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An Econometric Approach to Measuring Productivity: Australia as a Case Study

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ABSTRACT

Seminal papers of Solow (1957) and Swan (1956) stimulated debate among economists on the role of technical change in productivity improvements and for that matter economic growth. The consensus is that technological change accounts for a significant proportion of gross national product (GNP) growth in industrialised economies. In the case of Australia, the aggregate productivity performance was poor in the 1970s and 1980s, but picked up very strongly by the 1990s, and was above the OECD average growth level for the first time in its productivity growth history. However, this high productivity growth rate could not be sustained and Australia started to experience a slowdown in productivity growth since 2000.

This study empirically measures the performance of productivity in Australia's economy for the period 1950-2005, using an econometric approach. Time-series data are used to develop econometric models that capture the dynamic interactions between GDP, fixed capital, labour units, human capital, foreign direct investment (FDI) and information and communication technology (ICT). The Johansen (1988) cointegration techniques are used to establish a long-run steady-state relation between or among economic time series. The econometric analysis pays careful attention to the time-series properties of the data by conducting unit root and conintegration tests for the variables in the system.

This study finds that Australia experienced productivity growth in the 1950s, a slow down in the mid 1960s, a very strong productivity growth in the mid 1990s and another slowdown from 2000 onwards. The study finds evidence that human capital, FDI and ICT are very strong determinants of long-run GDP and productivity growth in Australia. The study finds that the three, four and the five factor models are likely to give better measures of productivity performance in Australia as these models recognise human capital, FDI and ICT and include them as separate factors in the production function, This study finds evidence that the previous studies on the Australia's productivity puzzle have made a very significant omission by not considering human capital, FDI and ICT as additional exogenous variables and by excluding them from the production function for productivity analysis.

Key Words: Technical Change, total factor productivity, cointegration, Granger causality, impulse response analysis, forecast error variance decomposition, human capital, FDI and ICT

Abbreviations

GDP Gross domestic product

GNP Gross national product

OECD Organisation for Economic Co-Operation and Development

TFP Total factor productivity

MFP Multifactor productivity

TFPGR Total factor productivity growth rate

CES Constant elasticity of substitution

MRTS Marginal rate of technical substitution

MR Marginal revenue

VAR Vector autoregressive model

VECM Vector error correction model

FDI Foreign direct investment

ICT Information and communication technology

ABS Australian Bureau of Statistics

ADF Augmented Dickey Fuller

DF Dickey Fuller

PP Phillips Perron

OLS Ordinary least square

IRF Impulse response function

MSE Mean square error

RSS Residual sum square

VMA Vector moving average

VET Vocational Education and Training

TAFE Technical and Further Education

DEST Department of Education, Science and Training

NCVER National Centre for Vocational Education Research

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CHAPTER ONE

INTRODUCTION

1.1 Background

Seminal papers of Solow (1957) and Swan (1956) stimulated debate among economists on the role of technical change in productivity improvements and for that matter economic growth. The consensus is that technological change accounts for a significant proportion of gross national product (GNP) growth in industrialised economies. In the case of Australia, the aggregate productivity performance was poor in the 1970s and 1980s, but picked up very strongly by the 1990s, and was above the OECD average growth level for the first time in its productivity growth history. Australian's productivity growth in the second half of the 20th century can be segmented into three phases namely: relatively fast growth in the 1950s through to the mid-1970s; a slowdown through the early 1990s; and since then, a strong resurgence that has continued till late 1990s.

The growth of GDP can be influenced by the intensity at which factors of production are used and this is normally measured in terms of an output-input ratio called productivity. The role of productivity in economic growth is well noted in the academic literature on economic growth. In most of the academic literature on economic growth, (Griliches, 1988; Jorgenson, 1988; and Denison, 1985), the slowdown in economic growth was primarily attributed to the decline in aggregate productivity growth. The decline in economic growth would be left unexplained without an econometric model to measure the rate of productivity growth.

Productivity is usually calculated by the ratio of a weighted index of outputs to a weighted index of inputs. In a simple economy with only one output and one input, productivity is simply the ratio of output to input. In an economy with a variety of outputs and many different inputs, productivity can be measured in a number of ways.

Tinbergen (1942) and Stigler (1947) introduced the concept of total factor productivity (TFP) into the economic literature, which was later refined by Abramotivz (1956). Solow (1957) gives a useful frame of reference for the main empirical approaches to measuring productivity, opening debates for Griliches and Jorgenson (1966). His estimates of productivity were computed using what has come to be known as the growth accounting method.

Most productivity studies tend to concentrate only on labour and capital inputs and some analysts identify the incompleteness of their input coverage by referring to the resulting measures as multifactor rather than TFP (Diewert and Lawrence, 1999). Different approaches are used in measuring productivity. At the most basic level, productivity change is often approximated by changes in labour productivity (output per worker or per hour worked) since the requisite information is usually readily available. However, complete reliance on labour productivity measures can mislead, as other inputs, such as capital, may be substituted for labour. It is therefore necessary to take into account the quantity of all outputs produced relative to the quantity of all inputs used in the production process. A better measure of productivity growth is TFP.

TFP is intended to be a comprehensive productivity measure and should ideally include not just labour and capital inputs but also natural resources, land, research and development, inventory and all other inputs that take part one way or the other in the productive process. Failure to take into account all inputs can lead to biased results, which may affect future economic policies. Changes in the TFP index tell us about how the amount of total output that can be produced from a unit of total input has changed over time. The problem associated with TFP is that its measurement is quite a complicated task and reported figures are often unreliable, especially within short time spans. A major problem encountered in measuring TFP is that different outputs (products and services) and inputs (labour, material, and energy) cannot be easily summed up.

Attention of economists has focused on trying to explain the reasons why output generally grows faster than measured inputs. Furthermore, attention is concerned with the scale effects on productivity growth because if the constant returns to scale assumption conditions are not satisfied, it will result to biased estimates. In this case, TFP measure can no longer be the same as technical change. The production function is the conceptual link between the econometric and some other approaches[1] to productivity measurement. These involve the measurement of productivity by estimating a production, cost or other related producer behavioural equations.

Hatemi-J and Irandoust (2001) argue that TFP emerges from a parsimonious specification of the aggregate production function. Harberger (1998) attributes TFP improvement to real cost reduction, changes in the quality of labour (direct contributions of human capital), research and development, and other types of externalities, such as economies of scale, trade liberation and spill overs. To understand the sources of TFP, there is a need to first explore the aggregate production function and estimate its parameters.

Economic growth is normally measured by GDP per capita growth and is an area of obvious interest to economists and policymakers. This interest is evidenced in the large academic literature on economic growth and the considerable efforts of policymakers to improve the growth of a country's economy. Projections of future growth have clear implications for any government budget policy, the soundness of the social security and health systems, level of education and future standards of living.

The importance of trade and capital as determinants of potential economic growth are also widely acknowledged. However, empirical studies based on aggregate production functions have always emphasised the importance of capital accumulation by the business sector, the importance of other types of capital accumulation such as government infrastructure capital, residential capital, and research and development capital received considerably less emphasis. Grossman and Helpman (1994) and Romer

[1] Approaches such as the stochastic frontier approach(SFA) and data envelopment analysis (DEA).

(1990, 1994), for example, survey the endogenous growth theory that emphasises market power, spillovers, and increasing returns to scale as important sources of aggregate growth.

However, there are some controversies surrounding the existence of the aggregate production function, particularly the objections to the concept of aggregate capital, which have been adequately surveyed by Walters (1963), Fisher (1965, 1969, 1983) and Harcourt (1969). Shaikh (1980, 1987), McCombie (1998, 2000/2001). Felipe (2001) and Felipe and McCombie (2003) argue that the aggregate production functions do not exist because they are derived from an income accounting identity, and therefore using it to derive TFP estimates is questionable. Some of these criticisms received response from Jorgenson and Griliches (1967), Solow (1987) and Jorgenson (1990).

While all other approaches offer valuable insights into analysing economic growth of a country, the aggregate production function remains the most appropriate tool for long-run growth projections. The inability to predict the impact of changes in market power or spillovers on the future economic growth leaves the more complicated, endogenous models subject to the same criticism as the Solow model. This suggests that the neoclassical model, even with the fundamental reliance on exogenous technological progress, is the appropriate starting point for projecting long-run economic growth.

The empirical works of Mankiw, Romer and Weil (1992) and Islam (1995) argue that the neoclassical framework does well in explaining cross-country growth patterns. The work of Jorgenson (1990) concludes that the aggregate production function provides a reasonable model for long-run economic growth. He notices that since the other important factors in the growth literature are either irrelevant for a single country or hard to project, the traditional aggregate production function remains the appropriate starting point for projecting long-run economic growth.

A very important implication of the neoclassical growth theory is that all countries eventually would converge towards the same level of productivity. The lack of evidence in support of this outcome prompted the development of new growth theories. The revival of interest in growth theory during the 1980s with the development of the new neo-classical endogenous growth models (Lucas, 1988; 1993; Romer, 1986; 1990) has opened new avenues of research and initiated several debates. These new theories are characterised by the endogenisation of technology.

In the 1990s, Australia achieved its highest ever productivity growth rates of 3.2% (for labour productivity) and 2.0% (for MFP[2]), consistently above the OECD average growth level. This growth rate has prompted a number of researchers to investigate into the sources of productivity growth improvement in Australia. All the studies adopt different approaches but the findings indicate that the performance of productivity growth in Australia has improved in the mid 1990s. Most of the studies attribute the productivity improvements in Australia to the policy reforms which were introduced in the economy in the mid-1980s and are still on going. (See Parham (2004) for a comprehensive survey of studies of Australian productivity growth).

Some of the productivity researchers use the MFP estimates computed by the ABS, Productivity Commission and OECD researchers for productivity analysis in Australia. ABS (2001, 2003-2004) provide (MFP) estimates for Australia that extend back to the mid-1960s. According to ABS, Australia has experienced 8 growth cycles and the highest MFP growth rate of 2.0 % per year on average was achieved in the 1993-94 to 1999-2000 growth cycle.

The ABS considers capital and labour inputs as the only factors of production in estimating the MFP for Australia. This study argues that the measurement of productivity in Australia demands the consideration of not only capital and labour inputs, but also other factors such as human capital, FDI and ICT, which might also be important in determining productivity growth. Failure to take into account all factors may affect productivity estimates, which may mislead policy decisions. This flaw suggests the need for further studies of the productivity performance in Australia.

[2] TFP and MFP are used interchangeably.

The current work is a continuation of the above studies and empirically attempts to measure the performance of productivity in Australia's economy, using an econometric approach. The approach to be adopted in this study is similar to that used by Agbenyegah et al. (2003) in their study on productivity measurement in New Zealand.

1.2 Objectives of the Research

The objectives of this research are to measure the performance of productivity in Australia over the period 1950 to 2005 by exploring the long-run and short-run dynamics for the variables of the system. The study also investigates and identifies production factors that are the main determinants of the long-run productivity improvement in Australia. The study empirically attempts to measure the performance of productivity in Australian economy, using an econometric approach. Cointegration techniques are used to establish the long-run steady-state relations between or among economic time series. The research prefers an econometric estimation of functional forms to estimate TFP rather than an index number approach, which can yield quite volatile results. The Granger causality test is conducted to determine causal relationship between GDP, productivity and production factors in Australia's economy. Furthermore, the impulse response and forecast error variance decomposition analyses are used to trace out the effect of one-time shocks to the system.

Time-series data are used to develop econometric models that capture the dynamic interactions between GDP, fixed capital, labour units, human capital, FDI and ICT. The econometric analysis pays careful attention to the time-series properties of these data. The study also recognises that the augmented Dickey Fuller (ADF) and the Phillips-Peron (PP) tests for a unit root are sensitive to non-linear data transformations and may lead to invalid inferences. In addition to the usual ADF and PP tests for a unit root, the study employs the Perron (1989, 1997) unit root tests, which take into account a structural break in the trend stationary process.

Detailed results of estimated long-run parameters for different factor production functions obtained from time-series data on the Australian economy are presented and discussed. In particular, estimates of the elasticity of factor with respect to GDP (factor shares) for the economy are reported. The Johansen cointegration methodology is used to estimate and test the long-run equilibrium parameters of production which are used to compute TFP estimates for Australia. Vector error correction models (VECMs) derived from the VAR models are used to test for the short-run dynamic shocks between GDP and factors of production and between productivity and production factors. That is, it assesses the response of GDP and productivity to a unit standard error shock to the factors of production. Furthermore, it uses the forecast error variance decomposition analysis to determine the proportion of the error forecast in GDP and productivity which are due to the innovations of each factor of production. A number of diagnostic tests including a test for constant returns to scale, and significance of human capital, FDI and ICT in the production functions are carried out in this study. Similar tests are carried out to determine the importance of production factors in productivity growth in Australia.

1.3. Significance of the Research

This study charts a new direction in solving the Australian productivity puzzle by identifying and recognising factors such as human capital, foreign direct investment and ICT as important determinants of long-run productivity growth and includes them in the productivity analysis. The study is the first of the sort to include human capital, foreign direct investment and ICT in the productivity analysis in Australia.

For policy makers and the Australian government, the findings and suggestions from this study may contribute to policy formulation, planning and budgeting. The identification of the determinants of long-run GDP and productivity growth will help in forecasting of certain economic indicators in Australia. The study provides policy makers with additional insights into what percentage of the forecast error variance of GDP and productivity are explained by the innovations of each production factor. The study further provides policy makers with information that a one standard error shock to each production factor is persistent and permanent in GDP and TFP.

As factors of production are analysed and the long-run elasticities estimated, it becomes much easier for policy makers and government to develop strategies that can help in making optimum use of these factors (limited resources at their disposal) to achieve optimum results. Policy makers and the government are be guided by the findings and recommendations of this research on the factors that deserve priority in policy formulation, planning and budgeting to achieve optimum results.

1.4 Thesis Organisation

This thesis comprises seven chapters. The first chapter provides an introduction to the subject matter of this research. The research problem is introduced and the significance and the expected contributions of this study are discussed. Chapter 2 identifies the main determinants of economic growth. Chapter 3 introduces the concept of aggregate production function, develops its general model and discusses the roles of human capital, ICT and foreign direct investment in economic growth. The chapter further explores the relationship between technical change and the aggregate production function. The chapter concludes by reviewing the literature on productivity growth in Australia.

Chapter 4 examines the methodology used to achieve the objectives of this study. The chapter reviews the literature on stationarity in regression, including the unit root test with structural break and cointergration test. It uses the Johansen cointegration technique to estimate and test for the long-run equilibrium parameters. The chapter discusses using the Granger causality test to determine which variables are considered to Granger cause GDP and productivity. Furthermore, the impulse response functions and the forecast error variance decomposition are examined as methods to enable us identify the main determinants of GDP and productivity in Australia’s economy. Discussion of a comprehensive measurement of productivity, usually referred to as total factor productivity, concludes this chapter.

Chapter 5 discusses the data used for the empirical analysis of this study. The dynamics of the variables are presented graphically in order to observe visually the presence of any significant structural break in the trend serries of any of the variables. The dynamics of the growth rates of the variables are also presented graphically and discussed. The chapter concludes by examining some of the problems encountered in measuring output and inputs, which are likely to affect the results of this study.

Chapter 6 presents and discusses the results of the empirical analysis of this study. It uses time-series data from the Australian economy for the period 1950-2005 with the help of econometric estimations to derive estimates of productivity growth. Estimates of various factor production functions for the Australia's economy for the period 1950-2005 are presented and discussed. Comparative analysis is made for the results obtained from a two-factor production function and those of the three-factor, four-factor and five-factor production functions. The Granger causality test and the impulse response analysis are used to determine the importance of production factors in GDP and productivity growth in Australia. The reports and discussions of the empirical results also appear in this chapter.

Chapters 7 presents a brief summary of the main findings of this research, highlights the contributions of this research to knowledge and the limitations of this study. The chapter finally gives pointers and recommendations for future research on measuring Australian productivity.

CHAPTER TWO

SOURCES OF ECONOMIC GROWTH

2.1 Introduction

The relative importance of different sources of economic growth has always been of considerable interest to economists and policymakers. Thus, the main objective of this chapter is to identify the main sources and contributors to economic growth. Two basic categories of economic growth are identified namely: those based on the traditional Solow (1956) growth model and those based on the concept of endogenous growth. The Solow model emphasises capital accumulation, exogenous rates of change in population and technological progress as sources of economic growth. The model predicts that all market-based economies will eventually reach the same constant growth rate if they have the same technological progress and population growth. The model further assumes that the long-run growth rate cannot be influenced by policymakers (Gould and Ruffin, 1993).

The study of Romer (1986) on endogenous growth theory argues that the traditional theory fails to reconcile its predictions with empirical findings that, over the long run, countries appear to have accelerating growth rates, and among countries, growth rates differ substantially. Endogenous growth theory argues that long-run growth is determined by economic incentives. The most popular models of this type maintain that inventions are intentional and generate technological spillovers that lower the cost of future innovations. Naturally, in these models, an educated work force plays a special role in determining the rate of technological innovation and long-run economic growth.

2.2 Determinants of Economic Growth

Economic growth is generally considered as a process whereby output, valued at constant prices, increases over some period of time. If the rate of development is greater than the population growth rate, then real income per head (per capita income) increases.

Solow (1956) proposes that the study of economic growth assumes a standard neoclassical production function with diminishing marginal product of capital. Considering the rate of saving and population growth as exogenous, Solow shows that the two variables determine the steady-state level of per capita income. Solow (1956) argues that since saving and population growth rates vary across countries, different countries reach different steady states. Solow’s model provides testable hypotheses about how these variables influence the steady-state level of income. Solow (1956) concludes that the higher the rate of saving, the richer the country and the higher the rate of the population growth, the poorer the country. This means the operation of forces over time that effect changes in certain variables result in productivity growth. The most important of these changes accompanying the rise in output are changes in factor supplies and changes in the structure of demand for products. Jones (2002) argues that Solow’s theories clarify the role of physical capital accumulation in economic growth and emphasise on the importance of technological progress as the ultimate driving force behind sustainable economic growth.

The role of changes in the terms of trade (the ratio of export price index to import price index) in national welfare has received much attention. Diewert and Lawrence (1999) argue that if a country’s terms of trade are declining, then it is able to purchase a smaller quantity of imports in exchange for a given quantity of exports over time. This implies national welfare is falling unless the country manages to create productivity improvements sufficient to offset the deteriorating terms of trade. Diewert and Lawrence (1999) further argue that productivity improvements enable the country to produce more exports from a given quantity of inputs over time, thereby maintaining or improving its ability to purchase imports from the rest of the world despite the adverse international price movements it faces.

Harberger (1998) identifies five standard pillars of growth namely: the rate of growth of the labour force in numbers or hours worked, the increase in the capital stock (net investment as a fraction of value added), the rate of return which investment yields, the

rate of increase in human capital or the rate of increment in average quality of labour, and the real cost reduction coming from different sources.
Harberger (1998) further identifies openness to trade as another important source of economic growth. Trade liberalization makes the international transfer of more modern technologies easier. Firms that may once have relaxed in ease and comfort behind high protective barriers end up a more open economy setting. Trade liberation also opens up new paths of real cost reduction, providing additional impetus to economic growth. In the mid-1980s, trade liberalization in Australia for example, has contributed significantly to productivity improvements and for that matter economic growth in the post-reform period (Chand (1999), Salgado (200), Mahadevan (2002) and Valadkhani (2003)).

Fox (1999) notes that most economic literature argues that economic growth comes from a variety of sources, namely productivity, labour employed, human capital, capital endowments, terms of trade and non-traded goods prices. In Australia for example, productivity improvement has played a significant role in GDP growth, while in New Zealand economic growth is influenced mostly by labour and physical capital endowments, changes in the terms of trade, productivity changes, the level of knowledge (the stock of human capital) and changes in non- traded goods prices (Fox and Kohli, 1998).

Jones (2002) argues that increase in the trade-intensity ratio can also enhance rapid economic development. He attributes the rapid economic growth achieved by the East Asian countries such as Hong Kong, Singapore, Taiwan and South Korea and Luxembourg to the high trade-intensity ratios of these economies. Economic growth can also be influenced by the level of ICT in a country. In Australia, there is evidence that spending on ICT and its use has contributed significant to economic growth (Bean (2000); Parham (1999, 2002) and Banks (2002)).

Michl (1999) observes that at the coarsest level, capitalist growth is characterised by impressive accumulations of capital per worker accompanied by steady increases in labour productivity and, for significant periods of time, declining capital productivity (measured by the output-capital ratio).

