0.6657 | 0.989 | 0.6731 | 1 | 1 | 1 | 0.6731 | 0.6731 | 1 | 1 | 1 | 0.6731 | 0.6731 | 0.6731 | |
| 57 | 3 | 1999 | 0.6477 | 1.2375 | 0.5234 | 0.989 | 0.5292 | 1 | 1 | 1 | 0.5292 | 0.5292 | 1 | 1 | 0.877 | 0.6034 | 0.5292 | 0.5292 | |
| 58 | 4 | 1999 | 0.7776 | 1.1191 | 0.6949 | 0.989 | 0.7026 | 1 | 1 | 1 | 0.7026 | 0.7026 | 1 | 1 | 1 | 0.7026 | 0.7026 | 0.7026 | |
| 59 | 5 | 1999 | 1.4912 | 1.5079 | 0.989 | 0.989 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 60 | 6 | 1999 | 0.6141 | 1.1259 | 0.5454 | 0.989 | 0.5515 | 1 | 1 | 0.9461 | 0.5829 | 0.5515 | 1 | 1 | 1 | 0.5515 | 0.5515 | 0.5515 | |
| 61 | 1 | 2000 | 0.7016 | 1.0641 | 0.6594 | 1.0056 | 0.6557 | 1 | 1 | 0.9844 | 0.6661 | 0.6557 | 1 | 1 | 0.9596 | 0.6833 | 0.6557 | 0.6557 | |
| 62 | 2 | 2000 | 0.6106 | 0.9083 | 0.6722 | 1.0056 | 0.6684 | 1 | 1 | 1 | 0.6684 | 0.6684 | 1 | 1 | 1 | 0.6684 | 0.6684 | 0.6684 | |
| 63 | 3 | 2000 | 0.5879 | 1.2263 | 0.4794 | 1.0056 | 0.4767 | 1 | 1 | 1 | 0.4767 | 0.4767 | 1 | 1 | 0.7943 | 0.6002 | 0.4767 | 0.4767 | |
| 64 | 4 | 2000 | 0.9271 | 1.0934 | 0.848 | 1.0056 | 0.8432 | 1 | 1 | 1 | 0.8432 | 0.8432 | 1 | 1 | 1 | 0.8432 | 0.8432 | 0.8432 | |
| 65 | 5 | 2000 | 1.3652 | 1.3576 | 1.0056 | 1.0056 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 66 | 6 | 2000 | 0.5957 | 0.9438 | 0.6311 | 1.0056 | 0.6276 | 1 | 1 | 0.9396 | 0.668 | 0.6276 | 1 | 1 | 1 | 0.6276 | 0.6276 | 0.6276 | |
| 67 | 1 | 2001 | 0.7792 | 1.0791 | 0.7221 | 0.9103 | 0.7932 | 1 | 1 | 1 | 0.7932 | 0.7932 | 1 | 1 | 1 | 0.7932 | 0.7932 | 0.7932 | |
| 68 | 2 | 2001 | 0.6696 | 0.9516 | 0.7037 | 0.9103 | 0.773 | 1 | 1 | 1 | 0.773 | 0.773 | 1 | 1 | 1 | 0.773 | 0.773 | 0.773 | |
| 69 | 3 | 2001 | 0.6267 | 1.2867 | 0.4871 | 0.9103 | 0.5351 | 1 | 1 | 1 | 0.5351 | 0.5351 | 1 | 1 | 0.7591 | 0.7049 | 0.5351 | 0.5351 | |
| 70 | 4 | 2001 | 0.9457 | 1.1196 | 0.8446 | 0.9103 | 0.9279 | 1 | 1 | 1 | 0.9279 | 0.9279 | 1 | 1 | 1 | 0.9279 | 0.9279 | 0.9279 | |
| 71 | 5 | 2001 | 1.2974 | 1.4253 | 0.9103 | 0.9103 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 72 | 6 | 2001 | 0.5583 | 1.0095 | 0.5531 | 0.9103 | 0.6076 | 1 | 1 | 1 | 0.6076 | 0.6076 | 1 | 1 | 1 | 0.6076 | 0.6076 | 0.6076 | |
| 73 | 1 | 2002 | 0.7686 | 1.1106 | 0.6921 | 0.9232 | 0.7496 | 1 | 1 | 1 | 0.7496 | 0.7496 | 1 | 1 | 0.954 | 0.7858 | 0.7496 | 0.7496 | |
| 74 | 2 | 2002 | 0.7058 | 0.9753 | 0.7237 | 0.9232 | 0.7839 | 1 | 1 | 1 | 0.7839 | 0.7839 | 1 | 1 | 1 | 0.7839 | 0.7839 | 0.7839 | |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 75 | 3 | 2002 | 0.6403 | 1.4318 | 0.4472 | 0.9232 | 0.4844 | 1 | 1 | 1 | 0.4844 | 0.4844 | 1 | 1 | 0.7662 | 0.6323 | 0.4844 | 0.4844 | |
| 76 | 4 | 2002 | 0.9545 | 1.2245 | 0.7794 | 0.9232 | 0.8443 | 1 | 1 | 1 | 0.8443 | 0.8443 | 1 | 1 | 1 | 0.8443 | 0.8443 | 0.8443 | |
| 77 | 5 | 2002 | 1.4091 | 1.5263 | 0.9232 | 0.9232 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 78 | 6 | 2002 | 0.6384 | 0.9992 | 0.6389 | 0.9232 | 0.6921 | 1 | 1 | 1 | 0.6921 | 0.6921 | 1 | 1 | 1 | 0.6921 | 0.6921 | 0.6921 | |
| 79 | 1 | 2003 | 0.7174 | 1.0887 | 0.659 | 0.7501 | 0.8785 | 1 | 1 | 1 | 0.8785 | 0.8785 | 1 | 1 | 0.9812 | 0.8954 | 0.8785 | 0.8785 | |
| 80 | 2 | 2003 | 0.6538 | 0.9546 | 0.6849 | 0.7501 | 0.913 | 1 | 1 | 1 | 0.913 | 0.913 | 1 | 1 | 1 | 0.913 | 0.913 | 0.913 | |
| 81 | 3 | 2003 | 0.6869 | 1.3226 | 0.5194 | 0.7501 | 0.6924 | 1 | 1 | 1 | 0.6924 | 0.6924 | 1 | 1 | 1 | 0.6924 | 0.6924 | 0.6924 | |
| 82 | 4 | 2003 | 0.9484 | 1.3512 | 0.7019 | 0.7501 | 0.9357 | 1 | 1 | 1 | 0.9357 | 0.9357 | 1 | 1 | 1 | 0.9357 | 0.9357 | 0.9357 | |
| 83 | 5 | 2003 | 1.1637 | 1.5514 | 0.7501 | 0.7501 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 84 | 6 | 2003 | 0.658 | 1.0859 | 0.6059 | 0.7501 | 0.8078 | 1 | 1 | 1 | 0.8078 | 0.8078 | 1 | 1 | 1 | 0.8078 | 0.8078 | 0.8078 | |
| 85 | 1 | 2004 | 0.5704 | 1.1326 | 0.5036 | 0.9292 | 0.542 | 1 | 1 | 1 | 0.542 | 0.542 | 1 | 1 | 0.8879 | 0.6104 | 0.542 | 0.542 | |
| 86 | 2 | 2004 | 0.6124 | 0.9341 | 0.6556 | 0.9292 | 0.7055 | 1 | 1 | 1 | 0.7055 | 0.7055 | 1 | 1 | 1 | 0.7055 | 0.7055 | 0.7055 | |
| 87 | 3 | 2004 | 0.6619 | 1.3706 | 0.4829 | 0.9292 | 0.5197 | 1 | 1 | 1 | 0.5197 | 0.5197 | 1 | 1 | 0.8629 | 0.6023 | 0.5197 | 0.5197 | |
| 88 | 4 | 2004 | 0.8905 | 1.2765 | 0.6976 | 0.9292 | 0.7507 | 1 | 1 | 1 | 0.7507 | 0.7507 | 1 | 1 | 1 | 0.7507 | 0.7507 | 0.7507 | |
| 89 | 5 | 2004 | 1.4828 | 1.5958 | 0.9292 | 0.9292 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 90 | 6 | 2004 | 0.5986 | 1.0079 | 0.5939 | 0.9292 | 0.6391 | 1 | 1 | 1 | 0.6391 | 0.6391 | 1 | 1 | 1 | 0.6391 | 0.6391 | 0.6391 | |
| 91 | 1 | 2005 | 0.6998 | 1.0941 | 0.6396 | 0.9004 | 0.7103 | 1 | 1 | 1 | 0.7103 | 0.7103 | 1 | 1 | 1 | 0.7103 | 0.7103 | 0.7103 | |
| 92 | 2 | 2005 | 0.6398 | 0.9408 | 0.68 | 0.9004 | 0.7552 | 1 | 1 | 1 | 0.7552 | 0.7552 | 1 | 1 | 1 | 0.7552 | 0.7552 | 0.7552 | |
| 93 | 3 | 2005 | 0.651 | 1.3055 | 0.4987 | 0.9004 | 0.5538 | 1 | 1 | 1 | 0.5538 | 0.5538 | 1 | 1 | 0.8818 | 0.6281 | 0.5538 | 0.5538 | |
| 94 | 4 | 2005 | 0.8352 | 1.1789 | 0.7085 | 0.9004 | 0.7868 | 1 | 1 | 1 | 0.7868 | 0.7868 | 1 | 1 | 1 | 0.7868 | 0.7868 | 0.7868 | |
| 95 | 5 | 2005 | 1.4063 | 1.5618 | 0.9004 | 0.9004 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 96 | 6 | 2005 | 0.7786 | 1.0843 | 0.7181 | 0.9004 | 0.7975 | 1 | 1 | 1 | 0.7975 | 0.7975 | 1 | 1 | 1 | 0.7975 | 0.7975 | 0.7975 | |
| 97 | 1 | 2006 | 0.7992 | 1.1745 | 0.6805 | 1.0089 | 0.6745 | 1 | 1 | 1 | 0.6745 | 0.6745 | 1 | 1 | 1 | 0.6745 | 0.6745 | 0.6745 | |
| 98 | 2 | 2006 | 0.7825 | 1.0584 | 0.7393 | 1.0089 | 0.7328 | 1 | 1 | 1 | 0.7328 | 0.7328 | 1 | 1 | 1 | 0.7328 | 0.7328 | 0.7328 | |
| 99 | 3 | 2006 | 0.7045 | 1.3993 | 0.5035 | 1.0089 | 0.4991 | 1 | 1 | 1 | 0.4991 | 0.4991 | 1 | 1 | 0.8428 | 0.5921 | 0.4991 | 0.4991 | |
| 100 | 4 | 2006 | 1.0348 | 1.2427 | 0.8327 | 1.0089 | 0.8253 | 1 | 1 | 1 | 0.8253 | 0.8253 | 1 | 1 | 1 | 0.8253 | 0.8253 | 0.8253 | |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 101 | 5 | 2006 | 1.5929 | 1.5788 | 1.0089 | 1.0089 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 102 | 6 | 2006 | 0.8516 | 1.2176 | 0.6993 | 1.0089 | 0.6932 | 1 | 1 | 1 | 0.6932 | 0.6932 | 1 | 1 | 1 | 0.6932 | 0.6932 | 0.6932 | |
| 103 | 1 | 2007 | 0.9162 | 1.2261 | 0.7473 | 1.1206 | 0.6669 | 1 | 1 | 1 | 0.6669 | 0.6669 | 1 | 1 | 1 | 0.6669 | 0.6669 | 0.6669 | |
| 104 | 2 | 2007 | 0.713 | 0.9629 | 0.7405 | 1.1206 | 0.6608 | 1 | 1 | 1 | 0.6608 | 0.6608 | 1 | 1 | 1 | 0.6608 | 0.6608 | 0.6608 | |
| 105 | 3 | 2007 | 0.7173 | 1.324 | 0.5418 | 1.1206 | 0.4835 | 1 | 1 | 1 | 0.4835 | 0.4835 | 1 | 1 | 0.8751 | 0.5525 | 0.4835 | 0.4835 | |
| 106 | 4 | 2007 | 0.9342 | 1.1979 | 0.7799 | 1.1206 | 0.696 | 1 | 1 | 1 | 0.696 | 0.696 | 1 | 1 | 0.9672 | 0.7196 | 0.696 | 0.696 | |
| 107 | 5 | 2007 | 1.923 | 1.7161 | 1.1206 | 1.1206 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 108 | 6 | 2007 | 0.989 | 1.1325 | 0.8733 | 1.1206 | 0.7793 | 1 | 1 | 1 | 0.7793 | 0.7793 | 1 | 1 | 1 | 0.7793 | 0.7793 | 0.7793 | |
| 109 | 1 | 2008 | 0.7941 | 1.1328 | 0.701 | 0.9926 | 0.7063 | 1 | 1 | 1 | 0.7063 | 0.7063 | 1 | 1 | 1 | 0.7063 | 0.7063 | 0.7063 | |
| 110 | 2 | 2008 | 0.7868 | 0.9549 | 0.8239 | 0.9926 | 0.8301 | 1 | 1 | 1 | 0.8301 | 0.8301 | 1 | 1 | 1 | 0.8301 | 0.8301 | 0.8301 | |
| 111 | 3 | 2008 | 0.6585 | 1.2685 | 0.5191 | 0.9926 | 0.523 | 1 | 1 | 1 | 0.523 | 0.523 | 1 | 1 | 0.8591 | 0.6088 | 0.523 | 0.523 | |
| 112 | 4 | 2008 | 0.9251 | 1.1217 | 0.8248 | 0.9926 | 0.8309 | 1 | 1 | 1 | 0.8309 | 0.8309 | 1 | 1 | 0.9862 | 0.8425 | 0.8309 | 0.8309 | |
| 113 | 5 | 2008 | 1.5058 | 1.5171 | 0.9926 | 0.9926 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 114 | 6 | 2008 | 0.7794 | 1.0632 | 0.733 | 0.9926 | 0.7385 | 1 | 1 | 1 | 0.7385 | 0.7385 | 1 | 1 | 1 | 0.7385 | 0.7385 | 0.7385 | |
| 115 | 1 | 2009 | 0.7951 | 1.0587 | 0.751 | 1.024 | 0.7333 | 1 | 1 | 1 | 0.7333 | 0.7333 | 1 | 1 | 1 | 0.7333 | 0.7333 | 0.7333 | |
| 116 | 2 | 2009 | 0.6466 | 0.8974 | 0.7205 | 1.024 | 0.7036 | 1 | 1 | 1 | 0.7036 | 0.7036 | 1 | 1 | 1 | 0.7036 | 0.7036 | 0.7036 | |
| 117 | 3 | 2009 | 0.6361 | 1.253 | 0.5076 | 1.024 | 0.4957 | 1 | 1 | 1 | 0.4957 | 0.4957 | 1 | 1 | 0.8092 | 0.6126 | 0.4957 | 0.4957 | |
| 118 | 4 | 2009 | 0.9024 | 1.0583 | 0.8527 | 1.024 | 0.8327 | 1 | 1 | 1 | 0.8327 | 0.8327 | 1 | 1 | 1 | 0.8327 | 0.8327 | 0.8327 | |
| 119 | 5 | 2009 | 1.4793 | 1.4446 | 1.024 | 1.024 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 120 | 6 | 2009 | 0.7556 | 0.9766 | 0.7737 | 1.024 | 0.7556 | 1 | 1 | 1 | 0.7556 | 0.7556 | 1 | 1 | 1 | 0.7556 | 0.7556 | 0.7556 | |
| 121 | 1 | 2010 | 0.8031 | 1.1033 | 0.7279 | 0.8922 | 0.8159 | 1 | 1 | 1 | 0.8159 | 0.8159 | 1 | 1 | 0.9906 | 0.8236 | 0.8159 | 0.8159 | |
| 122 | 2 | 2010 | 0.589 | 0.8972 | 0.6565 | 0.8922 | 0.7359 | 1 | 1 | 1 | 0.7359 | 0.7359 | 1 | 1 | 1 | 0.7359 | 0.7359 | 0.7359 | |
| 123 | 3 | 2010 | 0.671 | 1.3053 | 0.5141 | 0.8922 | 0.5762 | 1 | 1 | 1 | 0.5762 | 0.5762 | 1 | 1 | 0.8645 | 0.6666 | 0.5762 | 0.5762 | |
| 124 | 4 | 2010 | 1.0346 | 1.1597 | 0.8922 | 0.8922 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 125 | 5 | 2010 | 1.4295 | 1.611 | 0.8873 | 0.8922 | 0.9946 | 1 | 1 | 1 | 0.9946 | 0.9946 | 1 | 1 | 1 | 0.9946 | 0.9946 | 0.9946 | |
| 126 | 6 | 2010 | 0.6477 | 1.0434 | 0.6208 | 0.8922 | 0.6959 | 1 | 1 | 1 | 0.6959 | 0.6959 | 1 | 1 | 1 | 0.6959 | 0.6959 | 0.6959 | |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 127 | 1 | 2011 | 0.751 | 1.0339 | 0.7264 | 0.9688 | 0.7497 | 1 | 1 | 1 | 0.7497 | 0.7497 | 1 | 1 | 1 | 0.7497 | 0.7497 | 0.7497 | |
| 128 | 2 | 2011 | 0.6764 | 0.9334 | 0.7247 | 0.9688 | 0.748 | 1 | 1 | 1 | 0.748 | 0.748 | 1 | 1 | 1 | 0.748 | 0.748 | 0.748 | |
| 129 | 3 | 2011 | 0.6747 | 1.1878 | 0.568 | 0.9688 | 0.5863 | 1 | 1 | 1 | 0.5863 | 0.5863 | 1 | 1 | 1 | 0.5863 | 0.5863 | 0.5863 | |
| 130 | 4 | 2011 | 1.0247 | 1.1918 | 0.8598 | 0.9688 | 0.8875 | 1 | 1 | 1 | 0.8875 | 0.8875 | 1 | 1 | 1 | 0.8875 | 0.8875 | 0.8875 | |
| 131 | 5 | 2011 | 1.4646 | 1.5117 | 0.9688 | 0.9688 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | max |
| 132 | 6 | 2011 | 0.6494 | 1.0733 | 0.6051 | 0.9688 | 0.6245 | 1 | 1 | 0.9518 | 0.6562 | 0.6245 | 1 | 1 | 1 | 0.6245 | 0.6245 | 0.6245 | |