Nishimizu and Hulten (1978) argue that Japanese economic growth is mainly due to capital accumulation, intermediate input, labour input, and productivity growth. The high level of technology in Japan for instance is one of the main drivers for its sustainable high economic growth. The study of Elias (1978) also finds that labour and capital inputs are the main factors responsible for the economic growth in Latin American countries with capital the most influential factor.

The study of Coe and Reza (1993) finds that the growth of output in France has been spurred by increased trade integration within the European Community, and by the accumulation not only of business-sector capital, but also by government infrastructure capital, residential capital, and research and development capital. They present new estimates of an aggregate production function for France that focused on the role of trade and the importance of capital accumulation by government, households, and businesses, including expenditure on research and development. Their empirical findings are that trade and capital account for all of the growth in the French economy over the previous two decades.

Madden and Savage (1998); Lucas (1988); Romer (1989); Becker et al. (1990) and Gould and Ruffin (1993) all note the dynamic role of human capital in an economic growth process. Lucas (1988), for example, argues that human capital accumulation raises investment in both human and fixed capital and improves productivity. Benhabib and Spiegel (1994), Leamer and Taylor (1999) support the work of Mankiw et al. (1992), which provides evidence on the role of human capital in economic growth. These studies conclude that a regression equation based on an equilibrium condition of the neoclassical Solow growth model, augmented to include human capital, explained about 75% of the cross-country variation in per capita income across a broad range of countries. The Australian government for example, has initiated a migration program which makes it possible for certain skilled professionals to come to and live permanently in Australia. This policy has helped in increasing the Australian labour force over the past decades and this has had significant impact on the Australia’s economy.

Madden and Savage (1998) identify that the form of investment can also affect productivity. Their argument is supported by empirical research by De Long and Summers (1991), Levine and Renelt (1992) and Blomstrom et al. (1996), which show that fixed capital investment is an important determinant of economic growth. Aschauer (1989), De Long and Summers (1991) and Otto and Voss (1996) conclude that specific types of investment, such as investment in public infrastructure and machinery and equipment, have strong associations with productivity and economic growth in Australia.

Gould and Ruffin (1993) argue that human capital accumulation, political stability, well-defined property rights, low trade barriers and low government consumption expenditures are major determinants of economic growth. The Solow (1956) model also recognised human capital as an important input to production.

Miller and Upadhyay (2000) studied the effects of openness, trade orientation and human capital on TFP for a pooled sample of developed and developing countries. They conclude that openness, trade orientation and human capital are potential determinants of TFP. The study of Miller and Upadhyay (2000) emphasises that human capital generally contributes positively to TFP. However, Miller and Upadhyay (2000) find that in poor countries, human capital interacted with openness to achieve the positive effect on TFP.

The contribution of ICT to Australia's productivity improvement has been noted in the academic literature by studies such as Bean (2000), Banks (2002), Simon and Wandrop (2002), Parham (2002b; 2003) and Diewert and Lawrence (2004). Analysing Australia's productivity performance without taking into consideration the impact of ICT may produce unreliable results which can affect policy decision making. The studies of Dowrick (1994), Chand (1999) and Mahadevan (2002) emphasise the contribution of openness or trade liberalization to Australia's productivity growth. For these reasons, this study takes into account ICT and FDI in the productivity analysis and includes them in the production function to estimate TFP for Australia.

Benhabib and Spiegel (1994) use endogenous growth theory to model technological progress and the growth of TFP as a function of human capital. Their findings indicate that an educated labour force is better at creating, implementing and adopting new technologies, thereby generating growth. The impact of some ancillary variables, such as political instability and income inequality, on economic growth and factor accumulation is also emphasised.

In considering the possible sources of growth in productivity, it is necessary to distinguish between growth in economic potential, which is the ability or capability to produce marketable goods and services, and the growth in actual output of goods and services. The growth in "potential" output can occur as a result of advancing knowledge applied to the techniques of production. This results in the growth in output with fixed quantity of other resources or when there are increases in the quality of labour and capital employed or when the (physical) quantity of labour and capital employed increases.

Changes in the ratio of actual production to potential production are governed mainly by the relationship between aggregate demand and potential production. Changes in both actual and potential output levels between any two dates are interdependent. However, the causes of change, their interpretation, the policy measures that must be taken to effect change, and the implications of such policies for future growth, are entirely different matter.

As far as the process of economic growth is concerned, there are numerous interdependent relationships that need to be examined. On the factor supply side, the potential output that can be achieved by the economy is determined by: full employment of the labour force; the size of the labour force; average hours worked and labour quality; the nation's natural resources and capital equipment; and, the level of technical

knowledge. Labour quality in particular, depends upon the increasing skill of the labour force as determined by the general level of education available, manpower training, organisation and management of labour.
On the demand side, an interaction between actual and potential growth in output can be observed. The growth of potential output is alone sufficient to determine the rate of growth in output in a full-employment situation. However, if the actual growth of output is less than what is required for optimum use of the capital stock, entrepreneurs will revise their investment policies. At less than optimum utilization of productive capacity, there will be a dampening down of investment expenditures. The consequent low rates of capital formation will retard the growth rate of potential output (Francis, 1970).

Further causal relationships underlying each of the elements of final demand can also be observed. In particular, total capital formation depends upon the state of technology, the utilisation of existing capacity, and the rate of economic growth. The distribution of capital formation depends to some extent upon the relative growth rates of industries, and the existing capital stock mix of industries.

Government policy is another crucial element to be considered in the study of economic growth. Government policy on capital formation, investment in educational facilities and manpower training programs and in equating aggregate supply and demand for employment, may significantly affect the rate of economic growth.

Furthermore, factors affecting the rate of economic growth differ from country to country depending on their level of development. In third world countries for example, the rate of economic development can be affected by factors such as unstable government, intertribal and civil wars, high birth rate, high level of illiteracy and lack of infrastructure facilities. Moreover, for agricultural oriented countries (Africa, parts of Asia and Latin America) where proper irrigation systems are lacking or completely absent, output and thus economic growth are determined significantly by the weather. Failure of rainfall may also hindrance economic growth in these countries.

The rate of population growth, the age distribution of a population and geographical location of a country (resource endowment), the interest rate and the rate of inflation are among other factors that affect the rate of economic growth. Countries like China and India which account for more than 40% of the world population are supposed to experience lower growth rate compare to countries like the U.S.A., Germany, UK, Japan, France, Spain and the East Asian Miracle countries. However, this is not true and China continues to experience high growth rates.

For a complete analysis of economic growth, a country needs to consider all the different sources of growth indicated above and factors that affect productivity. From our study of economic growth, one can draw the following conclusions: The rate of economic growth varies substantially across countries with the richer economies experiencing higher growth rates. Furthermore, there is substantial variation in per capita income across countries.

2.4 Chapter Summary

This chapter first identifies that some of the main factors responsible for economic growth are TFP, labour employed, human capital, research and development, capital endowments, terms of trade and non-traded goods prices, unstable government, intertribal and civil wars, the birth rate, and illiteracy rate, the rate of population growth, the age distribution of a population, the geographical location of a country (resource endowment), the interest rate and the rate of inflation. It notes that factors affecting economic growth vary from country to country depending on their level of development. It concludes that the rate of economic growth varies substantially across countries, with the richer economies experiencing higher growth rates and there is a substantial variation in per capita income across countries.

CHAPTER THREE

LITERATURE REVIEW

3.1 Introduction

This chapter begins by exploring the aggregate production function with focus on the Cobb-Douglas type of production function. The chapter continues by explaining the Solow residual, and the effects of technical change on the aggregate production function and the rate of investment. The chapter further reviews the literature on productivity in Australia. A discussion of sectorial productivity performance in Australia concludes the chapter. Thus the overall purpose of this chapter is to explore the production function, highlight the role of technical change in productivity growth and review the literature on Australia's productivity performance.

3.2 The Aggregate Production Function

Studies of the sources of economic development and the possible ways it affects an increase in the rate of economic growth usually employ, either explicitly or implicitly, the concept of an aggregate production function. At both the macro- and micro-economic levels, the production function has been used as a tool for assessing what proportion of any increase in output over time can be attributed to an increase in the inputs of production or to the existence of increasing returns to scale or to what is commonly referred to as technical progress.

The neoclassical production function developed by Cobb and Douglas (1928), and Tinbergen (1942), assumes constant return to scale as does another by Arrow et al. (1961), subsequently called the Constant Elasticity of Substitution (CES) production function. Both production functions have been extensively analysed in the economics literature. There is already a substantial volume of research devoted to both the theoretical and empirical aspects of the Cobb-Douglas production function and CES production function.

Economists have been interested in the concept of an aggregate production function that posits a systematic relationship between the economy's total output and total primary inputs, for example capital and labour. Cobb and Douglas (1928) presented empirical support for both the existence of a well-defined aggregate production function and the marginal productivity theory of distribution. The seminal paper of Solow (1957) integrated this approach with national income data, and the aggregate production function now serves as the basis for most of the applied and theoretical work on economic growth.

For the purposes of this study, it is important to define precisely what is meant by the term "aggregate production function". The production function is a technological relationship, and as such it should ideally be estimated using physical data for outputs and inputs. However, constant price value data have nearly always been used, as heterogeneous physical outputs have to be aggregated using prices. Thus, the term aggregate production function refers to the production function when constant price value data (either value added or gross output) are used, whether these are for, say the whole economy or at a much lower Standard Industrial Classification level (McCombie, 2000/2001).

Michl (1999) assesses the ability of neoclassical theory to interpret the classical economy through the neoclassical production function. By considering a neoclassical model without technical change and then with technical change, he shows how two different economists, one neoclassical and the other classical, can interpret observable data generated by the classical economy. He illustrates this by considering the profile of capital intensity and labour productivity. Looking back in time in the classical economy, he uses a sequence of techniques arranged in descending order of capital intensity and labour productivity, which takes on the appearance of a neoclassical production function. According to Michl (1999), since more capital-intensive techniques have yet to be invented, the production function is truncated by the fixed-coefficient technology being used at the moment.

Weitzman (1970) represents the aggregate production function algebraically in a general form as:

$$\mathrm{Y}_t = \mathrm{A}_t F(K_t, L_t), \qquad (3.2.1)$$

where:

Y_t - aggregate output at time t

K_t - the flow of services provided by the existing capital stock rather than the capital stock itself.

L_t - Labour employed in production.

A_t - "level of technology"; a measure of total factor productivity.

F (.) is the function describing the connection between the variables K and L.

A_t in the production function (3.2.1) accounts for the influences of production factors not included in K and L, among which a major role is played by technical progress and assumes neutrality in the impact of these factors on the impact of K and L. A very important point to be noted at the outset is that, for a given level of K and L, expression (3.2.1) defines possible levels of output Y. However, the problem of deciding which input combination provides the given output at minimum cost (real cost reduction) remains the concern of the economist.

In an attempt to quantify technological change, and to understand its role in the historical economic growth record of the United States for example, a number of studies during the 1950's developed indices of total factor productivity using conventional measures of capital and labour. These studies employ the concept of an aggregate production function, either explicitly or implicitly, and the general consensus is that most economic growth is explained by the technological progress factor.

Solow (1957) finds that a bigger proportion of increase in output is explained by the increase in factor inputs as conventionally measured. Moreover, the rate of technological change is found to be constant neither over time nor among countries, and the range of measured technological change is found to be from four to five percent a year for short periods, to zero for other years. Solow (1957) uses the phrase “technical change” as shorthand for any kind of shift in the production function. Thus slowdowns, speed ups, improvement in the education of labour force, and all sorts of things will appear as “technical change”.

In the literature that follows Solow’s (1957) article, further factors affecting technical change are identified as non-constant returns to scale, non-neutral technical change, and inter-industry shifts of resources. The study of technological change in the context of aggregate production function by Solow, generally assumes competitive factor pricing (or some variant thereof, such as cost-minimisation in the competitive factor markets) and then employs the assumed optimality conditions to estimate the parameters of the aggregate production function. It is now generally observed that the explanation of the post-war growth in total output is largely due to increases in productivity.

Griliches (1963) however has a controversial hypothesis in which he considers the residual factors to be catch-all for errors in the measurement procedure. These errors are considered to be caused by several factors: misspecification of the variables affecting output; mismeasurement in changes in the included variables, particularly if quality changes are disregarded; and incorrect productivity coefficients attributed to the individual inputs. Griliches (1963) argues that if quantities of output and input are measured accurately, then growth in total output world-wide is largely explained by growth in total input.

Arrow et al. (1961) derives a family of production functions in which the elasticity of substitution is an unspecified constant. This family has both the Cobb-Douglas production function and a fixed-proportion (“Leontief”) production function as special cases. The study uses both cross-sectional (individual industries, observed across countries) and time-series data (from the United States economy) and shows that the elasticity of substitution is significantly different from both zero and unity.

Attempting to measure and understand the fundamental elements of this residual factor is obviously at the heart of understanding the process of economic development. The major limitation of the TFP approach from the viewpoint of planning economic development is that it does not provide a clear indication of the impact of each available policy variable on increases in productivity.

Concern over this limitation has led to a further stage of development in productivity analysis. An effort has been made to account for the sources of output growth that are left unaccounted for by the conventional measures of labour and capital inputs, after correcting for the measurement errors. These additional sources of output growth can be conveniently grouped under three headings:

(a) improvement in the quality of labour inputs as a result of a rise in the general level of education;
(b) improvement in the quality of plant and machinery services that have been disguised by biases in the standard price indices used to deflate capital expenditure;
(c) a new residual frequently identified as changes in allocative efficiency.

Efforts to quantify investment in education and research, to measure its quantitative effect on the labour input of the production process, and to identify the effect of such changes on output, have reduced the size of the productivity gap. Efforts are being made to adjust capital for quality improvements, and to measure the effects of such qualitative improvements on output. These efforts will pave the way towards a more effective treatment of the role of capital accumulation and investment in terms of their impact on the introduction of technical change into the production process.

All the studies mentioned above assumed “neutrality” in the sense that changes in A do not affect the relationship between Y, K and L, using the notation of equation (3.2.1) above. The entire production function is shifted by technical progress and an index number problem arises in deciding which point on the old production function to compare with which point on the new production function. This problem has led to alternative ways of defining neutral technical change.

The aggregate production function most frequently employed in early empirical work, F in equation (3.2.1) assumes a Cobb-Douglas functional form that has constant returns to scale. With constant return to scale, a stronger assumption is made that each of the two factors of production will receive a factor price, which is just equal to the value (in a competitive product market) of the respective factor's marginal product. As is well known, this assumption will, by virtue of Euler's theorem, aside from stochastic disturbances, ensure that the total output is exhausted by both of these factor payments (Bodkin and Klein, 1967). That is (3.2.1) becomes:

$$\mathrm{Y}_t = \mathrm{A}_t K_t{}^{\alpha} L_t{}^{\beta} u_t, \qquad \alpha + \beta = 1 \tag{3.2.2}$$

Where α and β measure the elasticities (assumed constant and lying between zero and unity) of output with respect to capital and labour, respectively. The parameter A may be regarded as a technology parameter since for fixed inputs of K and L, the larger is A, the greater is the maximum output Y obtainable from such inputs.

Based on the production function of the form (3.2.2), the marginal products of capital and labour are given by:[3]

$$\frac{\partial \mathrm{Y}}{\partial L} = \beta \mathrm{A}_t \mathrm{K}_t{}^{\alpha} L_t{}^{\beta-1} U_t = \beta \frac{\mathrm{Y}}{L}, \tag{3.2.3}$$

and

[3] Equation (3.2.2) is always treated as a linear relationship by making a natural logarithmic transformation, which yields: $\ln \mathrm{Y}_t = \ln \mathrm{A}_t + \alpha \ln K_t + \beta \ln L_t + \ln \mathrm{U}_t$

$$\frac{\partial \mathrm{Y}}{\partial \mathrm{K}} = \alpha \mathrm{A}_t \mathrm{K}_t^{\alpha-1} L_t^{\beta} U_t = \alpha \frac{\mathrm{Y}}{\mathrm{K}} . \qquad (3.2.4)$$

Expression (3.2.3) above implies that the marginal productivity of labour as well as the average, depends on the number of labour employed, L, and the volume of capital K. Terexou (1974) observes that with an increase in the number of workers with the volume of capital fixed, the marginal productivity of labour decreases. An increase in the volume of capital without changes in labour resources (that is with a rise in capital per unit labour) increases marginal productivity of labour.

The same time change in all variables can results in a fall, rise or no change in the value of marginal productivity of labour. Since $0<\beta<1$, a conclusion can be drawn that in the production function of the type (3.2.1), the marginal productivity of labour is always lower than the average productivity.

Analogously, expression (3.2.4) implies that the marginal and average productivities of capital depend on the volume of capital K and the number of labour employed L. With a rise in the volume of capital without a change in the number of workers, the marginal productivity of capital decreases. With an increase in labour resources without changes in the volume of capital, the marginal productivity of capital increases. With $0<\alpha<1$, the conclusion can be drawn that in the production function of the type (3.2.1), the marginal productivity of capital is always lower than the average productivity. The marginal products of both capital and labour diminish as the relevant factor input increases since both ($\alpha - 1$) and ($\beta - 1$) are negative quantities.

Assuming that the firm is a price-taker and a profit-maximiser, at the micro-level, the production function is usually set in a model of a firm behaviour in which profit (π) is given by:

$$\pi = \mathrm{pY\text{-}mK\text{-}wL} \qquad (3.2.5)$$

where:

p – price of output Y,

m – price of input K,

w –price of input L.

Assuming a perfect competition in the product and factor markets, the firm is a price-taker and p, m and w may be taken as given. The firm then maximises profit (π) in equation (3.2.5) subject to the constraint that inputs and outputs should satisfy the production function (3.2.1). Forming the Lagrangean equation yields

$$H = pY-mk-wL- \lambda \left[\; Y-Y(K, L) \; \right] \tag{3.2.6}$$

and the first-order conditions for a maximum are:

$$\frac{\partial H}{\partial Y} = p- \lambda = 0, \quad \frac{\partial H}{\partial K} =-m+ \lambda \frac{\partial Y}{\partial K} = 0 \quad \text{and} \quad \frac{\partial H}{\partial L} = -w + \lambda \frac{\partial Y}{\partial L} = 0 \tag{3.2.7}$$

Eliminating the Lagrangean multiplier, λ yields the equations for the marginal productivity conditions, which shows the existence of the following relationship among the variables: output Y, inputs K and L.

$$\frac{\alpha Y}{K} = \frac{m}{p}, \qquad \frac{\beta\, Y}{L} = \frac{w}{p}. \tag{3.2.8}$$

Notice that equation (3.2.8) can be written as:

$$\alpha = \frac{mK}{pY} \quad \text{and} \quad \beta = \frac{wL}{pY}. \tag{3.2.9}$$

Thus if the marginal productivity condition holds, the exponents α and β in the Cobb-Douglas production function are equal to the respective shares of capital and labour in the value of total output. For a given factor ratio, the greater $\frac{\alpha}{\beta}$, the greater the optimal capital-labour ratio. Thus the size of the exponent α relative to that of β determines the capital-intensity of the productive processes represented by a Cobb-Douglas function.[4]

Although the aggregate production function has an appealing and intuitive feel, there has been considerable controversy over the existence of such a relationship. For an aggregate production function to exist, one must be able to aggregate different production techniques into a single aggregate function and aggregate heterogeneous outputs and inputs into aggregate indices. Even those who developed the aggregate production function recognised these limitations. As Solow (1957, p. 312) states, "It takes something more than the usual `willing suspension of belief' to talk seriously of the aggregate production function."

The controversy regarding the existence of such aggregates, however, has been largely decided in favour of the aggregationists. Fisher (1992, p.8), for example, states "the existence of aggregate production functions in general and of an aggregate capital stock in particular is a purely technical question." These "technical" questions, however, impose stringent restrictions on the form of the production function.

Jorgenson (1990) enumerates the necessary conditions for the existence of an aggregate production function. According to him, technology is separable in value-added; value-added is a function of capital, labour and technology; all sectoral value-added functions are identical; the capital and labour aggregating functions are the same for all sectors and each input receives the same payment in all sectors. These are clearly highly restrictive assumptions that place very specific constraints on the means of production.
Despite the stringent technical conditions necessary for exact aggregation, the use of an aggregate production function is widespread in the academic literature. Modern growth

theory, international growth comparisons, aggregate productivity analyses, and long-run economic projections are typically based on an aggregate production function.