Note: State 1=NSW; 2=VIC; 3=QLD, 4=SA; 5=WA and 6=TAS

**Table A.3.3: Indexes of changes in productivity components**

| Fare-Primont Indexes Comparing Observation i to Observation 1 | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| obs | State | Period | dQ | dX | dTFP | dTech | dTFPE | dOTE | dOSE | dOME | dROSE | dOSME | dITE | dISE | dIME | dRISE | dISME | dRME |
| 1 | 1 | 1990 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 2 | 2 | 1990 | 0.7781 | 0.9382 | 0.8293 | 1 | 0.8293 | 1 | 1 | 1 | 0.8293 | 0.8293 | 1 | 1 | 1 | 0.8293 | 0.8293 | 0.8293 |
| 3 | 3 | 1990 | 0.7339 | 1.1742 | 0.625 | 1 | 0.625 | 1 | 1 | 1 | 0.625 | 0.625 | 1 | 1 | 0.9071 | 0.689 | 0.625 | 0.625 |
| 4 | 4 | 1990 | 1.0446 | 1.1293 | 0.925 | 1 | 0.925 | 1 | 1 | 1 | 0.925 | 0.925 | 1 | 1 | 1 | 0.925 | 0.925 | 0.925 |
| 5 | 5 | 1990 | 1.3956 | 1.2856 | 1.0855 | 1 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 6 | 6 | 1990 | 0.8548 | 1.0782 | 0.7928 | 1 | 0.7928 | 1 | 1 | 1 | 0.7928 | 0.7928 | 1 | 1 | 0.9345 | 0.8484 | 0.7928 | 0.7928 |
| 7 | 1 | 1991 | 0.8535 | 0.9645 | 0.885 | 1.024 | 0.8642 | 1 | 1 | 1 | 0.8642 | 0.8642 | 1 | 1 | 1 | 0.8642 | 0.8642 | 0.8642 |
| 8 | 2 | 1991 | 0.6247 | 0.8611 | 0.7255 | 1.024 | 0.7085 | 1 | 1 | 1 | 0.7085 | 0.7085 | 1 | 1 | 1 | 0.7085 | 0.7085 | 0.7085 |
| 9 | 3 | 1991 | 0.8249 | 1.1678 | 0.7064 | 1.024 | 0.6899 | 1 | 1 | 1 | 0.6899 | 0.6899 | 1 | 1 | 1 | 0.6899 | 0.6899 | 0.6899 |
| 10 | 4 | 1991 | 0.9632 | 1.0127 | 0.9511 | 1.024 | 0.9288 | 1 | 1 | 1 | 0.9288 | 0.9288 | 1 | 1 | 1 | 0.9288 | 0.9288 | 0.9288 |
| 11 | 5 | 1991 | 1.317 | 1.1848 | 1.1116 | 1.024 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 12 | 6 | 1991 | 0.808 | 1.0638 | 0.7596 | 1.024 | 0.7418 | 1 | 1 | 1 | 0.7418 | 0.7418 | 1 | 1 | 0.9055 | 0.8193 | 0.7418 | 0.7418 |
| 13 | 1 | 1992 | 0.9392 | 0.9795 | 0.9589 | 1.0332 | 0.9281 | 1 | 1 | 1 | 0.9281 | 0.9281 | 1 | 1 | 1 | 0.9281 | 0.9281 | 0.9281 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 14 | 2 | 1992 | 0.5546 | 0.793 | 0.6994 | 1.0332 | 0.6769 | 1 | 1 | 1 | 0.6769 | 0.6769 | 1 | 1 | 1 | 0.6769 | 0.6769 | 0.6769 |
| 15 | 3 | 1992 | 0.7953 | 1.088 | 0.731 | 1.0332 | 0.7075 | 1 | 1 | 1 | 0.7075 | 0.7075 | 1 | 1 | 0.8895 | 0.7954 | 0.7075 | 0.7075 |
| 16 | 4 | 1992 | 1.0511 | 1.0397 | 1.011 | 1.0332 | 0.9785 | 1 | 1 | 1 | 0.9785 | 0.9785 | 1 | 1 | 1 | 0.9785 | 0.9785 | 0.9785 |
| 17 | 5 | 1992 | 1.3286 | 1.1846 | 1.1216 | 1.0332 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 18 | 6 | 1992 | 0.7535 | 1.0423 | 0.7229 | 1.0332 | 0.6997 | 1 | 1 | 1 | 0.6997 | 0.6997 | 1 | 1 | 0.918 | 0.7622 | 0.6997 | 0.6997 |
| 19 | 1 | 1993 | 0.9194 | 0.9143 | 1.0056 | 1.1671 | 0.8616 | 1 | 1 | 1 | 0.8616 | 0.8616 | 1 | 1 | 0.9885 | 0.8716 | 0.8616 | 0.8616 |
| 20 | 2 | 1993 | 0.6618 | 0.7674 | 0.8625 | 1.1671 | 0.739 | 1 | 1 | 1 | 0.739 | 0.739 | 1 | 1 | 1 | 0.739 | 0.739 | 0.739 |
| 21 | 3 | 1993 | 0.8518 | 1.0453 | 0.8149 | 1.1671 | 0.6982 | 1 | 1 | 1 | 0.6982 | 0.6982 | 1 | 1 | 0.8713 | 0.8014 | 0.6982 | 0.6982 |
| 22 | 4 | 1993 | 1.2161 | 0.9803 | 1.2405 | 1.1671 | 1.0629 | 1 | 1 | 1 | 1.0629 | 1.0629 | 1 | 1 | 1 | 1.0629 | 1.0629 | 1.0629 |
| 23 | 5 | 1993 | 1.5043 | 1.1874 | 1.2669 | 1.1671 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 24 | 6 | 1993 | 0.8475 | 0.9745 | 0.8697 | 1.1671 | 0.7452 | 1 | 1 | 1 | 0.7452 | 0.7452 | 1 | 1 | 0.9183 | 0.8115 | 0.7452 | 0.7452 |
| 25 | 1 | 1994 | 0.9708 | 0.9192 | 1.0562 | 1.4641 | 0.7214 | 1 | 1 | 1 | 0.7214 | 0.7214 | 1 | 1 | 0.9973 | 0.7234 | 0.7214 | 0.7214 |
| 26 | 2 | 1994 | 0.6762 | 0.8048 | 0.8402 | 1.4641 | 0.5739 | 1 | 1 | 1 | 0.5739 | 0.5739 | 1 | 1 | 1 | 0.5739 | 0.5739 | 0.5739 |
| 27 | 3 | 1994 | 0.8899 | 1.0151 | 0.8767 | 1.4641 | 0.5988 | 1 | 1 | 1 | 0.5988 | 0.5988 | 1 | 1 | 1 | 0.5988 | 0.5988 | 0.5988 |
| 28 | 4 | 1994 | 1.1963 | 0.9362 | 1.2779 | 1.4641 | 0.8729 | 1 | 1 | 1 | 0.8729 | 0.8729 | 1 | 1 | 1 | 0.8729 | 0.8729 | 0.8729 |
| 29 | 5 | 1994 | 1.9434 | 1.2228 | 1.5893 | 1.4641 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 30 | 6 | 1994 | 0.8397 | 0.9012 | 0.9317 | 1.4641 | 0.6364 | 1 | 1 | 1 | 0.6364 | 0.6364 | 1 | 1 | 1 | 0.6364 | 0.6364 | 0.6364 |
| 31 | 1 | 1995 | 0.8963 | 0.9136 | 0.9811 | 1.2649 | 0.7756 | 1 | 1 | 1 | 0.7756 | 0.7756 | 1 | 1 | 0.9615 | 0.8067 | 0.7756 | 0.7756 |
| 32 | 2 | 1995 | 0.7015 | 0.7678 | 0.9136 | 1.2649 | 0.7222 | 1 | 1 | 1 | 0.7222 | 0.7222 | 1 | 1 | 1 | 0.7222 | 0.7222 | 0.7222 |
| 33 | 3 | 1995 | 0.8587 | 0.9935 | 0.8643 | 1.2649 | 0.6833 | 1 | 1 | 1 | 0.6833 | 0.6833 | 1 | 1 | 1 | 0.6833 | 0.6833 | 0.6833 |
| 34 | 4 | 1995 | 1.0857 | 0.8707 | 1.247 | 1.2649 | 0.9858 | 1 | 1 | 1 | 0.9858 | 0.9858 | 1 | 1 | 1 | 0.9858 | 0.9858 | 0.9858 |
| 35 | 5 | 1995 | 1.7104 | 1.2456 | 1.3731 | 1.2649 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 36 | 6 | 1995 | 1.0517 | 1.0455 | 1.006 | 1.2649 | 0.7953 | 1 | 1 | 1 | 0.7953 | 0.7953 | 1 | 1 | 0.8762 | 0.9077 | 0.7953 | 0.7953 |
| 37 | 1 | 1996 | 1.0254 | 0.9818 | 1.0445 | 1.5005 | 0.6961 | 1 | 1 | 1 | 0.6961 | 0.6961 | 1 | 1 | 1 | 0.6961 | 0.6961 | 0.6961 |
| 38 | 2 | 1996 | 0.7232 | 0.8319 | 0.8694 | 1.5005 | 0.5794 | 1 | 1 | 1 | 0.5794 | 0.5794 | 1 | 1 | 1 | 0.5794 | 0.5794 | 0.5794 |
| 39 | 3 | 1996 | 0.7933 | 1.0854 | 0.7309 | 1.5005 | 0.4871 | 1 | 1 | 1 | 0.4871 | 0.4871 | 1 | 1 | 0.8406 | 0.5795 | 0.4871 | 0.4871 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 40 | 4 | 1996 | 1.1847 | 0.9169 | 1.2921 | 1.5005 | 0.8612 | 1 | 1 | 1 | 0.8612 | 0.8612 | 1 | 1 | 1 | 0.8612 | 0.8612 | 0.8612 |
| 41 | 5 | 1996 | 1.9606 | 1.2037 | 1.6288 | 1.5005 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 42 | 6 | 1996 | 1.1001 | 1.0198 | 1.0787 | 1.5005 | 0.7189 | 1 | 1 | 1 | 0.7189 | 0.7189 | 1 | 1 | 0.9426 | 0.7627 | 0.7189 | 0.7189 |
| 43 | 1 | 1997 | 0.9772 | 0.9321 | 1.0483 | 1.6172 | 0.6483 | 1 | 1 | 1 | 0.6483 | 0.6483 | 1 | 1 | 1 | 0.6483 | 0.6483 | 0.6483 |
| 44 | 2 | 1997 | 0.8654 | 0.849 | 1.0193 | 1.6172 | 0.6303 | 1 | 1 | 1 | 0.6303 | 0.6303 | 1 | 1 | 1 | 0.6303 | 0.6303 | 0.6303 |
| 45 | 3 | 1997 | 0.8439 | 1.0346 | 0.8156 | 1.6172 | 0.5044 | 1 | 1 | 1 | 0.5044 | 0.5044 | 1 | 1 | 0.909 | 0.5549 | 0.5044 | 0.5044 |
| 46 | 4 | 1997 | 1.0869 | 0.9625 | 1.1292 | 1.6172 | 0.6983 | 1 | 1 | 1 | 0.6983 | 0.6983 | 1 | 1 | 1 | 0.6983 | 0.6983 | 0.6983 |
| 47 | 5 | 1997 | 2.2744 | 1.2956 | 1.7555 | 1.6172 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 48 | 6 | 1997 | 1.1981 | 1.1895 | 1.0072 | 1.6172 | 0.6228 | 1 | 1 | 1 | 0.6228 | 0.6228 | 1 | 1 | 1 | 0.6228 | 0.6228 | 0.6228 |
| 49 | 1 | 1998 | 1.0836 | 0.9941 | 1.09 | 1.5621 | 0.6978 | 1 | 1 | 0.9416 | 0.7411 | 0.6978 | 1 | 1 | 0.9427 | 0.7402 | 0.6978 | 0.6978 |
| 50 | 2 | 1998 | 1.0898 | 0.8409 | 1.296 | 1.5621 | 0.8296 | 1 | 1 | 1 | 0.8296 | 0.8296 | 1 | 1 | 1 | 0.8296 | 0.8296 | 0.8296 |
| 51 | 3 | 1998 | 0.8017 | 1.0931 | 0.7334 | 1.5621 | 0.4695 | 1 | 1 | 1 | 0.4695 | 0.4695 | 1 | 1 | 0.8496 | 0.5526 | 0.4695 | 0.4695 |
| 52 | 4 | 1998 | 1.3688 | 1.0631 | 1.2875 | 1.5621 | 0.8242 | 1 | 1 | 1 | 0.8242 | 0.8242 | 1 | 1 | 0.961 | 0.8577 | 0.8242 | 0.8242 |
| 53 | 5 | 1998 | 2.1372 | 1.2604 | 1.6957 | 1.5621 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 54 | 6 | 1998 | 0.9625 | 1.0448 | 0.9213 | 1.5621 | 0.5898 | 1 | 1 | 0.8606 | 0.6853 | 0.5898 | 1 | 1 | 0.9921 | 0.5945 | 0.5898 | 0.5898 |
| 55 | 1 | 1999 | 0.9565 | 0.9643 | 0.992 | 1.4349 | 0.6913 | 1 | 1 | 0.9478 | 0.7294 | 0.6913 | 1 | 1 | 0.9775 | 0.7072 | 0.6913 | 0.6913 |
| 56 | 2 | 1999 | 0.8978 | 0.8563 | 1.0484 | 1.4349 | 0.7307 | 1 | 1 | 1 | 0.7307 | 0.7307 | 1 | 1 | 1 | 0.7307 | 0.7307 | 0.7307 |
| 57 | 3 | 1999 | 0.9176 | 1.1132 | 0.8243 | 1.4349 | 0.5745 | 1 | 1 | 1 | 0.5745 | 0.5745 | 1 | 1 | 0.877 | 0.655 | 0.5745 | 0.5745 |
| 58 | 4 | 1999 | 1.1017 | 1.0067 | 1.0944 | 1.4349 | 0.7627 | 1 | 1 | 1 | 0.7627 | 0.7627 | 1 | 1 | 1 | 0.7627 | 0.7627 | 0.7627 |
| 59 | 5 | 1999 | 2.1127 | 1.3564 | 1.5576 | 1.4349 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 60 | 6 | 1999 | 0.87 | 1.0128 | 0.859 | 1.4349 | 0.5986 | 1 | 1 | 0.9461 | 0.6327 | 0.5986 | 1 | 1 | 1 | 0.5986 | 0.5986 | 0.5986 |
| 61 | 1 | 2000 | 0.9941 | 0.9572 | 1.0385 | 1.459 | 0.7118 | 1 | 1 | 0.9844 | 0.7231 | 0.7118 | 1 | 1 | 0.9596 | 0.7418 | 0.7118 | 0.7118 |
| 62 | 2 | 2000 | 0.865 | 0.8171 | 1.0587 | 1.459 | 0.7256 | 1 | 1 | 1 | 0.7256 | 0.7256 | 1 | 1 | 1 | 0.7256 | 0.7256 | 0.7256 |
| 63 | 3 | 2000 | 0.8329 | 1.1031 | 0.755 | 1.459 | 0.5175 | 1 | 1 | 1 | 0.5175 | 0.5175 | 1 | 1 | 0.7943 | 0.6515 | 0.5175 | 0.5175 |
| 64 | 4 | 2000 | 1.3135 | 0.9835 | 1.3355 | 1.459 | 0.9154 | 1 | 1 | 1 | 0.9154 | 0.9154 | 1 | 1 | 1 | 0.9154 | 0.9154 | 0.9154 |
| 65 | 5 | 2000 | 1.9342 | 1.2212 | 1.5838 | 1.459 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 66 | 6 | 2000 | 0.8439 | 0.849 | 0.994 | 1.459 | 0.6813 | 1 | 1 | 0.9396 | 0.7251 | 0.6813 | 1 | 1 | 1 | 0.6813 | 0.6813 | 0.6813 |
| 67 | 1 | 2001 | 1.1039 | 0.9707 | 1.1373 | 1.3207 | 0.8611 | 1 | 1 | 1 | 0.8611 | 0.8611 | 1 | 1 | 1 | 0.8611 | 0.8611 | 0.8611 |
| 68 | 2 | 2001 | 0.9487 | 0.856 | 1.1083 | 1.3207 | 0.8391 | 1 | 1 | 1 | 0.8391 | 0.8391 | 1 | 1 | 1 | 0.8391 | 0.8391 | 0.8391 |
| 69 | 3 | 2001 | 0.8879 | 1.1575 | 0.7671 | 1.3207 | 0.5809 | 1 | 1 | 1 | 0.5809 | 0.5809 | 1 | 1 | 0.7591 | 0.7652 | 0.5809 | 0.5809 |
| 70 | 4 | 2001 | 1.3398 | 1.0072 | 1.3303 | 1.3207 | 1.0073 | 1 | 1 | 1 | 1.0073 | 1.0073 | 1 | 1 | 1 | 1.0073 | 1.0073 | 1.0073 |
| 71 | 5 | 2001 | 1.8381 | 1.2821 | 1.4337 | 1.3207 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 72 | 6 | 2001 | 0.791 | 0.9081 | 0.8711 | 1.3207 | 0.6596 | 1 | 1 | 1 | 0.6596 | 0.6596 | 1 | 1 | 1 | 0.6596 | 0.6596 | 0.6596 |
| 73 | 1 | 2002 | 1.0889 | 0.999 | 1.09 | 1.3395 | 0.8138 | 1 | 1 | 1 | 0.8138 | 0.8138 | 1 | 1 | 0.954 | 0.853 | 0.8138 | 0.8138 |
| 74 | 2 | 2002 | 1 | 0.8773 | 1.1398 | 1.3395 | 0.8509 | 1 | 1 | 1 | 0.8509 | 0.8509 | 1 | 1 | 1 | 0.8509 | 0.8509 | 0.8509 |
| 75 | 3 | 2002 | 0.9072 | 1.288 | 0.7044 | 1.3395 | 0.5259 | 1 | 1 | 1 | 0.5259 | 0.5259 | 1 | 1 | 0.7662 | 0.6864 | 0.5259 | 0.5259 |
| 76 | 4 | 2002 | 1.3523 | 1.1015 | 1.2276 | 1.3395 | 0.9165 | 1 | 1 | 1 | 0.9165 | 0.9165 | 1 | 1 | 1 | 0.9165 | 0.9165 | 0.9165 |
| 77 | 5 | 2002 | 1.9964 | 1.373 | 1.454 | 1.3395 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 78 | 6 | 2002 | 0.9045 | 0.8988 | 1.0063 | 1.3395 | 0.7513 | 1 | 1 | 1 | 0.7513 | 0.7513 | 1 | 1 | 1 | 0.7513 | 0.7513 | 0.7513 |
| 79 | 1 | 2003 | 1.0164 | 0.9793 | 1.0379 | 1.0884 | 0.9536 | 1 | 1 | 1 | 0.9536 | 0.9536 | 1 | 1 | 0.9812 | 0.9719 | 0.9536 | 0.9536 |
| 80 | 2 | 2003 | 0.9263 | 0.8587 | 1.0787 | 1.0884 | 0.9911 | 1 | 1 | 1 | 0.9911 | 0.9911 | 1 | 1 | 1 | 0.9911 | 0.9911 | 0.9911 |
| 81 | 3 | 2003 | 0.9732 | 1.1897 | 0.818 | 1.0884 | 0.7516 | 1 | 1 | 1 | 0.7516 | 0.7516 | 1 | 1 | 1 | 0.7516 | 0.7516 | 0.7516 |
| 82 | 4 | 2003 | 1.3437 | 1.2155 | 1.1055 | 1.0884 | 1.0157 | 1 | 1 | 1 | 1.0157 | 1.0157 | 1 | 1 | 1 | 1.0157 | 1.0157 | 1.0157 |
| 83 | 5 | 2003 | 1.6488 | 1.3955 | 1.1815 | 1.0884 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 84 | 6 | 2003 | 0.9322 | 0.9768 | 0.9543 | 1.0884 | 0.8769 | 1 | 1 | 1 | 0.8769 | 0.8769 | 1 | 1 | 1 | 0.8769 | 0.8769 | 0.8769 |
| 85 | 1 | 2004 | 0.8082 | 1.0188 | 0.7932 | 1.3482 | 0.5884 | 1 | 1 | 1 | 0.5884 | 0.5884 | 1 | 1 | 0.8879 | 0.6626 | 0.5884 | 0.5884 |
| 86 | 2 | 2004 | 0.8676 | 0.8402 | 1.0325 | 1.3482 | 0.7659 | 1 | 1 | 1 | 0.7659 | 0.7659 | 1 | 1 | 1 | 0.7659 | 0.7659 | 0.7659 |
| 87 | 3 | 2004 | 0.9378 | 1.2329 | 0.7606 | 1.3482 | 0.5642 | 1 | 1 | 1 | 0.5642 | 0.5642 | 1 | 1 | 0.8629 | 0.6538 | 0.5642 | 0.5642 |
| 88 | 4 | 2004 | 1.2616 | 1.1483 | 1.0987 | 1.3482 | 0.8149 | 1 | 1 | 1 | 0.8149 | 0.8149 | 1 | 1 | 1 | 0.8149 | 0.8149 | 0.8149 |