As an alternative to the aggregate production function, one could model economic growth as an aggregate of growth in different production sectors. A complete sectoral model of the economy integrates sectoral gross output production functions with input-output matrices, value-added measures, and the familiar components of final demand-consumption, investment, government purchases, and net exports. However, this approach has considerable data requirements but dispenses with some of the restrictive assumptions of the aggregate production function.

Jorgenson (1990) argues that the aggregate production model is appropriate for studying long-term growth trends. However, he observes that the model is highly inappropriate for analysing the sources of growth over shorter periods. In the context of projecting long-run growth, therefore, the aggregate production function is empirically defensible.

For the purposes of the empirical analysis, the estimating equations in this thesis are based on the steady-state equilibrium conditions of the augmented Solow model, assuming a Cobb-Douglas aggregate production function, which includes human capital, FDI and ICT and which displays constant returns to scale in labour, physical capital, human capital, FDI and ICT taken together. Equation (3.2.2) therefore yields the following equations:

$$Y(t)=K(t)^{\alpha} X(t)^{\beta} [A(t))L(t)]^{1-\alpha-\beta} \varepsilon_t , \qquad (3.2.10)$$

$$Y(t)=K(t)^{\alpha} X_i(t)^{\beta} X_j(t)^{\gamma} [A(t))L(t)]^{1-\alpha-\beta-\gamma} \varepsilon_t , \qquad (3.2.11)$$

$$Y(t)=K(t)^{\alpha} H(t)^{\beta} FDI(t)^{\gamma} ICT(t)^{\phi} [A(t))L(t)]^{1-\alpha-\beta-\gamma-\phi} \varepsilon_t , \qquad (3.2.12)$$

where:

$X_i \neq X_j)$=H, FDI and ICT,

H(t) is the stock of human capital, FDI(t) is the foreign direct investment, ICT(t) is the investment in information and communication technology and ε_t is the error term, all other variables are defined as before, $\alpha+\beta$ <1, $\alpha+\beta+\gamma$ <1 and $\alpha+\beta+\gamma+\phi$ <1. These assumptions will be relaxed in the later part of this report.

Equation (3.2.12) above for example defines the key effective productivities namely: output per effective unit of labour y, (labour productivity); output per effective unit of capital Y/k, (capital productivity). The productivity relationships are in the form:

$$\frac{Y}{AL} = \text{y} = K(t)^{\alpha} H(t)^{\beta} FDI(t)^{\gamma} ICT(t)^{\phi} [A(t))L(t)]^{(-\alpha-\beta-\gamma-\phi)} \varepsilon_t \, , \qquad (3.2.13)$$

$$\frac{Y}{K} = \text{Y/k} = K(t)^{\alpha-1} H(t)^{\beta} FDI(t)^{\gamma} ICT(t)^{\phi} [A(t))L(t)]^{(1-\alpha-\beta-\gamma-\phi)} \varepsilon_t \; . \qquad (3.2.14)$$

Benhabib and Spiegel (1994), argue that a difficulty associated with estimating aggregate production functions such as equation (3.2.10)-(3.2.12) is that because physical and human capital are both accumulated factors, there is a possibility that they will be correlated with the error term ε_t. They conclude that this will lead to the possibility of biased estimates.

The role of technical progress in economic growth has been discussed at length in the earlier chapters of this study. It is also noted that technical progress depends on the purchase of new machines and equipment and investment in education to get qualified labour to match the technology required for modern equipment. This notion leads to the next section of this study, which reviews the relationship that exists between technical change and the aggregate production function.

3.3 Technical Change and the Aggregate Production Function

This section begins with an intuitive explanation of the Solow residual (technical change) and its relationship with the aggregate production function. It further explains the effects of technological changes on productivities and output.

Productivity indices are derived either from an explicitly defined production function or from a distribution theory where the production function is implicit. Thus the accurate specification of the form and estimation of the parameters of the production function, such as α and β in equation (3.2.2), are crucial to the measurement of productivity indices.

Nadiri (1970) defines the index of technical progress (residual) as output per unit of labour and capital combined. Technical change is the measure of the residual between the growth of output and a weighted sum of inputs. Haltmaier (1984) argues that the rate of technical change is generally identified with a proportionate amount of shift over time in an aggregate production function. The subsequent paragraphs show how this measurement is derived from the aggregate production function.

Traditionally, the estimation of an economy's production function has allowed for the influence of technological change. We begin with the assumption that output is produced by means of capital goods and labour; all being homogeneous variables. There are many identical firms and at each point in time there is one fixed coefficient of technology.

Solow (1957) derives an expression for an aggregate production function with neutral technical change as:

$$Y_t = A(t) F(K_t, L_t) \qquad (3.3.1)$$

where:

Y, K, and L are output, capital, and labour (total hours worked) respectively,

A(t) is a measure of disembodied technical change.

Writing the production function in an intensive form gives:

$$q_t = A(t)\, f\,(K_t/L_t) = A(t)\, f\,(k_t) \qquad (3.3.2)$$

where q is the labour productivity and k is capital per unit labour.

In order to estimate the production function (3.3.2), Solow (1957) deflates the function to correct for its upward shift over time due to technical progress. The general form of the production function to be estimated took the form:

$$\frac{q_t}{A_t} = f\,(k_t)\,. \qquad (3.3.3)$$

McCombie (2000/2001) argues that Solow invokes the neoclassical marginal productivity theory of factor pricing and, expressing the production function in growth rate form, calculates the rate of technical progress or what is termed the Solow residual as:

$$\dot{A} \equiv q - \alpha(k - l) \qquad (3.3.4)$$

where:

α is capital's share in total revenue (which, under the assumption of perfect competition equals the elasticity of output with respect to capital);

$\dot{A}$ and the lower case letters denote proportional growth rates.

Having calculated the annual growth of A(t) by this method, an index of A(t) is then estimated by setting A(t = 0) to unity and the calculated growth rates of A(t) are used to construct the index for subsequent years.

McCombie (2000/2001) finds that technical progress accounts for over seven-eighths of the growth of productivity in the US. He observed that there was only a very small role for the growth of the capital-labour ratio. According to McCombie (2000/2001), Solow explicitly estimated several different specifications of production functions using the "deflated" value of productivity as the regressand and the regression results were very close, with the R^2 in each case exceeding 0.99. If we specify a priori that technological advance raises the efficiencies of capital and labour exponentially over time, then the production function can be identified.

Sato and Beckman (1968) argue that if technology is restrictive in its effect on the factor efficiencies, then the production function can be identified. In particular, if relative factor prices and the capital intensity of the industry are correlated independently of the changing technology, then technical change is said to be Hicks neutral in its effect on factor efficiencies, and the production function is identified.

The usual criticism of the technique of applying the concept of a production function to macro-economic data is that since such a notion is questionable at the firm level, it is completely unrealistic when applied at the industry or sector level of aggregation. Such criticism is based on a fallacious understanding of the general methodology of econometrics (Francis, 1970).

In an econometric study, we are not really interested in whether the production function exists in reality or not. We only require that the industry acts as if such a function exists. The necessity for assuming the existence of a production function is intuitively obvious. Suppose we observe a change in output per worker whilst the capital-labour ratio remains constant, we can then conclude that at least one factor had become more productive. But this presupposes that for each combination of inputs, there is a unique level of output. Therefore, we are forced to assume a unique functional relationship between inputs and outputs. The concept of factor productivity is meaningless without this assumption.

In the analysis, we make a further assumption that the production function is invariant since if factors are weighted by their relative productivities, and are measured in efficiency units, then the functional relationship between the weighted inputs and the resulting output does not change over time.

The ease with which factors of production may be substituted for one another (the elasticity of substitution) is the determining parameter of any production function. The elasticity of substitution will in general be changed if technical progress is such as to change the relative productivities of the factors of production. Such technical change, causing unequal increase in the efficiency of capital and labour is said to be biased. If the productivities of capital and labour change equally, then technical change is said to be unbiased.[5]

Now differentiating equation (3.3.1) with respect to time, dividing by Y and rearranging terms, we get

$$\frac{\partial A}{A} = \frac{\partial Y}{Y} - \left[\frac{\partial LF_L}{Y} . \frac{\partial L}{L} + \frac{\partial KF_K}{Y} . \frac{\partial K}{K} \right], \qquad (3.3.5)$$

where F_L and F_K are the partial derivatives of output with respect to L and K and the variables preceded with a '∂' refer to time derivatives of the variables in (3.3.1).

Nadiri (1970) argues that the magnitude of the residual ($\partial A / A$) and its stability from equation (3.3.5) over time depend upon:

(a) the form of the production function that governs the behaviour of F_L and F_K;

(b) proper measurement of L and K and adjustment for their quality changes,

(c) the importance of variables other than L and K (such as the entrepreneurial ability or inventories) that are left out of the production function.

Suppose the production function (3.3.1) is of the form:

[5] The "bias" of technical change is not to be confused with the statistical bias of regression coefficients.

$$\mathrm{Y}_t = \mathrm{A}_t K_t^{\beta} L_t^{\alpha}, \tag{3.3.6}$$

and that the share of labour (α) is assumed to be invariant with respect to $\partial L / L$ and $\partial K / K$, and the constant return to scale prevails, then ($\beta = 1 - \alpha$). Thus any error due to misspecification of the form of the function will spill over into the measurement of $\partial A / A$. Similarly, if the inputs L and K are measured erroneously say by multiplicative factors z_l and z_k denoting the quality improvement of L and K, Nadiri (1970) shows that

$$\frac{\partial A}{A} = \frac{\partial Y}{Y} - \left[\alpha (\frac{\partial z_l}{z_l}) + (1 - \alpha)(\frac{\partial z_k}{z_k}) \right]. \tag{3.3.7}$$

That is the residual becomes a weighted sum of the growth rates of the quality changes embodied in the conventional inputs. He further shows that similar results are obtained even when a third factor is left out of the production function (3.3.1).

Nadiri (1970) argues that any misspecification or errors in estimating the parameters of the aggregate production function (errors in measuring the variables, errors due to omission of relevant inputs) would all spill over to the measure of TFP. He concludes that if all these sources of bias are successfully removed, the remaining portion of $\frac{\partial Y}{Y}$ unexplained by the combined rate of growth of all the factors of production is the measure of the true TFP or technical change. The rate of technical progress, T, can be thought of as the percentage change in output, which cannot be explained by the quantity changes of the factors of production (Solow, 1957).

Now re-write equation (3.3.2) in the form:

$$q = q(k , t), \tag{3.3.8}$$

where k is capital per worker, and t is time.

The production function satisfies the following conditions:

(a) Continuity:

q is twice continuously differentiable in k and once continuously differentiable in t.

(b) Positive marginal products:

$q_k > 0$

q - $kq_k > 0$

(c) Diminishing marginal products:

$q_{kk} < 0$.

These properties are assumed to hold at the intervals of:

$0 < k < +\infty$

$-\infty < T_1 \leq t \leq T_2 < \infty$.

Denoting the ratio of the marginal products (the marginal rate of technical substitution), by MRTS, gives the relationship below:

$$\text{MRTS} = \text{MRTS}(k,t) = \frac{q - kq_k}{q_k}. \tag{3.3.9}$$

From equation (3.3.9), we can obtain an expression of the elasticity of substitution, $\sigma(k,t)$, and the bias of technical change, D (k, t), in terms of the partial derivatives of MRTS.

By definition:

$$\sigma = \sigma(k, t) = \frac{\partial \ln k}{\partial \ln MRTS}, \tag{3.3.10}$$

and we can show that:

$$\sigma\,(\mathrm{k, t}) = -\,\frac{q_k\,(q - q_k)}{kqq_{kk}}\,. \tag{3.3.11}$$

The rate of technical progress is defined by:

$$\mathrm{T\,(k, t)} = \frac{q_t}{q} \tag{3.3.12}$$

and the bias of technical change is defined by:

$$\mathrm{D\,(k, t)} = -\,\frac{\partial \ln MRTS(k,t)}{\partial t}\ . \tag{3.3.13}$$

The relative shares of the product to capital and labour respectively are:

$$S_K = \frac{kq_k}{q} \quad \text{and} \quad S_L = \frac{q - kq_k}{q}\,. \tag{3.3.14}$$

Differentiating the production function (3.3.8) above with respect to time (a dot over a variable denotes its total derivative with respect to time):

$\dot{q} = q_k \dot{k} + q_t$, and this implies

$\dfrac{\dot{q}}{q} = \dfrac{kq_k}{q}\dfrac{\dot{k}}{k} + \dfrac{q_t}{q}$ and therefore

$$\frac{\dot{q}}{q} = S_K\,\frac{\dot{k}}{k} + \mathrm{T}\,, \tag{3.3.15}$$

by equation (3.3.12) and (3.3.14).

Differentiating the marginal rate of technical substitution, equation (3.3.9) above with respect to time:

$$\frac{M\dot{R}TS}{MRTS} = \frac{1}{\sigma}\frac{\dot{k}}{k} - D, \qquad (3.3.16)$$

where $\frac{1}{\sigma}$ is obtained using relation (3.3.11), and D follows from equation (3.3.13) since by equation (3.3.9):

$$D = -\frac{\partial \ln MRTS}{\partial t} = \frac{q_k t}{q_k} - \frac{q_t - kq_k t}{q - kq_k}. \qquad (3.3.17)$$

The rate of technical progress, T, can be thought of as the percentage change in output, which cannot be explained by the quantity changes of the factors of production (Solow, 1957). For the production function under consideration, it can be shown clearly by re-writing equation (3.3.15) as:

$$T = \frac{\dot{q}}{q} - S_K\frac{\dot{k}}{k} \qquad (3.3.18)$$

or,

$$T = \frac{\dot{Y}}{Y} - \left(S_K\frac{\dot{K}}{K} + S_L\frac{\dot{L}}{L} \right) \qquad (3.3.19)$$

This measure of technical change is quite independent of the manner in which technical change enters the production function.

More explicitly, suppose new technology is both factor and non-factor augmenting in its effect:

$$Y_t = F(\hat{K}_t, \hat{L}_t, t)^{6}. \qquad (3.3.20)$$

Then[7]:

[6] See Appendix A for details.

$$\frac{\dot{Y}}{Y} = (S_K \frac{\dot{K}}{K} + S_L \frac{\dot{L}}{L}) + (S_K \frac{\dot{E}_K}{E_K} + S_L \frac{\dot{E}_L}{E_L} + \frac{\dot{A}}{A}) \tag{3.3.21}$$

and,

$$T = (\sum Y_K \frac{\dot{E}_K}{E_K} + \sum Y_L \frac{\dot{E}_L}{E_L} + \frac{\dot{A}}{A} \tag{3.3.22}$$

since the relative factor share $(S_K$ or $S_L)$ is equal to the elasticity of output with respect to that particular factor ($\sum Y_K$ or $\sum Y_L$). Thus the rate of technical progress is equal to the relative rate of growth in non-factor technology, each weighted by its respective output elasticity-augmenting technology plus the weighted sum of the relative rates of growth in capital and labour-augmenting.

When all technical changes are factor-augmenting, the following relationship is obtained[8]:

$$\frac{M\dot{R}TS}{MRTS} = \frac{1}{\sigma}\frac{\dot{k}}{k} - (\frac{\dot{E}_K}{E_K} - \frac{\dot{E}_L}{E_L})(1 - \frac{1}{\sigma}). \tag{3.3.23}$$

Comparing equation (3.3.22) with equation (3.3.15), the bias is given by:

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[7] Y = F($(\hat{K}, \ \hat{L}, \ )A(t)$

$$\therefore \ \frac{\dot{Y}}{Y} = \frac{F_{\hat{K}}\hat{K}}{F} \ (\frac{\dot{K}}{K} + \frac{\dot{E}K}{EK}) + \frac{F_{\hat{L}}\hat{L}}{F} \ (\frac{\dot{L}}{K} + \frac{\dot{E}L}{EK}) + \frac{\dot{A}}{A}$$

But $Y_L = F_L A(t) = (E_L F_{\hat{L}} A(t))$ and $S_L = \frac{Y_L L}{Y} = \frac{E_L F_{\hat{L}} A(t).L}{F.A(t)} = \frac{F_{\hat{L}}\hat{L}}{F}$.

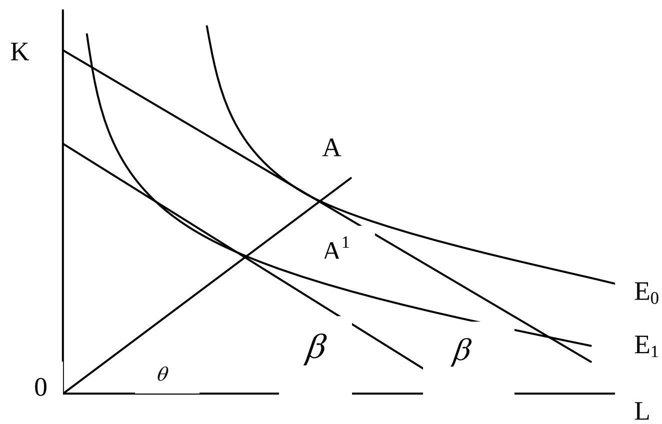
Similarly for Y_K and S_K, and hence equation (3.3.21).

[8] The derivation of equation (3.3.23) is direct but tedious and is therefore omitted.

$$D = \left(\frac{\dot{E}_K}{E_K} - \frac{\dot{E}_L}{E_L}\right)\left(1 - \frac{1}{\sigma}\right). \tag{3.3.24}$$

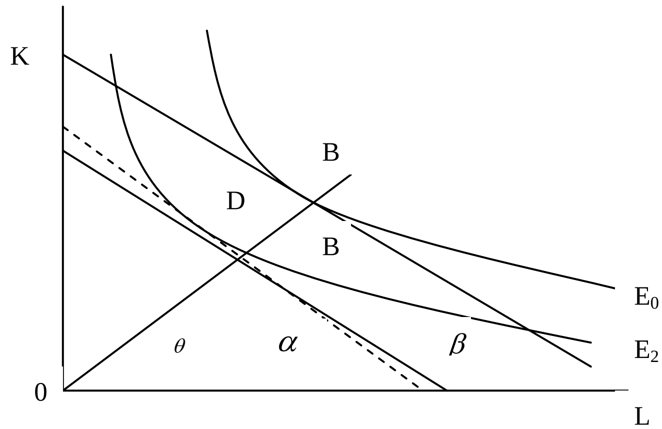
To demonstrate the effect of technological changes on aggregate production function, assume that between two periods called period zero and period one there is technical progress, in the sense that the same unit level of output can be produced with smaller quantities of inputs. If the technical progress is neutral, the isoquant has in effect moved bodily to the left by a constant amount throughout its whole length. Denoting the old isoquant by E_0 and the new one by E_1, then its slope is equal to the slope of E_0 on every straight-line ray from the origin (Figure1). Therefore at the original capital-labour ratio, the marginal rate of substitution has the same value as in period zero.

Figure1. Technical Change and the Production function



If the technical progress is 'biased', then asymmetrically, there is shift to the left of the isoquant, to E_2, say as illustrated in Figure 2. That is E_2 is not parallel to E_0. Hence, if the capital-labour ratio is to remain constant, (B on E_2), the ratio of the marginal products must change between the two time periods ($\tan\alpha \neq \tan\beta$). On the other hand if the ratio of the marginal products is to remain constant, the value of the capital-labour ratio must increase and be equal to the slope of OD. In either case, there is a change in the value of the elasticity of substitution.

Figure 2: The Effect of Technical Change on the Production Function



On the other hand if the factors are measured in efficiency units, then since we have assumed the production function to be invariant over time, the elasticity of substitution of the quality-corrected capital-labour ratio would be equal to the original value.

Algebraically, the production function can be written as expression (3.3.20):

$$Y_t = F(\hat{K}_t, \hat{L}_t, t), \qquad (3.3.25)$$

where:

$\hat{K} = a_k(t)K_t$ and $\hat{L}_t = a_L(t)L_t$.

Capital and labour measured in physical units at time t are denoted by K_t and L_t respectively, while $a_K(t)$ and $a_L(t)$ are indices of the respective efficiencies of capital and labour relative to some base period. Thus capital change may improve the quality of capital, but this new technology need not enter the production process through a change in a_K. In fact, it can result in a change in a_K or in a_L, or in both a_K and a_L. The increase in a_L will then be designated as labour-augmenting technical change despite the fact that it may be a consequence of the some base period. Thus capital change may improve the quality of capital, but this new technology need not enter the production process through a change in a_K. In fact, it can result in a change in a_K or in a_L, or in both a_K and a_L. The increase in a_L will then be designated as labour-augmenting technical change despite the fact that it may be a consequence of the introduction of better or new machines[9].