| 89 | 5 | 2004 | 2.1008 | 1.4355 | 1.4635 | 1.3482 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 90 | 6 | 2004 | 0.8481 | 0.9067 | 0.9354 | 1.3482 | 0.6938 | 1 | 1 | 1 | 0.6938 | 0.6938 | 1 | 1 | 1 | 0.6938 | 0.6938 | 0.6938 |
| 91 | 1 | 2005 | 0.9914 | 0.9842 | 1.0074 | 1.3064 | 0.7711 | 1 | 1 | 1 | 0.7711 | 0.7711 | 1 | 1 | 1 | 0.7711 | 0.7711 | 0.7711 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 92 | 2 | 2005 | 0.9064 | 0.8463 | 1.071 | 1.3064 | 0.8198 | 1 | 1 | 1 | 0.8198 | 0.8198 | 1 | 1 | 1 | 0.8198 | 0.8198 | 0.8198 |
| 93 | 3 | 2005 | 0.9224 | 1.1743 | 0.7854 | 1.3064 | 0.6012 | 1 | 1 | 1 | 0.6012 | 0.6012 | 1 | 1 | 0.8818 | 0.6818 | 0.6012 | 0.6012 |
| 94 | 4 | 2005 | 1.1833 | 1.0604 | 1.1159 | 1.3064 | 0.8541 | 1 | 1 | 1 | 0.8541 | 0.8541 | 1 | 1 | 1 | 0.8541 | 0.8541 | 0.8541 |
| 95 | 5 | 2005 | 1.9924 | 1.4049 | 1.4182 | 1.3064 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 96 | 6 | 2005 | 1.1032 | 0.9754 | 1.131 | 1.3064 | 0.8657 | 1 | 1 | 1 | 0.8657 | 0.8657 | 1 | 1 | 1 | 0.8657 | 0.8657 | 0.8657 |
| 97 | 1 | 2006 | 1.1323 | 1.0565 | 1.0717 | 1.4638 | 0.7322 | 1 | 1 | 1 | 0.7322 | 0.7322 | 1 | 1 | 1 | 0.7322 | 0.7322 | 0.7322 |
| 98 | 2 | 2006 | 1.1086 | 0.9521 | 1.1644 | 1.4638 | 0.7955 | 1 | 1 | 1 | 0.7955 | 0.7955 | 1 | 1 | 1 | 0.7955 | 0.7955 | 0.7955 |
| 99 | 3 | 2006 | 0.9981 | 1.2587 | 0.793 | 1.4638 | 0.5417 | 1 | 1 | 1 | 0.5417 | 0.5417 | 1 | 1 | 0.8428 | 0.6428 | 0.5417 | 0.5417 |
| 100 | 4 | 2006 | 1.4661 | 1.1179 | 1.3115 | 1.4638 | 0.8959 | 1 | 1 | 1 | 0.8959 | 0.8959 | 1 | 1 | 1 | 0.8959 | 0.8959 | 0.8959 |
| 101 | 5 | 2006 | 2.2567 | 1.4202 | 1.589 | 1.4638 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 102 | 6 | 2006 | 1.2065 | 1.0953 | 1.1015 | 1.4638 | 0.7525 | 1 | 1 | 1 | 0.7525 | 0.7525 | 1 | 1 | 1 | 0.7525 | 0.7525 | 0.7525 |
| 103 | 1 | 2007 | 1.2981 | 1.1029 | 1.177 | 1.6258 | 0.7239 | 1 | 1 | 1 | 0.7239 | 0.7239 | 1 | 1 | 1 | 0.7239 | 0.7239 | 0.7239 |
| 104 | 2 | 2007 | 1.0102 | 0.8661 | 1.1663 | 1.6258 | 0.7174 | 1 | 1 | 1 | 0.7174 | 0.7174 | 1 | 1 | 1 | 0.7174 | 0.7174 | 0.7174 |
| 105 | 3 | 2007 | 1.0162 | 1.191 | 0.8533 | 1.6258 | 0.5248 | 1 | 1 | 1 | 0.5248 | 0.5248 | 1 | 1 | 0.8751 | 0.5997 | 0.5248 | 0.5248 |
| 106 | 4 | 2007 | 1.3236 | 1.0776 | 1.2283 | 1.6258 | 0.7555 | 1 | 1 | 1 | 0.7555 | 0.7555 | 1 | 1 | 0.9672 | 0.7811 | 0.7555 | 0.7555 |
| 107 | 5 | 2007 | 2.7245 | 1.5437 | 1.7649 | 1.6258 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 108 | 6 | 2007 | 1.4011 | 1.0187 | 1.3754 | 1.6258 | 0.846 | 1 | 1 | 1 | 0.846 | 0.846 | 1 | 1 | 1 | 0.846 | 0.846 | 0.846 |
| 109 | 1 | 2008 | 1.1251 | 1.019 | 1.1041 | 1.4401 | 0.7667 | 1 | 1 | 1 | 0.7667 | 0.7667 | 1 | 1 | 1 | 0.7667 | 0.7667 | 0.7667 |
| 110 | 2 | 2008 | 1.1147 | 0.859 | 1.2977 | 1.4401 | 0.9011 | 1 | 1 | 1 | 0.9011 | 0.9011 | 1 | 1 | 1 | 0.9011 | 0.9011 | 0.9011 |
| 111 | 3 | 2008 | 0.933 | 1.1411 | 0.8176 | 1.4401 | 0.5678 | 1 | 1 | 1 | 0.5678 | 0.5678 | 1 | 1 | 0.8591 | 0.6608 | 0.5678 | 0.5678 |
| 112 | 4 | 2008 | 1.3107 | 1.009 | 1.299 | 1.4401 | 0.902 | 1 | 1 | 1 | 0.902 | 0.902 | 1 | 1 | 0.9862 | 0.9146 | 0.902 | 0.902 |
| 113 | 5 | 2008 | 2.1334 | 1.3647 | 1.5633 | 1.4401 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 114 | 6 | 2008 | 1.1042 | 0.9564 | 1.1545 | 1.4401 | 0.8017 | 1 | 1 | 1 | 0.8017 | 0.8017 | 1 | 1 | 1 | 0.8017 | 0.8017 | 0.8017 |
| 115 | 1 | 2009 | 1.1264 | 0.9524 | 1.1828 | 1.4858 | 0.7961 | 1 | 1 | 1 | 0.7961 | 0.7961 | 1 | 1 | 1 | 0.7961 | 0.7961 | 0.7961 |
| 116 | 2 | 2009 | 0.9161 | 0.8073 | 1.1348 | 1.4858 | 0.7638 | 1 | 1 | 1 | 0.7638 | 0.7638 | 1 | 1 | 1 | 0.7638 | 0.7638 | 0.7638 |
| 117 | 3 | 2009 | 0.9012 | 1.1272 | 0.7995 | 1.4858 | 0.5381 | 1 | 1 | 1 | 0.5381 | 0.5381 | 1 | 1 | 0.8092 | 0.665 | 0.5381 | 0.5381 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 118 | 4 | 2009 | 1.2785 | 0.9519 | 1.343 | 1.4858 | 0.9039 | 1 | 1 | 1 | 0.9039 | 0.9039 | 1 | 1 | 1 | 0.9039 | 0.9039 | 0.9039 |
| 119 | 5 | 2009 | 2.0958 | 1.2995 | 1.6129 | 1.4858 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 120 | 6 | 2009 | 1.0706 | 0.8785 | 1.2186 | 1.4858 | 0.8202 | 1 | 1 | 1 | 0.8202 | 0.8202 | 1 | 1 | 1 | 0.8202 | 0.8202 | 0.8202 |
| 121 | 1 | 2010 | 1.1378 | 0.9925 | 1.1464 | 1.2944 | 0.8857 | 1 | 1 | 1 | 0.8857 | 0.8857 | 1 | 1 | 0.9906 | 0.8941 | 0.8857 | 0.8857 |
| 122 | 2 | 2010 | 0.8345 | 0.807 | 1.034 | 1.2944 | 0.7988 | 1 | 1 | 1 | 0.7988 | 0.7988 | 1 | 1 | 1 | 0.7988 | 0.7988 | 0.7988 |
| 123 | 3 | 2010 | 0.9506 | 1.1741 | 0.8096 | 1.2944 | 0.6255 | 1 | 1 | 1 | 0.6255 | 0.6255 | 1 | 1 | 0.8645 | 0.7236 | 0.6255 | 0.6255 |
| 124 | 4 | 2010 | 1.4658 | 1.0432 | 1.4051 | 1.2944 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 125 | 5 | 2010 | 2.0253 | 1.4492 | 1.3976 | 1.2944 | 1.0797 | 1 | 1 | 1 | 1.0797 | 1.0797 | 1 | 1 | 1 | 1.0797 | 1.0797 | 1.0797 |
| 126 | 6 | 2010 | 0.9177 | 0.9386 | 0.9778 | 1.2944 | 0.7554 | 1 | 1 | 1 | 0.7554 | 0.7554 | 1 | 1 | 1 | 0.7554 | 0.7554 | 0.7554 |
| 127 | 1 | 2011 | 1.064 | 0.93 | 1.144 | 1.4056 | 0.8139 | 1 | 1 | 1 | 0.8139 | 0.8139 | 1 | 1 | 1 | 0.8139 | 0.8139 | 0.8139 |
| 128 | 2 | 2011 | 0.9583 | 0.8397 | 1.1413 | 1.4056 | 0.812 | 1 | 1 | 1 | 0.812 | 0.812 | 1 | 1 | 1 | 0.812 | 0.812 | 0.812 |
| 129 | 3 | 2011 | 0.9559 | 1.0684 | 0.8947 | 1.4056 | 0.6365 | 1 | 1 | 1 | 0.6365 | 0.6365 | 1 | 1 | 1 | 0.6365 | 0.6365 | 0.6365 |
| 130 | 4 | 2011 | 1.4518 | 1.0721 | 1.3542 | 1.4056 | 0.9634 | 1 | 1 | 1 | 0.9634 | 0.9634 | 1 | 1 | 1 | 0.9634 | 0.9634 | 0.9634 |
| 131 | 5 | 2011 | 2.075 | 1.3599 | 1.5259 | 1.4056 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1 | 1 | 1 | 1.0855 | 1.0855 | 1.0855 |
| 132 | 6 | 2011 | 0.9201 | 0.9655 | 0.953 | 1.4056 | 0.678 | 1 | 1 | 0.9518 | 0.7123 | 0.678 | 1 | 1 | 1 | 0.678 | 0.678 | 0.678 |