Given a production function consistent with observed data, (assumed to show positive technical progress), another neoclassical production function with an arbitrary elasticity of substitution, $\sigma^*(t)$, along the observed time path is derived. A new marginal rate of substitution $M\tilde{R}TS(k,t)$ is then defined as:

$$M\tilde{R}TS(k,t) = \varepsilon(k,t) \text{ MRTS (k,t).} \qquad (3.3.26)$$

Consequently, based on equation (3.3.25), the existence of a function in the form $\tilde{q}(k,t)$, which is the new productivity equation is established.[10]

However, Romer (1986) argues that the shift in the production functions in an economy over time is due to knowledge accumulation by labour. Lucas (1988) for instance focuses on human capital, not on its direct and remunerated productivity, but on the externalities that each increase in the stock of human capital is presumed to generate.

3.4 Technical Change and the Rate of Investment

Both technical change and increases in the capital employed per labour hour (capital intensity) contribute to the increasing average productivity of labour. Quantitative estimates of their relative importance provides a guide to the proportion of limited investment resources which should be channelled into education and increasing technological and managerial innovation, rather than expanding the existing types of capital equipment and structures.

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[9] Solow (1957)

[10] For the proof, see Francis (1970).

Technological change consists of not only increasing organisational skills which require no increase in factor inputs to raise the level of output per worker, but also innovations embodied in new capital goods and the new technical skills of the labour force as a result of a rise in the level of education.

In consequence, the rate of technical advancement is influenced by the rate of capital formation, comprising additions to the capital stock and the replacement of existing equipment. Significant embodied technological advance can still occur when net investment is negligible or even negative provided that only gross investment is occurring. It follows that an industry that is expanding its capital stock is likely to be achieving a high level of technical change. Conversely, the rate of net capital formation is likely to be the greatest where there is a high level of technological advancement, and for the rate of profit is also likely to be high[11].

Moreover, for an industry that is competitive in structure or open to foreign competition, the rate of investment will be causally related to the rate of technological progress. To justify this statement, first note that gross capital formation, obsolescence, and depreciation as a result of physical attrition determine net capital formation. Given the rate of gross investment, the rate of capital formation depends on the rate of deterioration, which is largely a technological consideration and the rate of obsolescence that is economically determined.

The sources of technological change need to be identified if the effects of alternative policies to accelerate economic development, the rate of net investment and obsolescence on output per worker are to be measured. Of concern to policy makers will be issues such as expenditure by firms on research and development, the policies of firms regarding the replacement of obsolescent equipment, and the personnel training programmes of both business and government.

[11] Massell (1960).

In this study we focus on some of those variables upon which the "process" of economic development is operating to bring about growth in the productivity of Australia's economy. Employing the concept of "production function", an attempt is made to empirically quantify the variables such as GDP, fixed capital, labour units, human capital, FDI and ICT.

In particular, we endeavour to measure productivity performance in Australia with the focus on TFP, the effects of technical change on the productivity of factors of production. The study is however historical rather than predictive in the sense that we measure the phenomena of change, but make no attempt to describe or explain the mechanism of change. The literature on Australia's productivity performance is reviewed next.

3.5 Productivity in Australia

This section starts by a brief introduction to Australia's economic performance and further discuses its productivity performance. It also examines any significant contributions of the economic reforms to productivity growth. Like any other country, the most commonly used productivity measures for analysis are labour productivity and multifactor productivity (MFP) or total factor productivity (TFP). For the purpose of this study, the term productivity refers to MFP or TFP since most of the variations in Australia's labour productivity growth are largely explained by variations in MFP growth. Improvement in productivity growth simply means increase in efficiency in the production of goods and services with less waste and increase in effectiveness (the use of resources in ways that generate more value added).

Australia entered the 20th century as a country which had one of the highest levels of labour productivity in the world. However, this high level of labour productivity could not be sustained for long and the rate of productivity growth in Australia was comparatively low over most of the 20th century. Australia's gross domestic product (GDP) per capita was about 81 % of the productivity leader, the USA in 1950 and it ranked 4th among a group of 22 developed or high–income countries (Parham, 2003). Australia's growth in average income (GDP per capita) was below the OECD average over the post-war period from 1950-1990. The consequent decades which were periods to catch-up with the USA and convergence in the productivity levels, saw some European countries including Japan and South Korea, started the catch up towards the USA and some even overtook the productivity leader. However, Australia did not take part in the convergence club and many countries overtook Australia as it slipped further behind the USA in the 1950s (Parham, 2003). Australia's productivity performance was relatively poor from the 1950s to 1990. Parham (2002a) notes that by 1990, by this relative poor productivity growth, Australia's ranking on level of GDP per capita moved from 4th to 15th among a group of 22 developed or high–income countries.

According to Parham (2003), a string of policy reviews in the 1960s, 1970s and 1980s attributed this relatively poor productivity performance to highly regulated product, capital and labour markets and the inefficient provision of economic infrastructure, which was dominated by government-owned enterprises operating without clear commercial imperative or performance regulation.

Surprisingly, most industrialised countries, including Australia, experienced a slowdown in productivity growth in the post-1973 period, despite their rapid technological advancement. The computer paradox for example, is part of this, but even if computers have not led to a productivity payoff, then it is still puzzling why the rate of productivity growth in the previous 30 years is relatively low compared to before 1950. Previous studies that attempt to measure productivity performance in Australia offer several explanations for the poor productivity growth rate. Many of these studies attribute the low TFP growth rate to measurement problems.

Australia had introduced microeconomic policy reforms in the 1980s and 1990 which were designed to raise productivity performance. The policy reforms adapted a strategy which created incentives to be more productive and allow businesses greater flexibility in order to meet stronger competition from Asian markets and to adjust to changing market circumstances. Parham (2002a) argues that the strength of this strategy was seen not only in better productivity outcomes, but in the resistance of the economy to adverse shocks (the Asian financial crisis) and the ability to take on new developments (the rapid advances in ICTs in the second half of the 1990s).

In the 1990s, Australia's annual average rate growth in GDP per capita increased from a previous rate of 1.7% to 2.5 %. Annual productivity growth at 2.3% accounted for about 90% of the 1990s average income growth and 96% of the 0.8 of a percentage point acceleration from the previous average. This acceleration in productivity growth rate pushed Australia ahead of the OECD GDP per capita growth (1.7 %) and productivity growth (1.8 %) in the 1990s (Parham, 2002a).

Australia was also ahead of the USA in both income (2.0%) and productivity (1.6%) growth. The strong productivity growth witnessed in the 1990s pushed up Australia's ranking on GDP per capita from 15 to 7 in 2001. Since the 1990s, Australia had an annual GDP growth average just under 4% for 10 years, a performance Australia had never witnessed since the 1960s and early 1970s. Even in the midst of the 1997 Asian financial crisis and the 2001 global downturn, Australia was able to witness strong economic growth.

Banks (2003) argues that Australia's productivity growth in the second half of the 20th century can be segmented into three phases namely: relatively fast growth in the 1950s through to the mid-1970s; a slowdown through the early 1990s; and since then, a strong resurgence that has continued till now. What is peculiar of Australia's productivity growth is that during the worldwide productivity boom of the post-war period, productivity performance though stronger than earlier periods was poor by the standard of similarly developed countries. In contrast, during the 1990s, when the world productivity record was irregular, Australia's productivity performance was outstanding.

Australia had witnessed the longest period ever of continuous positive growth in multifactor productivity on record of 9 years from 1990-91 to 1999-2000. Australia's high rate of productivity growth is in two phases. There was a period of strong growth, common to most high–income nations, during the Golden Age of growth in the post–war period until the mid 1970s. Australia's productivity growth then slowed as was witnessed in most other high-income countries and productivity growth was very strong again in the 1990s (Parham, 1999, 2002a).

ABS (2003-2004) notes that Australia had achieved its highest ever productivity growth rates of 3.2% (for labour productivity) and 2.0% (for MFP) in the 1990s, and these were above the OECD average growth rates for the first time in 35 years. At the same period, Australia's GDP grew by 3.5 percent a year and this was faster than even the USA's lauded performance and a third greater than that achieved by the OECD as a whole (Banks 2003). The strong growth exhibited by Australia's economy in the midst of the 1997 Asian financial crisis made the US economist Paul Krugman to label it the "miracle" economy (Banks, 2003, pp.1). However, this high productivity growth rate could not be sustained and Australia started to experience a slowdown in productivity growth since 2000.

The strong productivity growth rate in the 1990s has prompted a number of researchers to investigate into the sources of productivity growth in Australia. All the studies adopt different approaches but the findings indicate that the performance of productivity growth in Australia has improved in the mid 1990s.

The general consensus of the studies on Australia's productivity performance is that the microeconomic policy reforms which were introduced in the economy in the mid-1980s and are still on going have played a central role in productivity improvements. Parham et al. (2001) for instance argue that in contrast to earlier years, the uptake of the latest technologies have been very strong in the 1990s in Australia. The newly introduced technologies could be seen as the immediate source of stronger productivity growth and microeconomic policy reforms could be seen as the creator of a more conducive environment to the adoption of new technologies and other productivity enhancements. Parham et al. (2001) notice that a more open and competitive and less-regulated business environment provides greater incentives and flexibilities for firms to move toward best practice has led to a very strong productivity growth in Australia.

Otto and Voss (1994, 1996) provide empirical evidence which shows that investment in the core public infrastructure of transport and communication and water systems also stimulated the productivity growth. Dawkins and Rogers (1998), based on their comprehensive review of the productivity literature, attribute the productivity improvement at the aggregate level to capital intensity, international openness, factor prices, the union membership rate (as proxy for labour reforms) human capital investment, infrastructure and international competitiveness.

Chand (1999) uses a standard Solow Cobb-Dauglas methodology to estimate productivity for the manufacturing sector and finds that trade liberalization has contributed to productivity growth in the manufacturing industries. Mahadevan (2002) on the other hand uses the stochastic frontier model approach to estimate productivity in the manufacturing industries and arrives at a similar conclusion to that of Chand. Bean (2000) and Parham (2002b, 2003) conclude in their studies that that high ICT spending and the policy reforms contributed positively to productivity growth.

Salgado (2000) finds that structural policy reforms such as trade liberalization, increased competition and labour market reforms had contributed to Australia’s productivity growth in the 1990s. Valadkhani (2003) provides a formal model of Australia’s aggregate productivity growth to determine drivers of the 1990 productivity improvement and also arrives at conclusion similar to that of Salgado. Valadkhani (2003) examines Australia’s aggregate labour productivity for the period 1970–2001 and finds positive effects from physical and human capital accumulation on productivity growth.

Most of the studies mentioned above depend on the multifactor productivity estimates computed by the ABS, Productivity Commission and OECD researchers for productivity analysis in Australia. ABS (2003-2004) for instance argues that multifactor productivity (MFP) estimates for Australia extend back to the mid-1960s. It notes that since then, Australia has experienced 8 growth cycles and the highest MFP growth rate which is 2.0

% per year on average was achieved in the 1993-94 to 1999-2000 growth cycle. Table 1 shows the ABS estimates of labour and capital productivities and MFP growth rates for the 8 cycles within the period 1964-65 to 2003-04.

However, the ABS considers capital and labour inputs as the only factors of production in estimating the MFP for Australia. As noted earlier, the measurement of productivity in Australia demand the consideration of not only capital and labour inputs, but also other factors such as human capital, foreign direct investment and ICT that can be important in determining productivity growth. Failure to take into account all factors may bias productivity estimates which may mislead policy decisions.

Table 1: Productivity Measures–2003-2004-01 Issue

YEARS	**LABOUR**	**CAPITAL**	**MFP**
1964-65 to 1968-69	2.5	-0.6	1.3
1968-69 to 1973-74	2.9	-0.4	1.6
1973-74 to 1981-82	2.4	-1.2	1.1
1981-82 to 1984-85	2.2	-1.5	0.9
1984-85 to 1988-89	0.8	0.1	0.6
1988-89 to 1993-94	2.0	-1.2	0.7
1993-94 to 1999-00	3.2	0.1	2.0
1999-00 to 2003-04	2.3	-0.9	1.0

Sources: ABS 5204.0 – Table 20b (Extract)

Productivity estimates tend to vary from study to study. Zohar and Luski (1987) argue that when the average rate of productivity over a particular period is compared to the corresponding rate in another period, the extent of the difference depends, among other things, on the very definition of these averages. There are several ways to define and measure averages, and part of the observed slowdown in productivity rates may be attributable to the definition of the measures, rather than to an actual economic phenomenon.

The findings of the previous studies on Australia's productivity performance provide solid evidence of this phenomenon by producing different MFP growth rates at both sectoral and aggregate levels. The only similarity is that all the findings indicated that productivity performance have been high in the 1990s. For example, the MFP estimates presented by ABS (2003-2004) and the sectoral productivity estimates presented by Productivity Commission (2004), are slightly different from those estimated by the OECD (2001) and Diewert and Lawrence (2004).

The differences in MFP growth rates could be explained by the approach adopted by each study in defining and measuring MFP or in computing outputs and inputs of production. For instance, as noted by Diewert and Lawrence (2004), the ABS and Productivity Commission used unbalanced rates of return to compute most of the sectors to aggregate to a total capital services index but then the value of total capital inputs is chosen to balance the sum of labour and capital costs with gross income in the second stage aggregation. Diewert and Lawrence (2004) on the other hand use a 4 per cent real rate of return, which is used by a wide range of countries and is consistent with rational producer behaviour to compute input values. These controversial results point to the need for the present study.

In addition to physical capital and labour endowments, the level of knowledge (the stock of human capital), research and development, openness to trade, changes in the terms of trade, changes in non traded goods prices, the used of ICT are identified as the main contributors to productivity growth in Australia. Furthermore, a possible contributing factor to the 1990s productivity growth could be that some of the sectors of the economy have undergone major microeconomic reforms over the last two decades. Discussion on productivity analysis in Australia will be incompleted without a note on sectoral productivity performance and this is discussed next.

3.6 Sectoral Productivity growth in Australia

Diewert and Lawrence (2004) argue that the 1990s productivity performance in Australia was also partly due to the microeconomic reforms which were introduced to some of the sectors of the economy in the 1980s and are still on going. For the purpose of this analysis, the literature review will focus on the 12 main sectors normally considered by ABS, Productivity Commission, OECD and other productivity researchers for sectoral analysis.

The traditional sectors, Agriculture, Mining, and Manufacturing have contributed significantly to aggregate productivity growth in the 1988-89 to 1993-94 productivity growth cycles. Parham (2002a) argues that whilst productivity remained relatively strong in these sectors in the 1990s, Agriculture and Mining experienced a deceleration compared with the previous cycle. Manufacturing is the only sector whose MFP has increased steadily between 1980-2003 with an annual trend growth of 1.59% (Diewert and Lawrence, 2004).

The traditional sectors, Agriculture, Mining, and Manufacturing were joined in the early 1990s by the strong performing sectors such as Communication Services and Electricity, gas and water. The improved performance of these industry sectors resulted from the major reform-induced efficiencies achieved in government enterprises, which have dominated production in these sectors, as well as technological advances in some activities (Parham, 2002a). The Electricity, gas and water sector for example has undergone major microeconomic reforms over the last two decades but witness a trend annual productivity growth of only 0.75% and with 2003 MFP levels being 14% above those in 1980 (Diewert and Lawrence, 2004). The recent study of Diewert and Lawrence (2004) indicates that Communication Services and Agriculture both have the highest MFP trend growth rates of 2.75% per annum over the period 1980-2003.

The 1990s productivity performance was partly due to the success of the new set of service industries such as Wholesale Trade, Construction and Finance and Insurance which have increased their rate of productivity growth. The success of the new service industry contributors is linked with information and communication technologies. Parham et al. (2001) argue that the productivity gains are however being derived from the smart use of ICTs in Australia and not from the manufacture of ICTs. Sectors such as Wholesale Trade and Finance and Insurance show some productivity growth from around 1991 onwards but were not able to reattain their 1980 productivity growth levels by 2003.

Diewert and Lawrence (2004) argue that sectors such as Transport and Construction have also contributed significantly to productivity performance over the period 1980-2003. Within this period, Transport witnessed an annual trend growth rate of 0.76%, and Construction with 0.12%. Retail Trade on the other hand witnessed an annual negative trend growth rate of 0.78%. All the sectors suffered from productivity reversals over the first half of the period before recovering somewhat in the second half. The performance of Transport, Construction and Retail Trade, in particular appears to be very low with very little productivity advances for the first two over the two and half decade period and Retail Trade failed to retain its 1980 productivity growth level by 2003.

Sectors such as Cultural and Recreational Services and Accommodation, Cafes and Restaurants experience productivity declines over the period 1980-2003.

Diewert and Lawrence (2004) attribute the low and negative trend of productivity growth rates experienced by some of the sectors discussed above to the fact that measurement problems in these sectors are enormous and therefore under estimate the value of productivities.

3.7 Chapter Summary

The chapter first explores the existence of an aggregate production function with emphasis on the Cobb-Douglas type of production function. It concludes that despite the controversies surrounding the existence of the aggregate production function, it still remains the basis for analysing modern economic growth theory, aggregate productivity, long-run economic projections and making international growth comparisons.

This chapter also explores the relationship that exists between technical change and the aggregate production function. The chapter later demonstrates graphically the effects of technical change on the production function. It also discusses the relationship that exists between technical change and the rate of investment. The chapter argues that technological change consists of increasing organisational skills, innovations embodied in new capital goods and new technical skills possessed by the labour force due to rising level of education. The chapter explains how investment in the replacement of existing equipment can lead to technological advancement.

Furthermore, the chapter reviews the literature on productivity in Australia. It is argued that Australia's productivity and average income growth were relatively poor when there was a world-wide productivity boom in the catch-up and convergence era of the post-war period. It was only in the 1990s, a period of mixed performance across countries that Australia started to catch up on the USA. Australia did not only keep pace with the USA, but exceeded the US acceleration to record one of the highest accelerations in the OECD era. Finally, a review of sectoral productivity performance in Australia concludes the chapter.

CHAPTER FOUR

METHODOLOGY

4.1 Introduction

This chapter describes the procedures followed to achieve the objectives of this research. The chapter explains the methodology used in estimating the production function and measuring productivity in Australia.

Section 4.2 describes the estimation procedures for the empirical analysis. Time-series properties such as stationarity and cointegration tests of the variables are described in Section 4.3. The Granger causality test is discussed in Section 4.4 to determine the existence of a dynamic causal relationship between or among the variables selected for the empirical work of this research. This is followed by impulse response analysis to determine the size of the shock between GDP, productivity and production factors. Methods used to estimate the production function are described in Section 4.5. A description of productivity measurement concludes the chapter.

4.2 Estimation Procedures

The procedure for our econometric estimation follows the steps below.

1. All variables are converted into natural logarithms to facilitate the calculation of elasticities and to make it possible the transformation of the non-linear production function into log linear one.
2. Diagnostic tests on the appropriateness of the non-linear transformation are conducted on each variable.
3. Transformed variables are subjected to a unit root test with the aim to determine their order of integration.
4. Structural break tests are also carried out.
5. The lag lengths of estimated VAR models are selected.
6. Cointegration tests are carried out for the variables to investigate whether they jointly define the long-run equilibrium or not.

7. The Granger causality test is carried out to determine causality relationship between GDP, productivity and production factors.

8. The impulse response and the forecast error variance decomposition analyses are carried out to determine the dynamic interrelation between GDP, productivity and production factors. The variance decomposition analysis helps to determine the proportion of the forecast error variance of GDP and productivity cause by the innovations of each production factor.

9. The long-run elasticities of the different factor production functions are estimated.

10. Diagnostic tests for constant returns to scale are carried out to determine whether the production functions satisfy the constant returns to scale assumptions or not.

11. Diagnostic tests for significance of the additional exogenous variables, human capital, FDI and ICT are carried out to determine the extent of their significance in the production function.

12. Based on the long-run parameters of the different factor production functions, the estimates of TFP and the dynamics of TFP growth rates for Australia are computed, presented graphically and discussed.

Computer packages RATS (Doan, 1992; Enders, 1996), MICROFIT (Pesaran and Pesaran (1997) and EViews (Hill et al., 2001) are used for the estimation procedures.

4.3 Time-Series Properties

To ensure correct model specification and to avoid the possibility of obtaining misleading results, it is important first to check the time-series characteristics of the data by conducting unit root and cointegration tests for the variables selected for this analysis. I first test for the order of integration of each variable. A variable is integrated of order d, denoted I(d), if it must be differenced d times to achieve stationarity. In addition to the Augmented Dickey Fuller, Phillips Perron and Perron structural break tests for deciding the integration order of each variable, the Johansen (1991) multivariate cointegration test is used.