Note: State 1=NSW; 2=VIC; 3=QLD, 4=SA; 5=WA and 6=TAS

# Appendix to Chapter Four

**Table A.4.1: Selection of the strongest R&D lag**

| Dependent variable: Logarithm of TFP | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Regressors | Model1 | Model2 | Model3 | Model4 | Model5 | Model6 | Model7 | Model8 | Model9 |
| $LnRD_{t-8}$ | 0.129*** | | | | | -0.007 | | | |
| | (0.038) | | | | | (0.080) | | | |
| $LnRD_{t-10}$ | | 0.121*** | | | | | -0.032 | | |
| | | (0.034) | | | | | (0.069) | | |
| $LnRD_{t-12}$ | | | 0.143*** | | | | | 0.006 | 0.127*** |
| | | | (0.033) | | | | | (0.069) | (0.032) |
| $LnRD_{t-15}$ | | | | 0.152*** | | 0.157** | | | |
| | | | | (0.034) | | (0.073) | | | |
| $LnRD_{t-24}$ | | | | | 0.211*** | | 0.239** | 0.205** | |
| | | | | | (0.051) | | (0.087) | (0.094) | |
| LnFRD | 0.408 | 0.424 | 0.311 | 0.164 | -0.676 | 0.167 | -0.739 | -0.667 | 0.243 |
| | (0.319) | (0.290) | (0.295) | (0.311) | (0.559) | (0.326) | (0.580) | (0.583) | (0.296) |
| LnEDU | -1.385 | -1.292 | -0.852 | -0.033 | -0.165 | -0.014 | -0.318 | -0.135 | -0.959 |
| | (1.002) | (0.916) | (0.894) | (1.074) | (1.485) | (1.078) | (1.389) | (1.404) | (0.894) |
| Constant | 6.991* | 6.581* | 5.413 | 2.799 | 9.994 | 2.713 | 11.320* | 9.758 | 6.329 |
| | (4.000) | (3.856) | (3.717) | (4.045) | (6.613) | (4.157) | (6.425) | (6.056) | (3.788) |
| Observations | 39 | 39 | 39 | 39 | 33 | 39 | 33 | 33 | 39 |
| R-squared | 0.815 | 0.813 | 0.829 | 0.821 | 0.782 | 0.829 | 0.784 | 0.782 | 0.811 |
| AIC | -70.317 | -69.916 | -73.508 | -73.345 | -64.336 | -71.351 | -62.544 | -62.344 | -71.495 |
| SBIC | -61.999 | -61.598 | -65.189 | -65.027 | -56.854 | -61.369 | -53.565 | -53.364 | -64.840 |
| Log likelihood | 40.158 | 39.958 | 41.754 | 41.672 | 37.168 | 41.675 | 37.271 | 37.172 | 39.747 |
| D-W | 1.820 | 1.858 | 1.913 | 1.983 | 1.938 | 1.983 | 1.902 | 1.946 | 1.982 |
| Ramsey RESET | 0.131 | 0.522 | 0.728 | 0.728 | 0.421 | 0.391 | 0.405 | 0.411 | 0.962 |

Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

**Table A.4.2: Vector Error Correction Model**

**Panel A:** lntfp lnrd(-12) lnfrd(-12) lnedu

| Error Correction: | D(LNTFP) | D(LNRD(-12)) | D(LNFRD(-12)) | D(LNEDU) |
|---|---|---|---|---|
| $ECT_{t-1}$ | -0.923683 | -0.000658 | 0.632472 | -0.003886 |
| | (0.19762) | (0.18561) | (0.36133) | (0.01821) |
| D(LNTFP(-1)) | 0.001114 | 0.019160 | -0.414791 | 0.006796 |
| | (0.15312) | (0.14381) | (0.27996) | (0.01411) |
| D(LNRD(-13)) | -0.134035 | 0.008523 | 0.143047 | -0.002577 |
| | (0.17817) | (0.16734) | (0.32576) | (0.01642) |
| D(LNFRD(-13)) | -0.094480 | 0.021029 | -0.455419 | -0.004135 |
| | (0.08011) | (0.07525) | (0.14648) | (0.00738) |
| D(LNEDU(-1)) | -0.698104 | 1.024408 | 1.024934 | 0.351202 |
| | (1.69180) | (1.58900) | (3.09323) | (0.15589) |
| C | 0.036015 | 0.087612 | 0.048715 | 0.000106 |
| | (0.02139) | (0.02009) | (0.03910) | (0.00197) |
| R-squared | 0.518323 | 0.014624 | 0.280823 | 0.132389 |
| Adj. R-squared | 0.453231 | -0.118535 | 0.183637 | 0.015145 |
| Sum sq. resids | 0.328001 | 0.289351 | 1.096481 | 0.002785 |
| S.E. equation | 0.094154 | 0.088432 | 0.172147 | 0.008676 |
| F-statistic | 7.962980 | 0.109820 | 2.889535 | 1.129172 |
| Log likelihood | 43.81831 | 46.51395 | 17.87117 | 146.3473 |
| Akaike AIC | -1.758991 | -1.884370 | -0.552147 | -6.527782 |
| Schwarz SC | -1.513242 | -1.638621 | -0.306399 | -6.282034 |
| Mean dependent | 0.020521 | 0.089075 | 0.037640 | -0.000325 |
| S.D. dependent | 0.127331 | 0.083615 | 0.190528 | 0.008742 |