4.3.1 Stationary in Regression

Granger and Newbold (1974) argue that some economic time-series regressions, which produce impressive empirical fits, but had no statistical meaning were “spurious regressions” produced by non-stationary data. Ensuring stationarity of time-series data used for any kind of empirical analysis has since been recognised as an important first step.

A stochastic process Y_t is said to be stationary if:

1. EY_t = constant for all t;
2. Var Y_t =constant for all t;
3. Cov (Y_t, Y_{t-s}) = constant for all t $\neq$ s.

Many economic time series are non-stationary processes, rather they are trending and thus may not fulfil any of the above three conditions. A non-stationary process is described in the following equation.

$$Y_t = Y_{t-1} + \varepsilon_t \qquad (4.3.1.1)$$

where ε_t is a “white noise” process.

Equation (4.3.1.1) is a non-stationary stochastic process or “random walk”. Introducing a constant into equation (4.3.1.1) gives:

$$Y_t = \alpha + Y_{t-1} + \varepsilon_t . \qquad (4.3.1.2)$$

For $\alpha \neq 0$, in equation (4.3.1.2) produces a random walk with drift.

If the form of non-stationary process is a propensity of the series to move in one direction, this tendency is called a trend. The trend could be stochastic or deterministic. Consider for example,

$Y_t = \alpha_t + \varepsilon_t$, and $\alpha_t = \alpha + \delta\, t$.

Therefore,

$$Y_t = \alpha + \delta\ t + \varepsilon_t\,. \qquad (4.3.1.3)$$

The tendency in a non-stationary stochastic process where the mean of the process is itself a specific function of time as in equation (4.3.1.3) is called a deterministic trend.

Combining features of equations (4.3.1.2) and (4.3.1.3), produces

$$Y_t = \alpha + \delta\ t + Y_{t-1} + \varepsilon_t\,, \qquad (4.3.1.4)$$

which is a mixed stochastic-deterministic trend process.

4.3.2 Unit Root Test and Structural Break

The view that most economic time series are characterised by a stochastic process rather than a deterministic non-stationary process has become prevalent. Before any time-series data can be used for estimation and any meaningful empirical analysis, it must be checked for stationarity. A simple approach of testing the unit root of time-series variables is proposed in Dickey and Fuller (1979). Others who have contributed to the unit root test include Phillips and Perron (1988), Perron (1989, 1997), Granger and Hallman (1991) and Frances and McAleer (1998). There are three types of models involved in testing for a unit root of a variable, namely general model, random walk drift and random walk (no drift) (see Section 3.1 of this chapter for the various equations).

For the purpose of the Augmented Dickey-Fuller (ADF) test, consider the univariate AR(1) process:

$$y_t = \alpha + (1-\phi)\delta\,\mathrm{t} + \phi\ y_{t-1} + \varepsilon_t \qquad (4.3.2.1)$$

where:

t =1,2,3,....,n and ε_t - IN(0, σ^2), and

y_t = natural log Y.

If $|\phi|$ <1, it is a trend stationary, and if ϕ =1, it is difference stationary with a non-zero drift α .

The unit root generally takes a form of a one-sided test of the null hypothesis as against the alternative of stationarity. That is $H_{0:}$ ϕ =1 against $H_{1:}$ ϕ <1. Note that when using the t-statistic for testing ϕ =1, it is important to use the critical values of the non-standard Dickey-Fuller unit root distribution rather than the standard normal distribution. In a more general case where the disturbances ε_t, for t =1,2,3…,n are serially correlated, it is advisable to use the Augmented Dickey-Fuller unit root test statistic, which is proposed to accommodate error autocorrelation by adding lagged differences of y_t. Hence

$$y_t = \alpha + (1-\phi)\delta\, t + \phi\, y_{t-1} + \sum_{j=1}^{p}\phi_j y_{t-j} + \varepsilon_t, \text{ t =1,2,3…,n.} \tag{4.3.2.2}$$

Now consider in general AR(p) processes:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \phi_3 y_{t-3} ...... + \phi_{\,p} y_{t-p} + \varepsilon_t, \tag{4.3.2.3}$$

which can be written like this:

$$\Delta y_t = \phi^* y_{t-1} + \phi^*_1 \Delta y_{t-1} + \phi^*_2 \Delta y_{t-2} + \phi^*_3 \Delta y_{t-3} + ... + \phi^*_{t-(p-1)} \Delta y_{t-(p-1)} + \varepsilon_t \tag{4.3.2.4}$$

where $\phi^* = \phi_1 + \phi_2 + \phi_3 + ... + \phi_p - 1$ since all $\phi_j s$ are functions of the original $\phi\ s$.

This implies that:

$$\Delta y_t = (\phi_1 + \phi_2 + \phi_3 + ... + \phi_p - 1)\, y_{t-1} + \phi^*_1\, \Delta y_{t-1} + \phi^*_2\, \Delta y_{t-2} + \phi^*_3\, \Delta y_{t-3} + \phi^*_{t-(p-1)}\, \Delta y_{t-(p-1)} + \varepsilon_t . \qquad (4.3.2.5)$$

To carry out the unit root tests, we formulate the null hypothesis as follows:
H_o: $\phi^* = 0$ (non-stationary) versus H_a: $\phi^* < 0$, which implies stationary.

Now in order to carry out the test, we start with the general model, followed by the random walk drift and finally random walk (no drift) model. If we reject the H_o: $\phi^* = 0$ in favour of the alternative H_a: $\phi^* < 0$, it implies stationarity and we do not continue to test further. On the other hand if we do not reject the H_0, then we move from the general model to random walk drift model and if we still do not reject $H_{o,}$ then we move finally to random walk (no drift) model. The decision rule is to reject H_0 if the test statistic is greater than the critical value in absolute terms at a given level of significance.

Two critical assumptions that are inherent in the estimation of equation (4.3.2.5) are that the logarithmic transformation is correct and there are no structural breaks in the trend function. Granger and Hallman (1991) and Frances and McAleer (1998) argue that the ADF tests for a unit root are sensitive to non-linear transformations. They provide evidence, which shows that the ADF test on the logarithm of a variable often report stationarity, when the same variable measured in levels is found to be non-stationary. Frances and McAleer (1998) examine the effects of non-linear transformations on the ADF regression within the class of Box-Cox models. They therefore proposed a test for correct functional form in (4.3.2.5) by including an additional variable, $(\Delta\ y_{t-1})^2$ in the ADF regression equation which produces the following equation:

$$\Delta y_t = \phi^* y_{t-1} + \phi^*_1\, \Delta y_{t-1} + \phi^*_2\, \Delta y_{t-2} + \phi^*_3\, \Delta y_{t-3} + ... + \phi^*_{t-(p-1)}\, \Delta y_{t-(p-1)} + \phi_p (\Delta y_{t-1})^2 + \varepsilon_t . \qquad (4.3.2.6)$$

The test is carried out by examining the significance of ϕ_p in equation (4.3.2.6). Should the additional variable be statistically significant, the ADF regression is inappropriately transformed and does not yield a valid inference in testing for a single unit root in y_t. The above approach will be used to test for a single unit root and non-linear transformation in this study.

The standard ADF and PP tests for stationarity discussed above may not be appropriate when the sample (series) under consideration contain structural breaks. A number of authors point out this limitation of these conventional unit root tests (for example Perron, 1989, 1997 and Zivot and Andrews, 1992).

Perron (1989) for example argues that the ADF procedure is biased towards the non-rejection of the null hypothesis of stochastic trend, if the sample period contains a structural break. That is the ADF test is biased in favour of H_o: Yt~ I(1) when there is a structural break in a trend stationary process. He argues that this could lead to inappropriate detrending methods resulting in spurious conclusions. Furthermore, Perron (1989) emphasises that as far as macroeconomic theories are concerned, the most important implication of the unit root revolution is that under this hypothesis, random shocks have a permanent effect on the system. In order to take into account possible structural break in the unit root test, Perron (1989) develops a procedure that allows an exogenous structural break at time TB (i.e. the time of break is known *a priori*), against the alternative hypothesis that the series is trend stationary about a breaking trend. Throughout this study, TB denotes the time at which the change in the trend function occurs. The statistical methodology adopted by Perron is just an extension of the Dickey-Fuller methodology to test for the unit root in a univariate time series.

He computes the augmented “Perron” unit root test allowing under both null and the alternative hypothesis for the presence of a one-time change in the level or in the slope of the trend function using three different linear regression models. The models are constructed by nesting the corresponding null and alternative hypothesis, which are the null hypothesis such that Y_t is stationary around a breaking trend and the alternative hypothesis that Y_t is not stationary around a breaking trend.

Perron (1989) then developes 3 types of breaking-trend models, each nesting the corresponding null (H_0) and alternative (H_a) hypotheses.

<u>Model A</u>: a (single) break in just level of Y_t ("crash")

$$\Delta Y_t = \mu + \theta\ DMU_t + \beta t + dDTB_t + \alpha\ Y_{t-1} + \sum_{i=1}^{P} b_i \Delta Y_{t-1} + \varepsilon_t \qquad (4.3.2.7)$$

<u>Model B</u>: a (single) break in just the slope of the trend in Y_t ("changing growth")

$$\Delta Y_t = \mu + \beta t + \gamma\ DTS_t + \alpha\ Y_{t-1} + \sum_{i=1}^{P} b_i \Delta Y_{t-1} + \varepsilon_t \qquad (4.3.2.8)$$

Model C: a (single) break in both the level and the slope of the trend in Y_t

$$\Delta Y_t = \mu + \beta t + \gamma\ DTS_t + dDTB_t + \alpha\ Y_{t-1} + \sum_{i=1}^{P} b_i \Delta Y_{t-1} + \varepsilon_t \qquad (4.3.2.9)$$

where:

μ = a constant, t = linear trend (1, 2, 3…T), DTB_t =1 if t = TB +1, (TB = time of break), and 0 otherwise, DMU_t = 1 if t >TB, and 0 otherwise, DTS_t = t-TB if t > TB, and 0 otherwise DTS_t = t if t >TB, and 0 otherwise, and ε_t = "white noise process (necessary for validity of the tests).

Under the H_o: Y_t ~I(1) with break in level, slope or both, we should find:

Model A: $\mu \neq 0 ; \alpha = 1 ; \beta = \theta = 0 ;\ d \neq 0$

Model B: $\mu \neq 0 ; \alpha = 1 ; \beta = \gamma = 0 ;$

Model C: $\mu \neq 0 ; \alpha = 1 ; \beta = \gamma = 0 ;\ d \neq 0$

Under the H_a: Y_t ~I(0) with break, we should find:

Model A: $\mu \neq 0\,; \alpha < 1; \beta \neq 0; \theta \neq 0\,,\; d \neq 0$

Model B: $\mu \neq 0\,; \alpha < 1;\; \beta = \gamma = 0;\; \theta \neq 0$

Model C: $\mu \neq 0\,; \alpha < 1; \beta \neq 0; \gamma \neq 0;\; d \neq 0$

However, Zivot and Andrews (1992) argue that Perron (1989) treats the break point as exogenous instead of endogenous. By treating the break point as endogenous, Zivot and Andrews (1992) find less evidence against the unit-root hypothesis than Perron (1989) finds for many of the data series but stronger evidence against it for several of the series. Perron (1997) then re-develops the models in Perron (1989) to treat the break point TB as endogenous. This break point is first chosen such that the t-statistic for testing the null hypothesis of a unit root is smallest among all possible break points. Perron (1997) considers choosing the break point that corresponds to a minimal t-statistic on the parameter of the change in the trend function.

A large number of empirical studies have been conducted allowing structural breaks in the series in question in recent years (Hatemi-J and Shukur, 1999; Salman and Shukur, 2004; Hacker and Hatemi-J, 2005 and Narayan, 2005 among others). It seems reasonable to treat breakpoint as endogenous for the purpose of this study; Perron (1997) approach for testing a unit root is adopted.

Perron (1997) performs the unit root test by using the t-statistic for testing α =1 in the following auxiliary regression:

$$y_t = \mu + \theta\, DU_t + \beta t + \delta D(TB)_t + \alpha\; y_{t-1} + \sum_{i=1}^{k} b_i \Delta y_{t-1} + \varepsilon_t \qquad (4.3.2.10)$$

where:

DU_t = 1 (t >TB) and $D(TB)_t$ =1 (t=TB+1)

Under the second model, both a change in the intercept and the slope are allowed at time TB. The test by using the t-statistic for testing α =1 in the following auxiliary regression:

$$y_t = \mu + \theta\ DU_t + \beta t + \gamma DT_t + \delta D(TB)_t + \alpha\ y_{t-1} + \sum_{i=1}^{k} b_i \Delta y_{t-1} + \varepsilon_t\,, \tag{4.3.2.11}$$

with DT_t =1 (t >TB)t.

Under the third model, Perron (1997) allows a change in the slope but both segments of the trend function are joined at the time of the break. Perron (1997) first detrends the series using the following regression where $DTB_t^* = 1(t > TB)(t - TB)$:

$$y_t = \mu + \beta t + \gamma DTB_t^* + \bar{y}_t\,. \tag{4.3.2.12}$$

The test is then performed using the t-statistic for α =1 in the regression:

$$\bar{y}_t = \alpha\ \bar{y}_{t-1} + \sum_{i=1}^{k} c_i \Delta \bar{y}_{t-i} + \varepsilon_t\,. \tag{4.3.2.13}$$

Perron (1997) denotes by t_α(i, TB, k) (i=1,2,3), the t-statistic for testing α =1 under model I with a break date TB and truncated lag parameter k (using regressions equations (4.3.2.10), (4.3.2.11) and (4.3.2.13) for i= 1, 2 and 3, respectively. In these regression equations, TB and k are treated as unknown.

The structural break test is important in analysing time series data for a country like Australia, which has undergone major policy reforms. Australia has introduced major policy reforms in the 1980s that are still on going. One focus of this study is to test whether there are identifiable structural breaks in the rate of productivity growth around the time of the reforms.

4.3.3 Selection of Lag Lengths

In order to carry out the cointegration test, the order of the VAR model is first selected. The lag order, k, is chosen carefully by a combination of multivariate Schwarz (1978) Bayesian criterion (SBC), multivariate Hannan and Quinn (1979) criterion (HQC), Akaike Information Criterion (AIC), Maximum Likelihood (LL), and series of multivariate diagnostic tests.

The appropriate lag length is determined by several methods:

1) Minimising a selection criterion, for example AIC = nln($\hat{\sigma}^2$) + 2k, and SCB = nln($\hat{\sigma}^2$) + ln(T)k, where k is the number of augmenting lags.
2) Using a variety of k values and see if the results of the ADF test are robust.
3) Selecting the smallest k such that the errors are approximately white noise.
4) Choosing k = $T^{\frac{1}{3}}$, for example if the sample size T=125, then k =5.

Different software packages use different methods for determining the value of k. For the purposes of this study, we are going to be very flexible in the lag selection since the nature of a data being use for the analysis can also play a very important role. We may not necessarily go by the lag lengths that may be suggested by any of the above criterion.

4.3.4 Cointegration Test of Variables

In addition to the Augmented Dickey Fuller (ADF), Phillips Perron (PP) and Perron structural break tests for deciding the integration order of each variable, the Johansen (1991) multivariate test is used. The test for cointegration reported in this study follows the Johansen (1988; 1991) and Johansen and Juselius (1990) maximum likelihood estimator procedures.

Over the past few years, important advances have been made in cointegration techniques to estimate long-run relationships. The basic idea of cointegration is that two or more variables may be regarded as defining a long-run equilibrium relationship if they move closely together in the long run, even though they may drift apart in the short run. This long-run relationship is referred to as a cointegrating vector. The components of the vector X_t are said to be cointegrated of order r, d, denoted $X_t \sim$ CI(r, d), if all components of X_t are I(r); and there exists a vector $\alpha\ (\neq 0)$ so that $Z_t = \alpha' X_t \sim$ I(r-d). The vector α is called the cointegrating vector (Engle and Granger, 1987). Because there is a long-run relationship between the variables, a regression containing all the variables of a cointegrating vector will have a stationary error term even if none of the variables taken alone is stationary.

Stock (1987) argues that in the case of cointegrated non-stationary series, ordinary least squares (OLS) estimates of the cointegrating vector are not only consistent but they converge on their true parameter values much faster than in the stationary case. This property is referred to as "super consistency." The proof of consistency does not require the assumption that the regressors be uncorrelated with the error term. In fact, the estimates will remain (super) consistent if any of the variables in the cointegrating vector is used as the dependent variable.

More generally, most of the classical assumptions underlying the general linear model are not required in order for OLS or maximum likelihood estimates of the cointegrating vector to have desirable properties. This is particularly important because errors in variables and simultaneity; both of which would normally be a cause for concern in the data set used for any analysis would not affect the desirable properties of the estimates. Moreover, because the cointegration approach focuses on long-run relationships, problems associated with variations in factor utilisation and with autocorrelation do not arise.

A popular approach to cointegration testing has been the use of a unit-root tests such as the Dickey-Fuller (DF) or the ADF test (Dickey and Fuller, 1981), to determine the degree of integration of the relevant variables. Next we apply the Engle and Granger (1987) two-step procedure, which is based on an OLS estimate of the cointegrating vector and a unit-root test of its residuals. Although it is easy to implement, there are a number of problems associated with the Engle and Granger (1987) two-step procedure.

Banerjee et al. (1986) show that there may be significant small-sample biases in such OLS estimates of the cointegrating vectors. Hendry and Mizon (1990) argue that the conventional DF and ADF tests generally suffer from parameter instability. In addition, the limiting distributions for the DF and ADF tests are not well defined, implying that the power of these tests is low (Phillips and Ouliaris, 1990). Perhaps more damaging is the possibility that any given set of variables may contain more than one long-run relationship: there may be multiple cointegrating vectors. OLS estimates of the cointegrating vector cannot identify multiple long-run relationships or test for the number of cointegrating vectors.

The residual-based approach of testing cointegration is inefficient and can lead to contradictory results, especially when there are more than two I(1) variables involved in the model. Johansen (1988) and Johansen and Juselius (1990) advance a cointegration estimation methodology that overcomes most of the problems of the Engle and Granger (1987) two-step approach. The Johansen procedure is based on maximum likelihood estimates of all the cointegrating vectors in a given set of variables and provides two likelihood ratio tests for the number of cointegrating vectors. This provides a unified framework for estimating and testing of cointegrating relations in the context of vector autoregressive (VAR) models.

In the VAR model, no distinction is made between endogenous and exogenous variables. All variables are endogenous. In order to implement the Johansen (1988) procedure, we formulate the econometric model that underlies the following general unrestricted VAR (p) model for the q series which is in the form:

$$\mathrm{X}_t = \Pi_1 \mathrm{X}_{t-1} + \Pi_2 \mathrm{X}_{t-2} + ... + \Pi_p \mathrm{X}_{t-p} + \mu + \phi\, D_t + \varepsilon_t , \qquad (4.3.4.1)$$

where:

X_t = a vector of q variables

D_t = a vector of deterministic terms such as (centered) seasonal and trend dummies

Πi = (q x q) matrices of parameters (i = 1,2,…p)

μ = (q x 1) vector of constants, and

ε_t ~ white noise with positive definite covariance matrix Ω. ie. "well behaved" random disturbances.

Economic time series are often non-stationary, and systems such as the above vector autoregressive representation (VAR) can be written in the conventional first-difference form:

$$\Delta X_t = \Gamma_1 \Delta X_{t-1} + \Gamma_2 \Delta X_{t-2} + ... + \Gamma_p \Delta X_{t-p+1} + \Pi X_{t-p} + \mu + \phi D_t + \varepsilon_t \,, \qquad (4.3.4.2)$$

where:

$\Gamma i = -Iq + \Pi_1 + \Pi_2 + ... + \Pi_i$ for i = 1,2, p-1 and

$\Pi = -Iq + \Pi_1 + \Pi_2 + ... + \Pi_p$.

The (q x q) matrix Π contains information about the long-run equilibrium relations among the series, and the rank of Π gives the number of cointegrating relationships between the variables in the data vector.

We now examine for example the relationship between Y, K, L, H, FDI and ICT in equation (3.2.12) using cointegration techniques. Assuming each of the variables has p = 2 lags, then

$$X_t = \Pi_1 X_{t-1} + \Pi_2 X_{t-2} + \mu + + \varepsilon_t \,, \qquad (4.3.4.3)$$

where:

$$\Pi_1 = \begin{bmatrix} \pi_{11} & \pi_{12} & \pi_{13} & \pi_{14} & \pi_{15} & \pi_{16} \\ \pi_{21} & \pi_{22} & \pi_{23} & \pi_{24} & \pi_{25} & \pi_{26} \\ \pi_{31} & \pi_{32} & \pi_{33} & \pi_{34} & \pi_{35} & \pi_{36} \\ \pi_{41} & \pi_{42} & \pi_{43} & \pi_{44} & \pi_{45} & \pi_{46} \\ \pi_{51} & \pi_{52} & \pi_{53} & \pi_{54} & \pi_{55} & \pi_{56} \\ \pi_{61} & \pi_{62} & \pi_{63} & \pi_{64} & \pi_{65} & \pi_{66} \end{bmatrix} \text{ and } \Pi_2 = \begin{bmatrix} \pi_{17} & \pi_{18} & \pi_{19} & \pi_{110} & \pi_{111} & \pi_{112} \\ \pi_{27} & \pi_{28} & \pi_{29} & \pi_{210} & \pi_{211} & \pi_{212} \\ \pi_{37} & \pi_{38} & \pi_{39} & \pi_{310} & \pi_{311} & \pi_{312} \\ \pi_{47} & \pi_{48} & \pi_{49} & \pi_{410} & \pi_{411} & \pi_{412} \\ \pi_{57} & \pi_{58} & \pi_{59} & \pi_{510} & \pi_{511} & \pi_{512} \\ \pi_{67} & \pi_{68} & \pi_{69} & \pi_{610} & \pi_{611} & \pi_{612} \end{bmatrix}$$

which facilitates comparison with the single-equation approach, which can be expressed in a scalar algebraic notation.

By algebraic manipulation of equation (4.3.4.3), above, we obtain:

$$\Delta X_t = \Gamma \Delta X_{t-1} + \Pi X_{t-2} + \mu + \varepsilon_t \text{ [12]}, \tag{4.3.4.4}$$

which is the vector error correction (VEC) model counterpart to the VAR model expressed previously as equation (4.3.4.3),
where:

$$\Gamma = -I + \Pi_1 \text{ and } \Pi = -I + \Pi_1 + \Pi_2 .$$

The Γ matrix for the first differenced variables in ΔX_{t-1} contains the contemporaneous short-run adjustment parameters, whereas the Π parameter matrix for the levels variables X_{t-p} contains the information about the long-run equilibrium relationship between the variables in the data vector. The rank of Π gives the number of distinct cointegrating vectors. There are three cases to consider:

(a) If the rank (Π) = 0, this implies that Π is a null matrix and (4.3.4.4) reduces to:

$$\Delta X_t = \Gamma \Delta X_{t-1} + \mu + \varepsilon_t , \tag{4.3.4.5}$$

[12] For detailed proof, see Amisano and Giannini (1992), Enders (1995) and Franses (1998).

which is a VAR(1) model in first differences. That is, since variables in the vector X are each I(1), ΔX is I(0) and there is no cointegration.

For the general VAR model [i.e, equation (4.3.4.2) with (q and p) > 2], if rank (Π) = 0, then the model reduces to a general VAR (p-1) model in first differences as follows:

$$\Delta X_t = \Gamma_1 \Delta X_{t-1} + \Gamma_2 \Delta X_{t-2} + ... + \Gamma_{p-1} \Delta X_{t-p+1} + \Pi X_{t-p} + \mu + \varepsilon_t . \qquad (4.3.4.6)$$

(b) If the rank (Π) = q (in general, q), which occurs only if the vector X is stationary contradicts the assumption that (the variables in X) ~ I(1). In this case ΔX is over differenced and the correct specification would be a VAR (p) model in levels, as in equation (4.3.4.3), rather than in first differences as in above.

(c) If 0 < [rank (Π) = r] < q, this implies that there are r cointegrating vectors. For example in equation (4.3.4.4) if the maximum rank (Π) =1, cointegrating occurs and Π can be decomposed into the product of two q by r matrices α and β such that $\Pi = \alpha\beta'$. Since the β matrix contains the long-run equilibrium parameters (the r cointegrating vectors), then $\beta' X_{t-p}$ comprises the r error correction terms which are stationary, even though X_t itself is non-stationary. The parameters in the α matrix measure the speed at which ΔX_t adjusts to the lagged error correction terms $\beta' X_{t-p}$. That is, it gives the weights with which the cointegrating vectors enter each equation of the system.

To determine the number of cointegrating vectors, r, Johansen and Juselius (1990) describe two likelihood ratio tests. In the first test, which is based on the maximum eigenvalue, the null hypothesis is that there are at most r cointegrating vectors against the alternative of r +1 cointegrating vectors. In the second test, which is based on the trace of the stochastic matrix, the null hypothesis is that there are at most r cointegrating vectors against the alternative hypothesis that there are r or more cointegrating vectors. The first test is generally considered to be more powerful because the alternative hypothesis is equality. These tests can also be used to determine if a single variable is stationary by including only that variable in ΔX_t.

Johansen (1988) argues that the likelihood ratio tests have asymptotic distributions that are a function only of the difference between the number of variables and the number of cointegrating vectors. Therefore, in contrast with the DF and ADF tests, the Johansen likelihood ratio tests have well-defined limiting distributions. Johansen and Juselius (1990) provide a methodology for testing hypotheses about the estimated coefficients of the cointegrating vectors based on likelihood ratio tests with standard chi-squared distributions.

The main hypothesis considered by Johansen and Juselius (1990) is the hypothesis of r cointegration vectors,

$$H_1 : \Pi = \alpha\beta' . \qquad (4.3.4.7)$$

We now examine the Granger causality test and the impulse response analysis, which enables us to test for dynamic interrelation between GDP, productivity and factors of production.

4.4 The Granger Causality Test and the Impulse Response Analysis

4.4.1 Introduction

In this study, we examine for the short-run dynamic interrelation between variables. To be precise, we examine the causal relationships between GDP, productivity and factors of production, the responses of GDP and productivity to a unit standard error shock to each production factor and the proportion of the forecast error variances of GDP and productivity caused by the innovation of each production factor included in the VAR model. The Granger causality testing, impulse response and forecast error variance decomposition analyses are used to achieve these objectives. The purpose is to determine by the use of econometric models the production factors that dominate the long-run GDP and productivity growth in Australia.

One of the reasons for building a VAR model is to carry out empirical analysis of the dynamic interrelation amongst the variables chosen for the system. Two set of procedures have been developed for this analysis, namely the Granger causality testing and innovation accounting. For the purpose of this study, we use the two approaches in our empirical analysis to make it possible for us to compare the test results. The aim is to test for the short-run dynamic shock among variables; that is, to investigate which variables included in the VAR models cause which. We now examine the methodology behind each of the two approaches.

4.4.2 Granger Causality Test

Narayan and Smyth (2005) argue that significant statistical correlation between variables does not necessarily mean a significant causal effect and unless the analytical tool accounts for the dynamic interaction between the variables. Brooks (2002) argues that when a VAR model includes many lags of variables, it is very difficult to know which sets of variables have significant effects on each dependent variable and which do not. In order to address this issue, tests are usually conducted that restrict all of the lags of a particular variable to zero.

The literature on productivity performance in Australia for instance suggests that bi-directional causal effects between GDP, capital, labour units, human capital, FDI and ICT are plausible. It is therefore, important to explore these potential feedback effects maintaining the policy relevance of the interaction of these macroeconomic variables. To investigate how these variables are related to each other in the short run and the long run, we use the VAR and VEC models developed in Section 3.4 of this chapter to test for the existence of Granger causality.

For the econometric illustration, consider the following more general three-equation VAR (p) model in standard form:

$$\begin{bmatrix} x_{1t} \\ x_{2t} \\ x_{3t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix} + \begin{bmatrix} A_{11}(L) & A_{12}(L) & A_{13}(L) \\ A_{21}(L) & A_{22}(L) & A_{23}(L) \\ A_{31}(L) & A_{32}(L) & A_{33}(L) \end{bmatrix} \begin{bmatrix} x_{1t-1} \\ x_{2t-1} \\ x_{3t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix}, \qquad (4.4.2.1)$$

where:

μ_i is a matrix of deterministic terms (intercept, trend, dummies variables etc) in the i^{th} equation, for i =1,2,3.

A_{ij} are polynomials in the lag operator L, with individual parameters denoted by $a_{ij}(1)$ for the first lag on the j^{th} variable in the i^{th} equation, $a_{ij}(2)$ for the second lag, ….,$a_{ij}(p)$ for the final lag, and

e_{ij} are vectors of white-noise error terms that are usually contemporaneously correlated, i.e. $\sum_e$ (sum of the error terms) is usually non-diagonal.

Granger (1969) suggests an optional definition of causality that is based on the notion of predictability. Suppose, for example, that we can predict values for the variable x_{1t} using two different information sets namely:

$$\Omega^1{}_{t-1} = \left[(L)x_{1t-i} \ ; \ (L)x_{2t-i} \right] \qquad (4.4.2.2)$$

$$\Omega^2{}_{t-1} = \left[(L)x_{1t-i} \ ; \ (L)x_{2t-i} \ ; \ (L)x_{3t-1} \right]. \qquad (4.4.2.3)$$

According to Granger, if the mean square error (MSE) of the prediction using $\Omega^2{}_{t-1}$ is less than the MSE from using $\Omega^1{}_{t-1}$, then x_3 Granger causes x_1. A formal procedure for testing Granger causality based on the preceding trivariate VAR (p) model is as follows:

H_0:a_{13} (1) = a_{13}(2) = ….=a_{13}(p) = 0, i.e. x_3 does not Granger cause x_1

Ha: Not $H_{0,}$ i.e. x_3 does Granger cause x_1.

Since individual e_{it} error terms are assumed to be white noise, and since each individual set of restrictions involves parameters drawn from only one equation, we can test the restrictions in H_0 with the usual F-test.

A test of related null hypothesis that x_3 does not Granger cause either of the other two variables, that is x_3 should not even be in the VAR model at all. The null hypothesis for this block exogeneity (block Granger causality) test is in terms of parameter restrictions:`

H_0: $a_{13(1)}$=$a_{13(2)}$=….=$a_{13(p)}$ and $a_{23(1)}$ = $a_{23(2)=}$ …= $a_{23(p)}$ = 0.

In this case, H_0 involves cross-equation restrictions and can be tested with a likelihood-ratio test. The equations are estimated separately using OLS to obtain the unrestricted RSS, then the restrictions imposed and the models re-estimated to obtain the restricted RSS. The F-statistic would then take the usual procedure. Thus, evaluation of the significance of variables in the context of a VAR model almost invariably occurs on the basis of joint tests on all the lags of a particular variable in an equation, rather than by examination of the individual coefficient estimates. We now discuss the impulse response analysis, the second approach to analysing the dynamic interaction among variables chosen for a given system.

4.4.3 The Impulse Response Analysis

The examination of causality in a VAR model will suggest which of the variables in the model have statistically significant impacts on the future values of each of the variables in the system. Brooks (2002) argues that F-test results will not, by construction, be able to explain the sign of the relationship or how long these effects require to take place. In order words, F-test results will not reveal whether changes in the value of a given variable have positive or negative effects on other variables in the system or how long it would take for the effect of that variable to work through the system. According to Brooks (2002), such information will, however, be given by examination of the VAR's impulse responses and variance decompositions.

Impulse responses trace out the responsiveness of the dependent variables in the VAR model to shocks to each of the variables. For each variable from each equation separately, a unit shock is applied to the error and the effects upon the VAR system over time are noted. Thus if there are v variables in a system, a total of v^2 impulse responses could be generated (Brooks, 2002).

The variance decompositions give the proportion of the movements in the dependent variables that are due to their own shocks and shock to other variables. For example a shock to capital will of course directly affect capital, but it will also be transmitted to all of the other variables, such as GDP, labour employed, human capital, foreign direct investment and ICT through the dynamic structure of the VAR model. The variance decompositions determine how much of the z-step-ahead forecast error variance of a given variable is explained by innovations to each explanatory variable for z = 1, 2,…, z. Empirical investigations show that own series shocks explain most of the (forecast) error variance of the series in the VAR model. Brooks (2002) notices that the impulse responses and the variance decompositions, to some extent offer a very similar result.

For the purpose of illustration, for two-variable case, the moving average representation of equation (4.3.4.10) is given by:

$$\begin{bmatrix} X_t \\ Z_t \end{bmatrix} = \begin{bmatrix} \overline{X} \\ \overline{Z} \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} \phi_{11}(i) & \phi_{12}(i) \\ \phi_{21}(i) & \phi_{22}(i) \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \end{bmatrix} \text{[13]} \qquad (4.4.3.1)$$

This is the vector moving average (VMA) (∞) representation that provides the basis for developing one of the main sets of analytical tools for impulse response functions and forecast error variance decomposition (Enders, 1995). The parameters in the ϕ_i matrix, that is each $\phi_{jk}(i)$, may be used to generate the numerical effects of ε_{1t} and ε_{2t} shocks on the entire time paths of the $\{X_t\}$ and $\{Z_t\}$, series. Normally, each $\phi_{jk}(i)$ parameter is interpreted as the time–specific partial derivative of the VMA (∞) function. That is the matrix ϕ_i has the interpretation:

[13] See Enders (1995, p. 305-306) for the proof of equation (4.4.3.1).

$$\phi_{jk}(i) = \frac{\partial y_{ji}}{\partial \varepsilon_k}, \tag{4.4.3.2}$$

which measures the numerical change in the jth variable in period one resulting from a unit shock to the kth variable in the present period.

Enders (1995) shows that accumulating $\phi_{jk}(i)$ impact multipliers up to period m gives the period multipliers for period m. He gives an example that the accumulated sum of effects of the unit shock (impulse) to ε_{zt} on the $\{X_t\}$ series is given by:

$$\Psi_{12} = \phi_{12}(0) + \phi_{12}(1) + \phi_{12}(2) + ... + \phi_{12}(m) = \sum_{i=0}^{m} \phi_{12}(i)\,. \tag{4.4.3.3}$$

Finally, letting m$\rightarrow \infty$, we obtain the long-run multipliers. Given the assumption that $\{y_t\}$~ I(0), it follows that for all j and k,

$\sum_{i=0}^{\infty} \phi_{12}(i)$ is finite.

Recall that each $\phi_{jk}(i)$ parameter of the impulse response function is intended to be a measure of the change in the jth variable induced by a unit shock (impulse) to the ε_{kt} disturbance term, with the values of all other ε_t terms held constant. For a bivariate VAR (1) model, $\phi_{jk}(i)$ can be meaningfully interpreted as the partial derivative of the VMA (∞) model only if ε_1 or ε_2 remains constant when ε_1 or ε_2 is shocked. This requires that Cov ($\varepsilon_1, \varepsilon_2$) = 0.

In general, however this will not be the case, so we must create orthogonal impulse response functions (IRF) by orthogonalising the $\{\varepsilon_t\}$ terms through Choleski decomposition. For any real symmetric positive definite matrix such as $\sum_{\varepsilon}$, it can be shown that there exists a unique lower triangle matrix C with '1s' along the main diagonal and a unique diagonal matrix D with positive elements on the main diagonal satisfying: $\sum_{\varepsilon}$ = **CDC'** which implies that $C^{-1}\sum_{\varepsilon} C'^{-1}$ **= D**. The implication of this result is that once the appropriate numerical values for the elements of the matrix **C** are known (i.e. estimated), they can be used to construct an (nx1) vector of transformed errors: $\varepsilon *_t = C^{-1} \varepsilon_t$ that are uncorrelated with each other.

Enders (1995) shows that the parameters of the orthogonalised IRF are computed as:

$$\phi *_{jk} (i) = \frac{\partial y_{ji}}{\partial \varepsilon *_k} . \qquad (4.4.3.4)$$

It is important to note that it has become conventional practice to compute the impulse response function parameters from the standardised orthogonalised errors $v_{j_t} = \frac{\varepsilon *_{jt}}{\sqrt{djj}}$ such that a one-unit shock to v_{jt} is the same as one-standard-deviation shock to $\varepsilon *_{jt}$.

It is also important to note that imposing the recursive structure with the Choleski decomposition is not the only way in which identification of the structural parameters is secured. The structural VAR methodology with long-run restrictions proposed by Blanchard and Quah (1989) can also be used to obtain an estimate of the permanent and transitory components of GDP. By this method, suppose that labour units, fixed capital, human capital, FDI and ICT are affected by the same two shocks as GDP and that labour units, fixed capital, human capital, FDI and ICT are stationary. The infinite moving average representation of the VAR model in equation (4.3.4.10) can be expressed as a linear combination of current and past structural shocks[14]. This approach is carried out by imposing restrictions on the b_{ij} parameters and/or the ε_t structural error terms themselves.

In addition to the Granger causality test, the study uses the impulse response and forecast error variance decomposition analyses to test for the short-run dynamic shocks

[14] Claus (1999) uses a similar approach to estimate potential output for New Zealand's economy.

between GDP, productivity and production factors and determine the proportion of the forecast error variance in GDP due to the innovations of each production factor respectively. The same procedures are used to test for the short-run dynamic shock between productivity and production factors.

4.5 Estimation of the Production Function

In this study, estimates of the short-run elasticities of the production function based on approaches such as ordinary least square (OLS), non-linear and the unrestricted VAR models are omitted. Instead, vector error correction models (VECMs) derived from the VAR models are used to estimate the long-run elasticities. This study prefers the VEC model to other approaches to estimate the long-run parameters because of its power and can be used to carry out various diagnostic tests as identified in Sections 4.3 and 4.4 of this chapter.

4.6 Measurement of Productivity

4.6.1 Introduction

This section focuses on the comprehensive productivity measure known as total factor productivity (TFP), and reviews two of its methods of measurement namely the growth accounting and as the econometric approaches. TFP measurement attempts to include not only factors of production, but all inputs, whether indirectly or directly used in the production process. The outcome of this gives a more accurate picture of performance than partial productivity measures such as labour and capital productivities.

Productivity is determined by the efficiency with which resources are combined to produce a given output. It is usually measured by calculating the ratio of a weighted index of outputs to a weighted index of inputs. In a simple economy with only one type of output and one type of input, productivity is simply the ratio of output to input. In an economy with a variety of outputs and many different inputs, productivity can be measured in a number of ways.

Diewert and Lawrence (1999) define the TFP index in general as the ratio of an index of output growth divided by an index of input growth. They argue that the growth rate for individual outputs and inputs are weighted together using revenue and cost shares, respectively. Changes in the TFP index tell us how the amount of total output that can be produced from a unit of total input has changed over time.

As already noted in Chapters One and Two of this study, along with increases in factor endowments and changes in the terms of trade, productivity improvement is another major determinant of economic growth in most countries. In the case of Australia, sectors such as Agriculture, Mining and Manufacturing have contributed significantly to GDP growth over the years. These sectors have achieved remarkable productivity improvements since the late 1980s.

Different approaches are used in measuring productivity. At the most basic level, productivity change is often approximated by changes in labour productivity (output per worker or per hour worked) since the requisite information is usually readily available. However, complete reliance on labour productivity measures can mislead as other inputs such as capital may be substituted for labour. The observed labour productivity will be increasing rapidly whenever this happens but if all inputs are considered, overall productivity will be increasing far less rapidly and, in the extreme case, a decreasing. It is therefore necessary to take into account the quantity of all outputs produced relative to the quantity of all inputs used in the production process.

TFP is intended to be a comprehensive productivity measure and should ideally include not just labour and capital inputs but also natural resources, land, research and development, inventory and all other inputs that take part in the productive process. Failure to take into account all inputs can lead to biased productivity estimates, which may affect economic policies. Most productivity studies tend to concentrate only on labour and capital inputs and some analysts identify the incompleteness of their input coverage by referring to the resulting measures as multifactor rather than total factor productivity measures (Diewert and Lawrence, 1999).

Tinbergen (1942) and Stigler (1947) introduced the concept of TFP into the economics literature. Solow (1957) gives a useful frame of reference for the main empirical approaches to measuring TFP. His estimates of productivity were computed using what has come to be known as the growth accounting approach.

The definition of TFP focused the attention of economists on trying to explain the reasons why output generally grows faster than measured inputs. This methodology can be used to produce a balance sheet showing the contribution of each factor of production to economic growth. The production function is the conceptual link between growth accounting and some of the other approaches to productivity measurement. These involve the measurement of productivity using estimated coefficients from production, cost or other related producer behavioural equations.