**Panel B: lntfp lnrds_pim lnfrds_pim lnedu**

| Error Correction: | D(LNTFP) | D(LNRDS_PIM) | D(LNFRDS_PIM) | D(LNEDU) |
|---|---|---|---|---|
| $ECT_{t-1}$ | -0.936533 | 0.040703 | 0.041365 | -0.016348 |
| | (0.17652) | (0.02294) | (0.03499) | (0.01504) |
| D(LNTFP(-1)) | 0.074174 | -0.018856 | 0.004387 | 0.015152 |
| | (0.13713) | (0.01782) | (0.02718) | (0.01168) |
| D(LNRDS_PIM(-1)) | 1.271427 | 0.898066 | -0.046855 | -0.002737 |
| | (0.44833) | (0.05825) | (0.08888) | (0.03820) |
| D(LNFRDS_PIM(-1)) | 1.755252 | 0.012633 | 0.672408 | 0.047364 |
| | (0.56797) | (0.07380) | (0.11260) | (0.04839) |
| D(LNEDU(-1)) | -1.273997 | 0.020200 | 0.080988 | 0.341879 |
| | (1.62469) | (0.21110) | (0.32208) | (0.13842) |
| C | -0.184527 | 0.007122 | 0.019788 | -0.002535 |
| | (0.04707) | (0.00612) | (0.00933) | (0.00401) |
| R-squared | 0.509250 | 0.907088 | 0.572827 | 0.154689 |
| Adj. R-squared | 0.459173 | 0.897607 | 0.529238 | 0.068432 |
| Sum sq. resids | 0.374009 | 0.006314 | 0.014699 | 0.002715 |
| S.E. equation | 0.087366 | 0.011352 | 0.017320 | 0.007444 |
| F-statistic | 10.16943 | 95.67589 | 13.14152 | 1.793360 |
| Log likelihood | 59.20563 | 171.4462 | 148.2099 | 194.6566 |
| Akaike AIC | -1.934750 | -6.016227 | -5.171270 | -6.860240 |
| Schwarz SC | -1.715768 | -5.797245 | -4.952288 | -6.641258 |
| Mean dependent | 0.018568 | 0.088331 | 0.048924 | -0.000323 |
| S.D. dependent | 0.118799 | 0.035475 | 0.025243 | 0.007712 |

**Panel C: lntfp lnrds_gamma lnfrds_gamma lnedu**

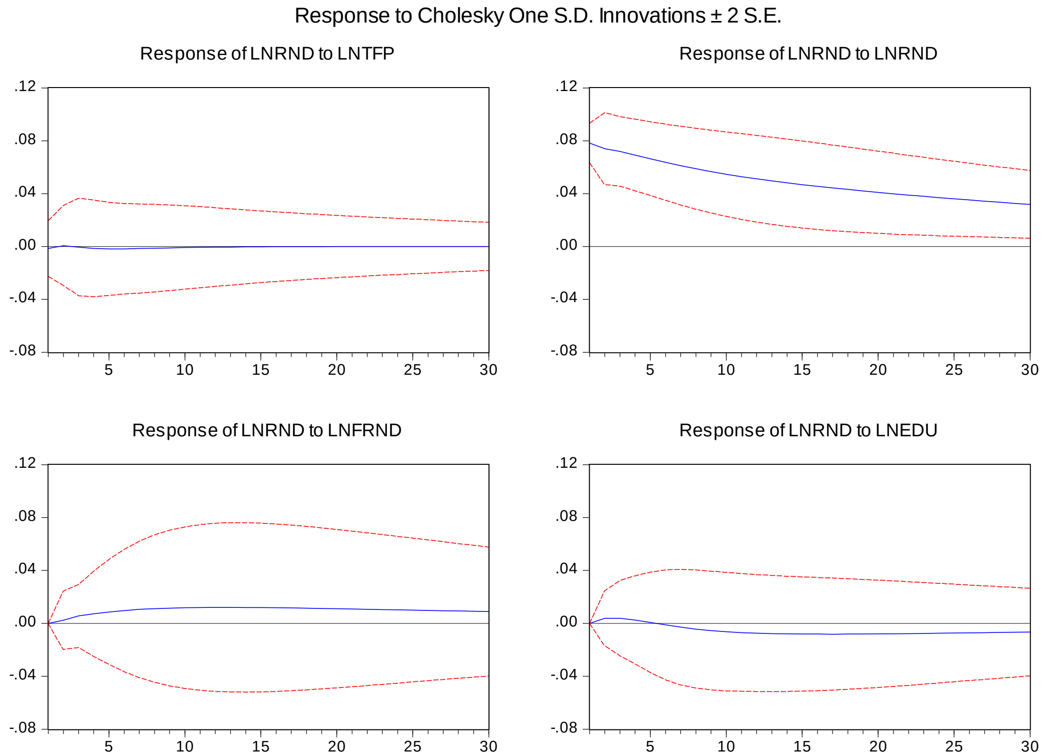
| Error Correction: | D(LNTFP) | D(LNRDS_GAMMA) | D(LNFRDS_GAMMA) | D(LNEDU) |
|---|---|---|---|---|
| $ECT_{t-1}$ | -0.092051 | -0.027212 | 0.000965 | 5.71E-05 |
| | (0.07773) | (0.00408) | (0.00433) | (0.00536) |
| D(LNTFP(-1)) | -0.390205 | 0.017066 | 0.008736 | 0.005945 |
| | (0.13236) | (0.00694) | (0.00737) | (0.00913) |
| D(LNRDS_GAMMA(-1)) | -1.019522 | 0.718370 | -0.024121 | -0.003267 |
| | (0.79853) | (0.04187) | (0.04444) | (0.05509) |
| D(LNFRDS_GAMMA(-1)) | 0.906417 | 0.442587 | 0.951337 | -0.034038 |
| | (0.96645) | (0.05068) | (0.05379) | (0.06668) |
| D(LNEDU(-1)) | -2.231255 | 0.015017 | 0.019633 | 0.330345 |
| | (1.96767) | (0.10318) | (0.10952) | (0.13575) |
| C | 1.96767 | -0.000538 | 0.003308 | 0.001364 |
| | (0.05170) | (0.00271) | (0.00288) | (0.00357) |
| R-squared | 0.229158 | 0.986928 | 0.895374 | 0.129410 |
| Adj. R-squared | 0.150501 | 0.985594 | 0.884698 | 0.040575 |
| Sum sq. resids | 0.587471 | 0.001616 | 0.001820 | 0.002796 |
| S.E. equation | 0.109495 | 0.005742 | 0.006094 | 0.007554 |
| F-statistic | 2.913379 | 739.8983 | 83.86694 | 1.456738 |
| Log likelihood | 46.78806 | 208.9327 | 205.6573 | 193.8463 |
| Akaike AIC | -1.483202 | -7.379370 | -7.260267 | -6.830774 |
| Schwarz SC | -1.264220 | -7.160388 | -7.041285 | -6.611792 |
| Mean dependent | 0.018568 | 0.065958 | 0.042175 | -0.000323 |
| S.D. dependent | 0.118799 | 0.047840 | 0.017947 | 0.007712 |

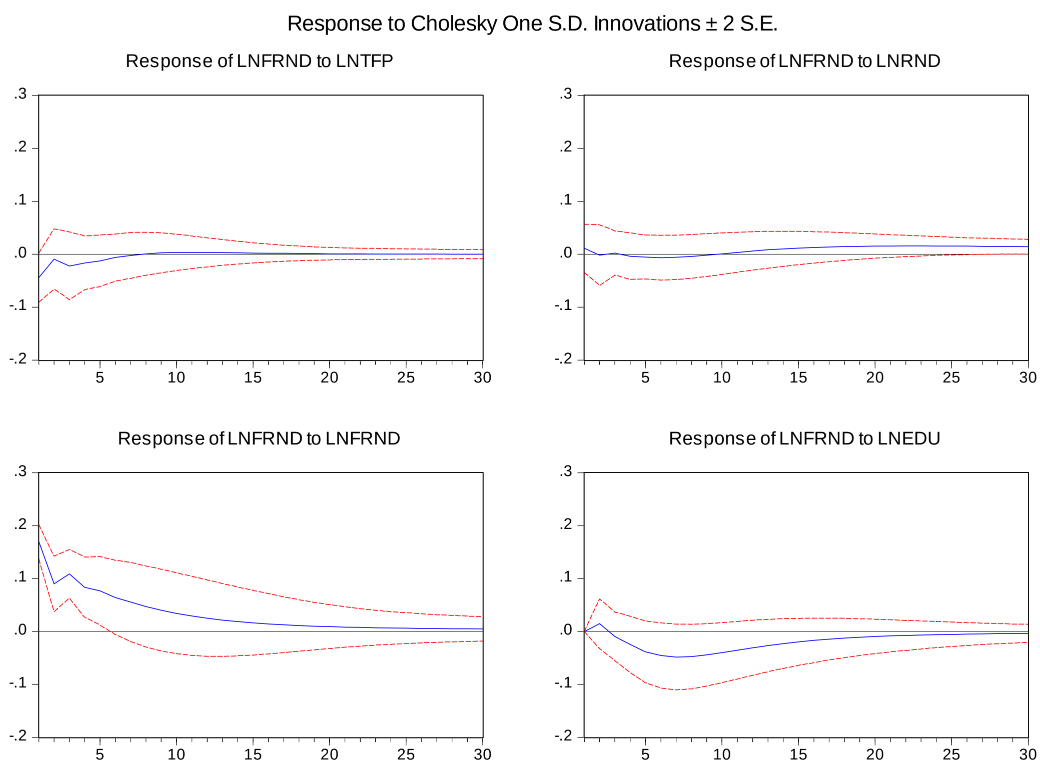
**Table A.4.3: Variance decompositions**