TFP can also be measured as a ratio of output and input quantity indices in what is known as the index number approach to productivity measurement. This was the approach used by Diewert and Lawrence (1999) in their study on measuring New Zealand's productivity performance. As noted at the beginning of this study, most researchers on productivity measurement in Australia depend on productivity estimates computed by ABS, Productivity Commission and OECD which have their associated shortcomings for their productivity analyses. This study is one of the first to measure the aggregate productivity performance in Australia by considering factors such as human capital, foreign direct investment and ICT in addition to capital and labour. This study is also one of the first to investigate the dynamic interaction between GDP, productivity and production factors using econometric models.

4.6.2 Growth Accounting and Econometric Approaches to Measuring Productivity

A number of factors are believed to lie behind the phenomenon of TFP growth. These factors can cause an increase in output, which is not fully compensated by the market mechanism. Oulton (1997) identifies some of the factors responsible for TFP growth as:

advances in scientific technical knowledge; organisational changes; legislative and regulatory changes; transfers of inputs from low to high marginal productivity areas; economies of scale; development of more specialised inputs and errors in the data used to compute TFP.

The rate of growth of TFP is defined as the difference between the rate of growth of real product and the rate of growth of real factor input. The rates of growth of real product and real factor input are defined, in turn, as weighted averages of the rates of growth of individual products and factors. The weights are relative shares of each product in the value of total output and of each factor in the value of total input. If a production function exhibits constant returns to scale, and if all marginal rates of substitution are equal to the corresponding price ratios, a change in total productivity may be identified with a shift in the production function. Changes in real product and factor input not accompanied by a change in TFP may be identified with movements along a production function.

In the neo-classical framework, growth stems from two sources namely: factor accumulation and productivity (TFP) growth. The key point of debate is the relative importance of each of these two components. Most of the debate has, nevertheless, focused on TFP. The reason is that its *modus operandi* is less well known than that of factor accumulation, and the problems inherent in its estimation are not simple (Felipe, 1999).

Measurement of TFP is based on the economic theory of production. The computation of TFP is so standard that it is virtually never questioned. For classification purposes, Felipe (1999) conceptualises the notion of TFP through an index or through a production function. Solow (1957) shows how a measure of TFP could be derived from an aggregate production function (the indices are consistent with different production functions). In its simplest form, the aggregate production function, assumed to be continuous, twice differentiable and linearly homogeneous, can be written as:

$$Y_t = \mathrm{F}(K_t, L_t, t), \tag{4.6.2.1}$$

or

$$Y_t = \mathrm{A_t F}(K_t, L_t) \tag{4.6.2.2}$$

where:

Y_t, K_t and L_t are as defined before.

From equation (4.6.2.2.) we derive an expression for total factor productivity (A_t) as:

$$A_t = \frac{Y_t}{F(K_t, L_t)} \tag{4.6.2.3}$$

The "A_t" is referred to as exogenous, disembodied, and Hicks-neutral with respect to technical progress, and is measured by how output changes as time elapses and inputs are held constant, that is, as a shift in an aggregate production function. Therefore, the notion of overall or TFP can be reinterpreted as an index of all those factors other than labour and capital not explicitly accounted for, but which contribute to the generation of output. Felipe (1999) argues that "A_t" is a measure of elements such as managerial capabilities and organisational competence, research and development, inter-sectoral transfer of resources, increasing returns to scale, embodied technical progress, and diffusion of technology.

Since productivity is a technical concept, (a ratio of output to input), a measure of the efficiency with which the factors of production are used, there are as many indices of productivity as there are factors of production. Nadiri (1970) argues that the most important and most often used indices of productivity are the partial productivity indices of labour and capital and the total or multifactor productivity index.

Zohar and Luski (1987) define the annual rate of TFP growth by:

$$TFP_t = (\frac{\Delta Y_t}{Y_{t-1}}) - (\frac{\partial Y}{\partial K})(\frac{K}{Y})(\frac{\Delta K_t}{K_{t-1}}) - (\frac{\partial Y}{\partial L})(\frac{L}{Y})(\frac{\Delta L_t}{L_{t-1}}), \qquad (4.6.2.4)$$

where:

$\Delta n \equiv n_t - n_{t-1}$, for n = Y, K, L,

and

$$TFP_t \equiv \frac{A_t - A_{t-1}}{A_{t-1}}. \qquad (4.6.2.5)$$

Under the assumptions of constant returns to scale and perfect competition, where the price of each factor of production is equal to its marginal product, Zohar and Luski (1987) show that the rate of TFP growth can be measured by the following equation:

$$TFP_t = (\frac{\Delta Y_t}{Y_{t-1}}) - S_K(\frac{\Delta K_t}{K_{t-1}}) - S_L(\frac{\Delta L_t}{L_{t-1}}). \qquad (4.6.2.6)$$

In other words, productivity change is equal to the rate of output growth less the rates of growth in capital and labour inputs weighted by their respective GDP shares. The factor shares equal the respective elasticities under the assumptions stated in Section 3.2.

Having calculated the annual growth of TFP_t on the basis of 4.6.2.6, an index of TFP_t is then estimated by normalising $A_{(t-1\ =\ 0)}$ to unity in (4.6.2.5). The calculated growth rates of TFP_t are then used to construct the index for subsequent years.

Solow (1957) argues that if all factor inputs are classified as K or L, then S_K and S_L in (4.6.2.6) above will always sum to unity. Solow (1957) assumes that factors are paid their marginal products, that the hypotheses of Euler's theorem are satisfied, and that the function F is homogeneous of degree one. The capital and labour input quantities are expressed per unit of the aggregate labour input as:

$$\frac{Y}{L} = q \text{ and } \frac{K}{L} = k \ . \qquad (4.6.2.7)$$

Then using S_L = 1- S_K , Solow (1957) restates that the production function that gives rise to (4.6.2.6) is:

$$\frac{\dot{q}}{q} = \frac{\dot{A}}{A} + S_k \frac{\dot{k}}{k} \qquad (4.6.2.8)$$

Solow (1957, p.313) notes that if this model is an adequate simplification, then 'all we need to disentangle the technical change index A(t) are the series for output per man hour, capital per man hour and the share of capital'. This is the basis of the growth accounting estimation results Solow (1957) presents for the effects of technical change on the US economic growth. Solow's estimates for A(t) are obtained devoid of econometric estimation of the parameters of any equation such as (4.6.2.8). Instead, Solow (1957) uses the national income data to calculate factor shares for labour and capital which are used to compute A(t) series for the US economy. Solow (1957) only uses the production function framework as the basis for year-by-year calculations involving output and input quantity aggregates.

The Divisia index is a weighted sum of growth rates, where the weights are the components' shares in total revenues. Since the national accounts and other statistics provide values of all the right-hand side variables, one can easily obtain the rate of productivity growth as a residual category. Expression (4.6.2.4) is the so-called `Solow-residual', and the procedure is called growth accounting (see Nadiri, 1970; Denison, 1972, 1993; Star and Hall, 1976; Nelson, 1981; Haltmaier, 1984 and Maddison, 1987 for comprehensive surveys of this method). This approach is to basically determine how much economic growth is due to accumulation of inputs and how much can be attributed to technical progress. (Nelson, 1973).

What makes this procedure controversial is that TFP is treated as a residual category. The development of this method dates back to the pioneering works of Abramovitz (1956); Solow (1957); and Kendrick (1961) who, working with either productivity indices or production functions, derived similar expressions. Today, standard growth accounting exercises using Divisia index [15] follow the method developed by Solow (1957) in order to estimate the rate of productivity growth in the manufacturing sector of the US economy for the period 1909-49.

The econometric approach to measuring productivity assumes the existence of an aggregate production function like equation (3.2.2), homogeneous of degree one and positive but diminishing returns to each input factor. For this purpose, the theory consists of a production function with constant returns to scale together with the necessary conditions for producer equilibrium. The volume of outputs and inputs entering the production function are identified with real product and real factor inputs as measured for social accounting purposes. Marginal rates of substitution are identified with the corresponding price ratios. Employing data on both quantities and prices, movements along the production function may be separated from shifts in the production function. Shifts in the production function are associated with changes in TFP.

Taking logarithms of equation (3.2.2), we have:

$$LnY_t = A^*_t + \alpha\, LnK_t + \beta\, LnL_t + \varepsilon_t \qquad (4.6.2.9)$$

Equation (4.6.2.9) is estimated with the assumption that the error term ε is identically and independently distributed with mean zero and a constant variance. Using the parameter estimates of $\hat{\alpha}$ and $\hat{\beta}$, TFP levels can be calculated using (4.6.2.6) or (4.6.2.5) above.

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[15] For the detailed derivation of the Divisa index, see Star and Hall (1976)

The main difference between the two approaches to productivity measurement is that with the growth accounting approach, factor shares are calculated direct from the national income data without any form of econometric estimation of parameters and statistical analysis. With the econometric approach, the parameters of the production function (3.2.2) are estimated by the use of econometric computer packages and statistical analyses are carried out on the results. This study uses the econometric approach to measure TFP because this approach enables us to carry out various diagnostic tests on the estimated results.

One important problem in computing TFP has to do with the difficulty of measuring inputs. Generally, labour is considered homogeneous, while physical capital is valued at its deflated book or constant-dollar replacement value. When labour is not differentiated by skill level, TFP measurements implicitly include relative growth in human capital in estimates of productivity growth. When physical capital is valued by deflating book or replacement values, biases from mismeasured price indices can creep into estimates of productivity. Furthermore, during a recession, if firms do not adjust factors immediately (because of the fixed nature of capital, labour hoarding, or work effort effects), some of the changes in productivity growth could be attributed to underemployed resources.

Estimates of TFP and its growth rates are computed, presented graphically and discussed in Chapter Six, where these estimates are based on the estimated long-run elasticities of the different factor production functions developed in this study, and using equations (4.6.2.5) and (4.6.2.6).

4.6.3 Biases in Estimates of Total Factor Productivity Growth (TFPG)

There are several practical reasons for thinking that many productivity studies overestimate the size of TFPG. First, compared with estimates of output growth, estimate of growth rates of inputs is often rather crude. Substitution in favour of inputs that are growing rapidly and should receive a high weight may be underestimated. An example is machinery in general and computers in particular. Machinery has a higher depreciation rate than buildings and within the machinery category computers are subject to rapid obsolescence. The weight attributed to such assets ought to be higher than is given to them if they are bundled in with other assets.

Another bias is the use of value added rather than gross output which biases estimated TFPG upwards. Oulton (1997) shows that TFPG based on the value added approach equals TFPG based on gross output divided by the share of value added in gross output. He refers to this as an upward bias since the gross output production function, which has intermediate input as one of its arguments, is the fundamental concept and the value added one is a special case. At the whole economy level, intermediate inputs means goods and services purchased from abroad, which are used up in the process of production, for example imported raw materials. The difference between the value added and the gross output concept of TFPG is likely to be larger, the smaller and more open the economy.

Finally, errors in the price indices for capital goods bias TFPG upwards. Gordon (1990) shows that there are large errors in such indices. They are widely held to make insufficient allowance for quality changes in existing goods and to be slow to introduce new goods (whose prices typically fall for a while after their first appearance in the market). These errors bias downwards the estimated growth rate of output (GDP) since investment spending is one component of output, but they also bias downwards the estimated growth rate of capital. The net effect is an upwards bias in estimated TFPG if the share of capital in GDP exceeds the ratio of investment to GDP, which is almost always the case (Griliches and Jorgenson, 1966). Note that these price index errors are conceptually distinct from the bias arising from failure to take into account increased variety.

4.7 Chapter Summary

The issues discussed in this chapter are preparatory towards the subsequent analysis of the production function and measurement of TFP in Chapter Six. The chapter begins by highlighting the various stages involved in the estimation procedure. It further describes each step involved in the methodology this research uses to achieve its objectives.

The chapter also examines time-series properties of the variables by discussing various tests such as stationarity, the unit root and cointegration tests to determine whether the variables selected for this analysis satisfy these properties. The chapter identifies the ADF unit root test as one of the most popular approaches for testing stationarity in time-series variables. However, we argue that the ADF unit root test is sensitive to non-linear transformations and biased towards the non-rejection of the null hypothesis of a stochastic trend if the sample contains a structural break.

Two methods for testing for cointegration namely, Engle and Granger (1987) two-step procedure, which is based on an OLS estimate of the cointegrating vector and a unit-root test of its residuals, and Johansen cointegration technique are identified in this chapter. The chapter further elaborates on the disadvantages of the Engle and Granger (1987) two-step procedure and recommends that the Johansen cointegration technique be used for this study. The chapter continues by identifying the two procedures developed for testing the dynamic interrelation among variables chosen for a given system as Granger causality testing and innovation accounting. The chapter further examines the methodology behind the Granger causality test and the impulse response analysis and gives explanation for conducting these tests in this research. The chapter notes that VEC models derived from the VAR models are used to estimate the long-run elasticities.

Finally, the chapter presents a discussion of a comprehensive productivity measure known as the TFP. The growth accounting and the econometric approaches to measuring TFP are reviewed and a description of how each approach is computed is given. The chapter further elaborates on the main difference between the two approaches. A discussion of the bias in TFPG estimates concludes the chapter.

CHAPTER FIVE
DATA AND MEASUREMENT ISSUES

5.1 Introduction

This chapter explains the sources of the data used to carry out the empirical work of this study. It also explains how some of the variables are computed and provides information on what are used as proxies for measuring some selected variables. Furthermore, the chapter outlines some of the measurement problems associated with the data collection, which are likely to affect the result of this study.

5.2 Data

Six variables are selected for the purposes of this study: gross domestic product (Y), fixed capital (K), labour force (L), human capital (H), foreign direct investment (FDI) and information and communication technology (ICT). The reason for selecting these variables is that we argue that these variables are likely to be the key determinants of productivity growth in Australia. Annual data for Y_t (GDP), K_t (fixed capital), L_t (labour force), H_t (tertiary student enrolment), FDI_t (foreign direct investment in goods and services) and ICT_t (the investment in capital stock of computers and internet service, electrical machinery and communication equipment) from Australia's economy are used for the empirical analysis of this research. Data on these variables cover a 56 year period from 1949-50 to 2004-05. For the purpose of this study, the entries for the year 1950 refer to the year that ends on 30 of June, represent the 1949-50 financial year.

Although the study attempts to cover a relatively long period of time, as far back as possible in the 20th Century, the sample period has been limited by availability of reliable data and also the possibility of inconsistencies in the data for earlier periods of the sample. For the purposes of this research, all the variables are transformed into their natural logarithm denoted by LY, LK, LL, LH, LFDI and LICT in order to facilitate the calculation of elasticities and to be able to transform the production function from a non-linear form into log linear one. This transformation will however be tested later to determine whether it is statistically appropriate or not.

Annual data on GDP, fixed capital, labour force, human capital, FDI and ICT are collected from the Australian database (Australian Bureau of Statistics and Education Statistics of Australia). Data on GDP are taken from ABS catalogue 5204.0 Table 1. Data on fixed capital are taken from catalogue 5204.0 Table 93 and ICT data from Table 105. The GDP, fixed capital and ICT annual data are all ABS Chain Volume Measures at 2004 constant prices. Data on GDP and fixed capital prior to 1960 are constructed using nominal values from the Yearbooks Australia 1952-1964. The GDP deflator is used to convert the nominal figures into ABS Chain Volume Measures 2004 constant prices equivalents. Data on postal and telecommunication expenditure from the Yearbooks Australia 1950-1970 are used as proxies to construct the ICT data for the period 1950-1959. The postal and telecommunication services expenditure within the period 1950-1959 is used as a proportion of the sum of the postal and telecommunication services expenditure for the period 1960-1970 to compute the ICT data for the period 1950-1959. For example the ICT data for 1950 is obtained by dividing the postal and telecommunication services expenditure for 1950 by the sum of the postal and telecommunication services expenditure for the period 1960-1970 multiplied by the sum of the ICT capital expenditure for the period 1960-1970.

Data on labour force and FDI are taken from the Yearbooks Australia 1952-2006. The annual data for FDI are ABS Chain Volume Measures equivalent at 2004 constant prices. The stock of FDI in Australia is supposed to be used as a proxy for measuring the FDI variable. However, there is no data available on the stock of FDI and for the purpose of this study, the inflows of foreign direct investment into Australia are used as proxies to measure the FDI variable. The data for human capital are compiled from the Commonwealth Government Department of Education, Science and Training (DEST) database, the Australian VET database, and the Yearbooks Australia 1952-2006. Data on students' enrolments at the universities are constructed from the Yearbooks Australia 1952-2006, Commonwealth of Australia (1990a, 1990b, 1991, 1993, 1994a, 1995a) and

DEST (1995-2004, 2005), Higher Education Statistics Table 1. Data on students' enrolments at TAFE are taken from the Yearbooks Australia 1952-1997, Commonwealth of Australia (1994b, 1995b, 1996, 1997) and NCVER (1997-2004, 2005), Vocational Education Training Statistics Table 1. The data on each of the six variables are reported in Table A2.

An unusual feature associated with the capital data is the treatment of gross fixed capital. The physical capital stock is broadly defined to include the stock of government infrastructure capital and residential capital, in addition to the capital of private and public enterprises. The potentially important role of infrastructure capital in increasing productivity and output has received considerable attention in recent years, although it has proven difficult to estimate separate elasticities for infrastructure capital. Including residential capital is appropriate since value added in the business sector includes imputed services from the housing stock. More generally, housing is an important aspect of an economy's infrastructure, which, like roads, bridges, and non-residential structures, contributes to its ability to produce real goods and services. This focuses on a very broad definition of capital that differs from most empirical studies, which typically consider only the business sector capital stock. Although infrastructure capital may not be an important determinant of short-run movements in output, it is particularly important to include infrastructure capital when studying the long-run determinants of output.

Mahadevan (2004) argues that the production function Q = F (K, L) is conventionally interpreted as a relationship between the flow of output and the flow of inputs' services. However, there are no data available on the flow of capital services and the easiest option is to assume that capital flows are proportional to net capital stock after depreciation. Another important aspect of capital measurement is valuation of capital input given by the rental price of capital.

To demonstrate how physical capital stock is usually calculated, we employ the method of Harberger (1978). This method begins with the observation that if the capital-output ratio is constant in a given period, the rate of growth of capital and output are equal during that period. The perpetual inventory equation to measure capital services is given by:

$$\frac{K_t - K_{t-1}}{K_{t-1}} = -\delta + \frac{I_t}{K_{t-1}}, \qquad (5.2.1)$$

where

δ is the rate of depreciation and I_t the gross domestic investment at time t.

Re-writing equation (5.2.1) in its advanced form and re-arranging like terms gives:

$$K_t = (1-\delta)K_{t-1} + I_t \qquad (5.2.2)$$

Equation (5.2.2) is normally used to construct fixed capital data by setting the rate of depreciation to be equal to 0.04 for most countries. The ABS for instance, assumes that the flows of capital services are proportional to productive capital stock. Parham and Zheng (2006) argue that capital services based on productive capital stock is a better measure of the actual input of capital to production and is therefore more appropriate for productivity analysis. However, Diewert and Lawrence (2005) questioned the consistency of the ABS's approach to constructing rental prices of capital.

For the purpose of this study, we assume that capital flows are proportional to gross investment in capital goods. The usual perpetual inventory method assumes that the rate of depreciation is constant in different category of capital assets and across industries. Investment in computers for example, contributes faster to production as computers have high rental price. Computers are also short-lived assets and therefore have high rates of depreciation value. It is therefore inappropriate to assume that the rate of depreciation in computer assets is the same as those of machinery, building and other capital assets. We argue that in long-run equilibrium the gross investment in capital is proportional to the long-run net capital stock. In equilibrium, all variables, in respective of the proxies of measurement, eventually converge. This study uses the gross investment in capital goods as a proxy for measuring capital rather than the net capital stock. Data on gross capital formation in Australia for the period 1950-2006 are used as proxies for measuring fixed capital variable.

In empirical studies, the most commonly used proxies to measure labour are number of workers employed, labour force, number of hours worked and in some cases wages and salaries. Each of these approaches to measuring labour has its associated empirical measurement shortcomings. It is generally argued that using the number of hours worked as a proxy to measure labour accounts more accurately for full-time and part-time employees in terms of actual hours worked than using the number of workers employed. However, total number of hours worked does not provide information on the number of hours worked by highly skilled professional and those of the unskilled employees. This differentiation is very important in measuring labour since hours of work contributed by highly skilled workers generally contribute more to production than those of unskilled workers. Mahadevan (2004) points out that in order to incorporate quality into labour input, employment matrices crossed classified by sex, education, employment and regional status of workers are constructed.