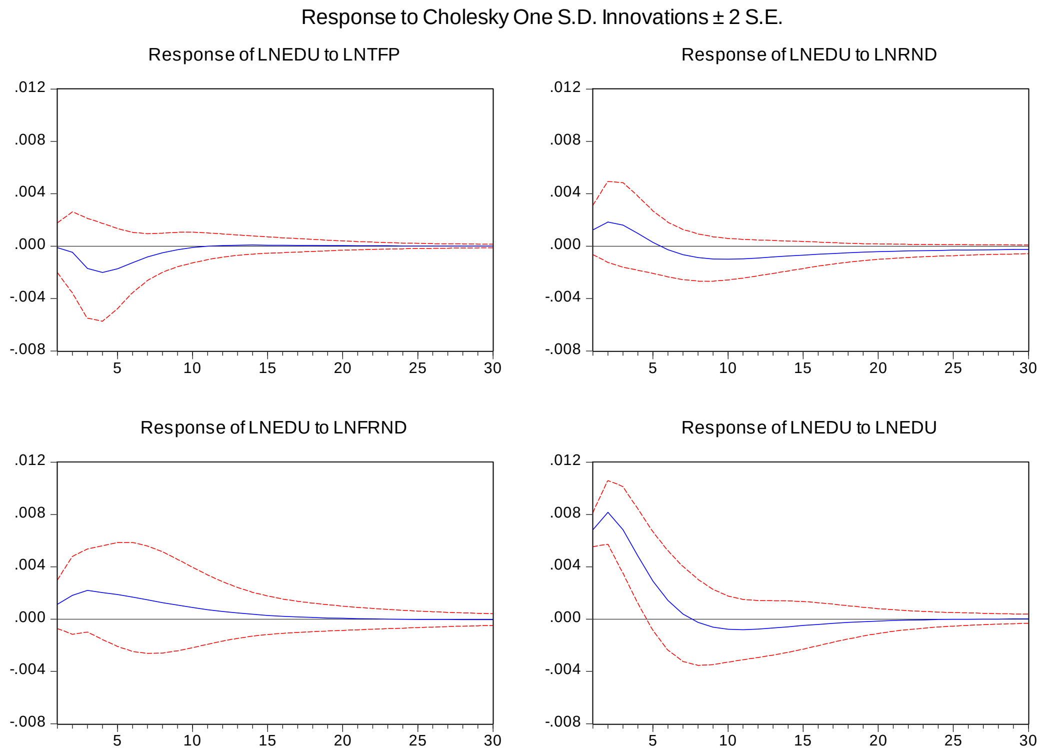
| Variance Decomposition of LNTFP: | | | | | |
|---|---|---|---|---|---|
| Period | S.E. | LNTFP | LNRND | LNFRND | LNEDU |
| 1 | 0.090 | 100 | 0 | 0 | 0 |
| | | (0.000) | (0.000) | (0.000) | (0.000) |
| 2 | 0.096 | 89.339 | 0.575 | 5.960 | 4.126 |
| | | (8.054) | (4.182) | (5.664) | (4.015) |
| 3 | 0.098 | 85.464 | 1.089 | 5.703 | 7.744 |
| | | (8.154) | (4.412) | (5.722) | (4.935) |
| 4 | 0.100 | 81.955 | 1.881 | 5.584 | 10.580 |
| | | (8.673) | (4.629) | (5.924) | (5.626) |
| 5 | 0.102 | 79.864 | 2.695 | 5.446 | 11.995 |
| | | (9.124) | (4.875) | (6.139) | (6.424) |
| 6 | 0.103 | 78.262 | 3.723 | 5.374 | 12.641 |
| | | (9.553) | (5.315) | (6.447) | (7.080) |
| 7 | 0.104 | 76.957 | 4.890 | 5.309 | 12.844 |
| | | (9.875) | (5.687) | (6.735) | (7.506) |
| 8 | 0.104 | 75.751 | 6.152 | 5.259 | 12.838 |
| | | (10.212) | (6.087) | (7.150) | (7.763) |
| 9 | 0.105 | 74.615 | 7.434 | 5.214 | 12.738 |
| | | (10.504) | (6.455) | (7.575) | (7.921) |
| 10 | 0.106 | 73.533 | 8.689 | 5.177 | 12.602 |
| | | (10.797) | (6.821) | (8.060) | (8.033) |
| 11 | 0.107 | 72.512 | 9.884 | 5.147 | 12.457 |
| | | (11.068) | (7.142) | (8.535) | (8.120) |
| 12 | 0.107 | 71.557 | 11.005 | 5.124 | 12.314 |
| | | (11.341) | (7.433) | (9.032) | (8.192) |
| 13 | 0.108 | 70.667 | 12.045 | 5.108 | 12.180 |
| | | (11.599) | (7.694) | (9.517) | (8.248) |
| 14 | 0.109 | 69.841 | 13.005 | 5.098 | 12.056 |
| | | (11.852) | (7.942) | (10.003) | (8.293) |
| 15 | 0.109 | 69.074 | 13.890 | 5.093 | 11.942 |
| | | (12.094) | (8.182) | (10.463) | (8.332) |
| 16 | 0.110 | 68.363 | 14.706 | 5.092 | 11.839 |
| | | (12.332) | (8.420) | (10.900) | (8.374) |
| 17 | 0.110 | 67.702 | 15.459 | 5.094 | 11.745 |
| | | (12.562) | (8.654) | (11.305) | (8.424) |
| 18 | 0.111 | 67.087 | 16.155 | 5.098 | 11.660 |
| | | (12.789) | (8.883) | (11.690) | (8.484) |
| 19 | 0.111 | 66.514 | 16.800 | 5.104 | 11.582 |
| | | (13.010) | (9.105) | (12.061) | (8.552) |
| 20 | 0.112 | 65.979 | 17.400 | 5.111 | 11.511 |
| | | (13.228) | (9.320) | (12.429) | (8.627) |
| 21 | 0.112 | 65.478 | 17.957 | 5.119 | 11.446 |

| | | | | | |
|---|---|---|---|---|---|
| | | (13.443) | (9.528) | (12.797) | (8.706) |
| 22 | 0.113 | 65.010 | 18.477 | 5.128 | 11.386 |
| | | (13.653) | (9.729) | (13.169) | (8.788) |
| 23 | 0.113 | 64.570 | 18.962 | 5.136 | 11.331 |
| | | (13.860) | (9.921) | (13.545) | (8.872) |
| 24 | 0.113 | 64.158 | 19.417 | 5.145 | 11.280 |
| | | (14.063) | (10.105) | (13.921) | (8.955) |
| 25 | 0.114 | 63.771 | 19.842 | 5.154 | 11.232 |
| | | (14.263) | (10.281) | (14.294) | (9.037) |
| 26 | 0.114 | 63.407 | 20.242 | 5.163 | 11.188 |
| | | (14.458) | (10.448) | (14.660) | (9.117) |
| 27 | 0.114 | 63.064 | 20.617 | 5.172 | 11.147 |
| | | (14.648) | (10.606) | (15.016) | (9.195) |
| 28 | 0.115 | 62.742 | 20.970 | 5.180 | 11.109 |
| | | (14.832) | (10.755) | (15.360) | (9.269) |
| 29 | 0.115 | 62.438 | 21.302 | 5.188 | 11.072 |
| | | (15.011) | (10.895) | (15.690) | (9.340) |
| 30 | 0.115 | 62.151 | 21.614 | 5.196 | 11.039 |
| | | (15.182) | (11.025) | (16.007) | (9.407) |

## Figure A.4.1: Impulse Response Function



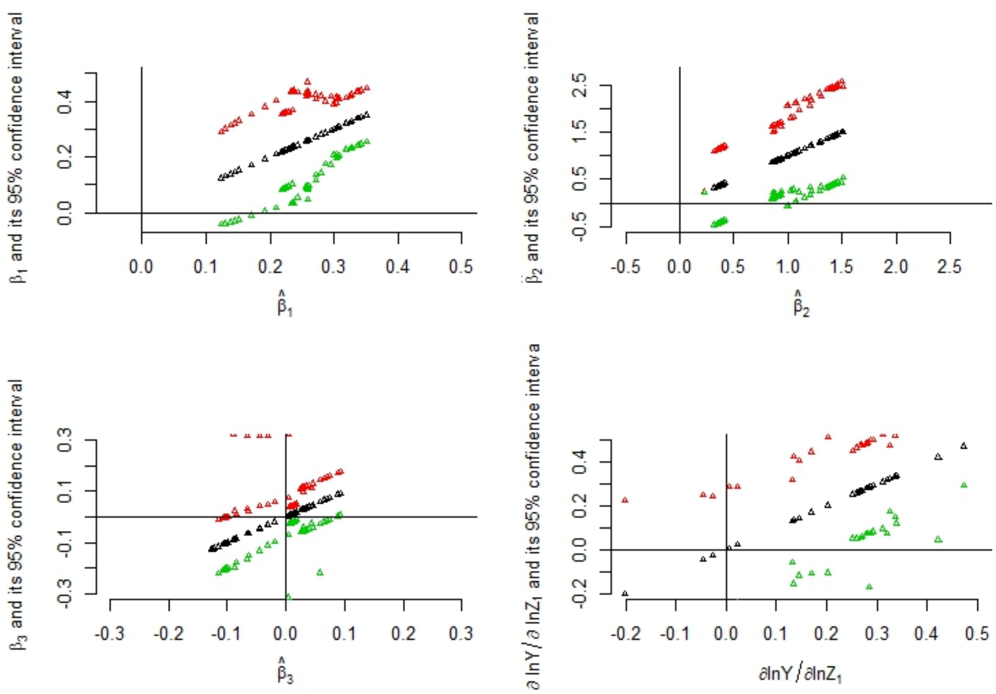






Note: The broken lines indicate confidence limits around the estimates based on asymptotic impulse standard errors.

# Appendix to Chapter Five

**Figure A.5.1: Semi parametric fits with panel data**



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