The use of the number of workers employed as a proxy to measure labour ignores the number people whose services in one way or the other contribute to production but not considered as people who are employed. In addition, this approach to measuring labour does not include people who earn income on regular basis but do not count themselves as being employed since the income they earn do not pass through the tax system or any kind of financial record. The use of wage rate alone to obtain the wages and salaries of workers gives inaccurate measure of the price of labour. Earnings such as estimates of employer's contribution to workers' benefit, labour compensation based on wage and end of year bonuses among others which are more reflective of workers' worth and affect workers' productivity are normally left out when computing the wages and salaries of workers. Hence, the use of wages and salaries as a proxy for measuring labour is also inadequate. The measure of labour used in this study is similar to that employed by Madden and Savage (1998), which uses labour force as a proxy to measure labour. This approach is suitable for measuring labour units for a country like Australia as the entitlement of unemployment benefit in the country makes some people who earn incomes, which are paid directly to them in cash, not to declare that they are employed.

Human capital is included in this study as a distinct factor of production in order to allow the process of technological progress to be modelled explicitly, as suggested by Griliches (1988). The importance of human capital has been emphasised in endogenous growth theories (Lucas (1988); Helpman (1992) and Benhabib and Spiegel (1994)). However, the measurement of human capital has proven to be a very difficult task. Various authors have employed different measures, such as data on literacy rates, school enrolment rates, years of schooling, and public expenditure on education among others, as proxies for human capital. Each of these approaches has its associated empirical measurement problems.

Harberger (1998) argues that if aggregate expenditure on labour is used to measure TFP, then the direct measured contribution of human capital is captured in the labour expenditure, since different categories of professionals are rewarded in proportion to their educational qualifications. With this approach too, it will be very difficult to assess separately the contributions of human capital to economic growth.

Mankiw et al. (1992) argue that a good proxy for human capital is investment in education. This approach also has its peculiar measurement problems. It is important to note that a large part of investment in education takes the form of forgone labour earnings on the part of students. Mankiw et al. (1992) maintain that the problem associated with this method of measuring human capital is difficult to overcome since forgone earnings vary with the level of human capital investment. For example, a worker with little human capital forgoes a low wage in order to accumulate more human capital, whereas a worker with much human capital forgoes a higher wage. More over, expenditure on education takes place at all levels of government as well as by the parents, hence making spending on education very difficult to measure precisely. Mankiw et al. (1992) further argue that not all spending on education is intended to yield productive human capital. Thus it is easy to conclude that investment on education as a whole is not a true measure of human capital.

Mankiw et al. (1992) go further to propose the percentage of the working-age population having completed secondary school as a proxy for measuring human capital. Benhabib and Spiegel (1994) on the other hand use enrolment ratios or the literacy rates as proxies for measuring human capital. A serious problem associated with the use of data on school enrolment ratios to measure human capital is that, especially in developing countries, the educational institutions at times inflate these data for various reasons and this could lead to an upward bias in the enrolment figures (Barro and Lee, 1993). Accordingly, this approach is also not a good proxy for human capital in developing countries. Hence it is clear that each of these measurement methods as proxies for human capital has associated empirical measurement problems.

The measure of human capital used in this study is similar to that employed by Romer (1989), World Bank (1994) and Madden and Savage (1998). This method assumes that all human capital formation takes place in the tertiary institutions. This study argues that the contribution of intellectual capital to economic growth is proportional to the length of time spent in accumulating the skill or training to acquire that skill. However, this approach excludes human capital augmenting through on the job training. It is assumed that for a country like Australia, the skills necessary for rapid economic growth and productivity are acquired mostly from the tertiary institutions. This approach to measuring human capital is also suitable for a country like Australia since data on student enrolments in tertiary education are readily available. In Australia, tertiary education is mainly provided by the universities and Vocational Education and Training (VET) institutions such as Technical and Further Education (TAFE) institutions, secretarial colleges, and private business or commercial colleges. The student enrolment numbers in these institutions are used as a proxy to measure human capital. The flows of students' enrolments in the tertiary institutions across Australia are used as proxies to measure human capital since the data are readily available. There is no data available on the stock of human capital and the only possible approach is to use the flows of students' enrolments in the tertiary institutions as proxies to measure human capital.

For the purpose of this study, the gross expenditure on computers and software, internet capital services, electrical machinery and telecommunication services is used as a proxy for measuring ICT. Studies such as Banks (2002), Parham (2002b, 2004) and Diewert and Lawrence (2004) argue that the use of ICT is one of the main drivers of Australia's productivity surge and not the gross investment in ICT. As a result, this study prefers the use of ICT in Australia as a proxy for measuring the ICT variable to the investment in ICT. The data on consumption of ICT are used in order to achieve this goal. Note that since there is no data available on the stock expenditure of ICT capital, this study uses the flow of ICT expenditure as a proxy for measuring the ICT variable. It is important to note that the net FDI and investment in ICT capitals are implicitly included in fixed capital formation. This suggests that any impact each of the variables FDI or ICT variables may has on GDP and productivity is the impact in addition to whatever impact is picked up by fixed capital.

The dynamics of the variables used for the empirical analysis of this study are presented graphically in Figure 3A. As can be seen from the graphs presented in Figure 3A, all the variables have tendencies of growth over the 1950-2005 period considered for this analysis. The graphs of the GDP and ICT series indicate no obvious sign of considerable structural break over the period. However, the graphs of fixed capital, labour and human capital series do suggest some structural breaks in the trend within the period 1950-2005. The FDI series on the other hand suggests several structural break points in the trend within the sample period for our analysis. Since the plots of logs of some of our series suggest that the data might be stationary with structural breaks (Figure 3A), in addition to the normal ADF and PP unit root tests, we apply Perron (1989, 1997) structural break test in testing for unit roots in this study.

Figure 3B reports the graphs of the growth rates of the series GDP (Y), fixed capital (K), labour force (L), human capital (H), FDI and ICT with fluctuations for all the series throughout the sample period. The growth rates of GDP (Y) series increase on average by 5.09% per annum over the period 1950-2005. The highest growth rate of 32.67% is achieved in 1951 and the lowest growth rate of -2.37% is recorded in 1983 for GDP series. The growth rates of capital series increase on average by 5.93% each year within the period considered for this study. The highest growth rate of 43.24% is achieved in 1951 and the lowest growth rate of -10.21% is recorded in 1991 for fixed capital series. The growth rates of labour series increase on average by 2.64% per year within the

Figure 3A: Graph of LY, LK, LL, LH, LFDI and LICT Series for the Period 1950-2005

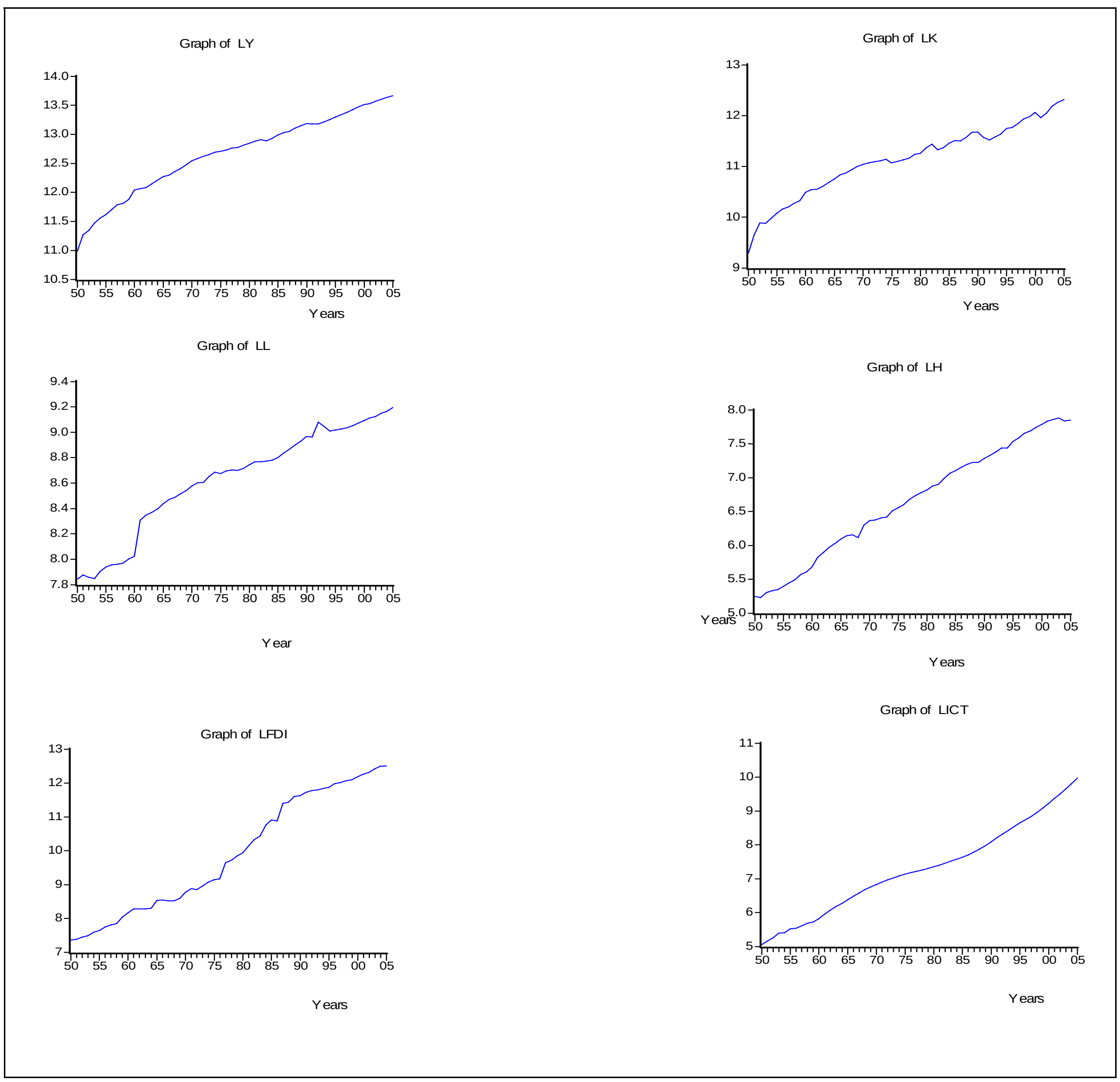
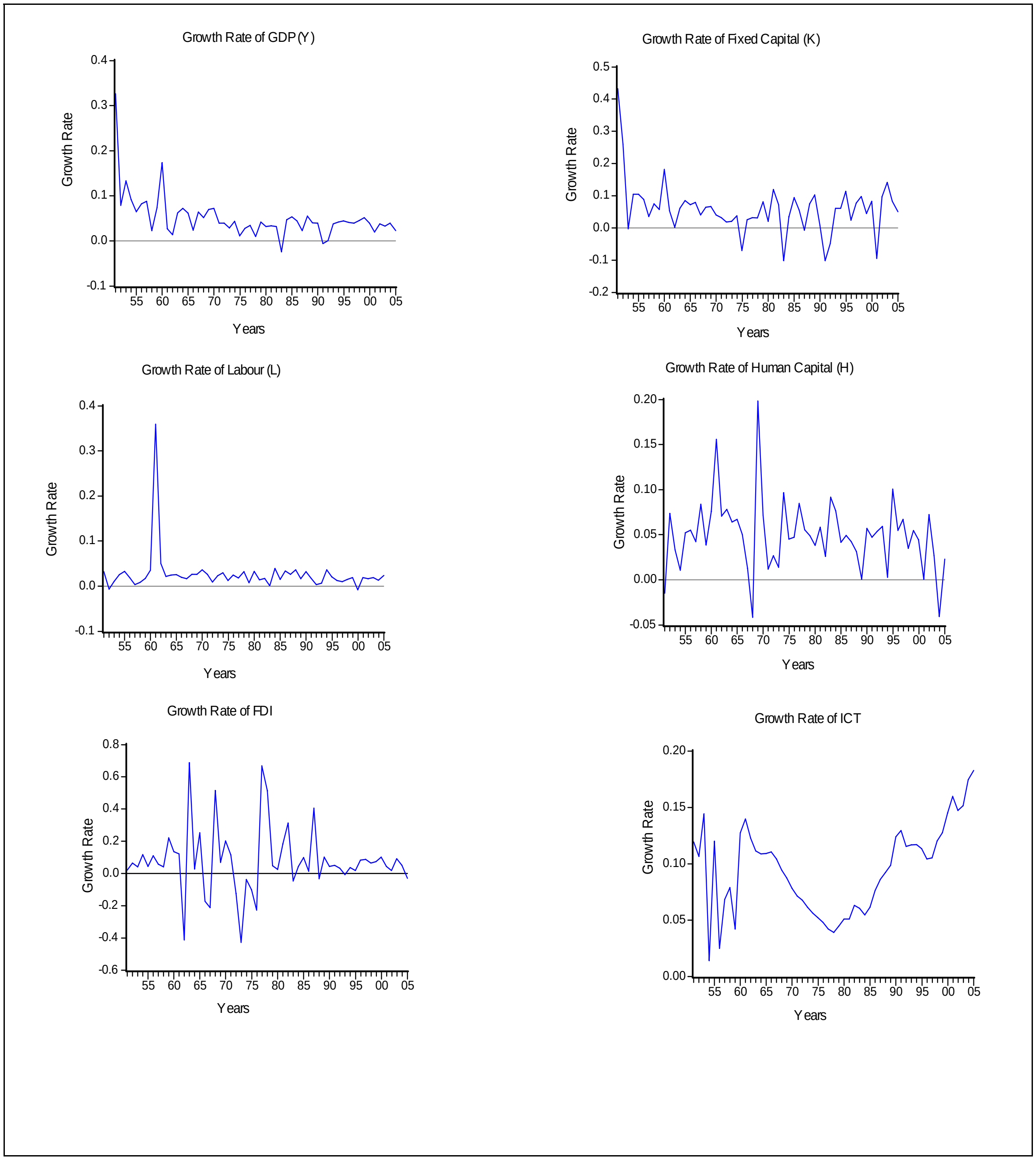


Figure 3B: Graph of the Growth Rates of GDP (Y), Fixed Capital (K), Labour (L), Human Capital (H), FDI and ICT Series for the Period 1950-2005



period 1950-2005. The highest growth rate of 35.96% is achieved in 1961 and the lowest growth rate of 0.87% is recorded in the year 2000 for labour series.

The growth rates of human capital series increase on average by 4.95% per year within the period 1950-2005. The highest growth rate of 19.8% was achieved in 1969 and the lowest growth rate of -4.17% was recorded in 1968 for human capital series (Figure 3B).

The growth rates of FDI series increase on average by 7.68% per year within the period 1950-2005. The highest growth rate of 68.78% was achieved in 1963 and the lowest growth rate of -42.82% was recorded in 1973 for FDI series (Figure 3B). The growth rates of our last series considered for this study, ICT series increase on average by 9.49% per year within the period 1950-2005. The highest growth rate of 18.28% was achieved in 2005 and the lowest growth rate of 1.4% was recorded in 1954 for ICT series (Figure 3B). We now examine some of the problems associated with the computation of the variables selected for this analysis which may affect our result. These are discussed next.

5.3 Measurement Issues

This section outlines some of the issues associated with measuring the variables considered for this study that are likely to affect the results of this analysis. To obtain a better measure of productivity, we need acceptable measures of output, and inputs that are engaged in the productive process.

As noted in the earlier part of this chapter, data on most of our variables are collected from the ABS source and most of the data related issues are similar. ABS uses different approaches to measuring output and capital inputs. Formerly, output and capital inputs are measured at constant prices by ABS until recently when this has been replaced by Chain Volume Measures. The ABS constant price estimates of gross product by industry are derived using three different methods, namely the gross output method, double deflation and extrapolation using hours worked or input cost data. The method used to obtain constant price estimates for a particular industry depends on the availability of data in respect of that industry. The method used to obtain constant price estimates varies across industries and this could affect the measurement of the aggregate level data. For a comprehensive discussion of the ABS data related issues, refer to Aspden (1990, 2000).

Labour force is used as a proxy to measure the quantity of labour in this study. These data are derived from the Yearbooks Australia 1954-2006, which are compiled by ABS, using data on population census conducted in Australia. However, population census is conducted in Australia once in every 5 years and not on yearly basis. As a result, the in-between census figures for labour are mere forecasts and projections. This may result in either overstating or understating the labour figures for those years in which census are not conducted and may eventually affect the results of this analysis. ABS often changes the definition and construction methods of computing labour force for Australia. Such revision for instance is responsible for the large jump in the labour force in 1961. This approach to labour measurement may also not accurately account for full-time and part-time employees in terms of actual people engaged in the productive process.

Another data related issue deals with measuring human capital. In this study, tertiary enrolment is used as proxy for measuring human capital. Furthermore, the classification of tertiary students in Australia changes over time as policy reforms were introduced to the educational system. In the earlier years of our sample period, tertiary education in Australia was made up of Advanced Education, Universities, Higher Education and Technical Education. In the mid-1990s, tertiary education in Australia was mainly provided through the universities and Vocational Education and Training (VET) institutions such as Technical and Further Education (TAFE) institutions, secretarial colleges, and private business or commercial colleges. The process of reclassifying institutions is likely to result in double counting of some of the tertiary students. In addition to the above issues, some of the course streams in the Vocational institutions, for an example, streams 100 courses (handicraft students) were removed from TAFE and classified under secondary education. This affects the student enrolment numbers in TAFE for the subsequent years since those students who choose to study streams 100 courses had to continue at high schools.

Foreign direct investment into Australia is used as proxy for measuring FDI data in this study. Australia's economy has opened more fully to foreign investment as policy reforms were introduced. This led to the flows of FDI in the early 1950s to mid 1970s to be relatively smaller compare to the FDI in Australia from the 1980s onwards. This results in the several apparent structural breaks in the FDI series (Figure 3A).

The measurement of ICT inputs prior to before 1960 is quite difficult since the ABS data base has no record of ICT inputs. The variable ICT was non existing until the 1980s and the expenditure on postal services, telecommunication and information services are used as proxies for measuring ICT for those years. These approximations are likely to affect the outcome of this study.

5.4 Chapter Summary

This chapter provides information on the variables included in the data for the empirical analysis of the study. It further specifies the sources of the data and gives explanation to how these variables were computed. The chapter explains some of the reasons for using certain proxies as measures for some of the variables used in this study. The dynamics of the series and their growth rates are presented graphically and discussed. Discussion of measurement problems associated with the data, which are likely to affect the results of this analysis, concludes the chapter.

CHAPTER SIX

EMPIRICAL RESULTS AND ANALYSIS

6.1 Chapter Overview

This chapter presents the results of the empirical research. It discusses the main empirical findings of this research by analysing the estimated and computed results. The ADF and PP unit root tests, structural break and cointegration tests are all carried out in this chapter. The chapter also presents the results of all diagnostic tests carried out in this study and describes the outcome of the tests results. The chapter further conducts the Granger causality test and the impulse response analysis to detect the effect of shocks to a unit standard error of production factors to GDP. The estimated long run elasticities for the two-factor model, three-factor models, four-factor models and the five-factor model are presented and discussed.

The latter part of the chapter measures the performance of labour productivity and capital intensity in Australia's economy, and the results are presented graphically. This is followed by a comprehensive measurement of productivity usually referred to as total factor productivity (TFP). Identification of important determinants of productivity growth in Australia concludes the chapter.

6.2 Unit Root and Perron's Structural Break Tests

To carry out unit root tests for the variables, we first test for the appropriateness of the logarithmic transformation of the non-linear equation (3.2.12) for each of the variables. For the ADF auxiliary equation in each variable, we test for the hypothesis that Ho: ϕ_p (in equation (4.3.2.6) = 0, which implies appropriate logarithmic transformation versus the alternative of Ha: $\phi_p \neq 0$, which implies inappropriate logarithmic transformation.

The results presented in Table 2 do not reject the null hypothesis of $\phi_5 = 0$ in equation (4.3.2.6), for any of the variables. The test results indicate that the natural logarithmic transformation of equation (3.2.12) is appropriate for testing a single unit root.

The results of the unit root tests by applying both the ADF and the PP tests to GDP, fixed capital, labour, human capital, FDI and ICT are presented in Table 3. The ADF and PP statistics for levels series of GDP are greater in absolute terms than their critical values at 5% level of significance. The null hypothesis of the presence of a unit root in GDP is rejected and this implies GDP is stationary in levels. The ADF and PP statistics for levels series of fixed capital, labour, human capital, FDI and ICT do not exceed their critical values (in absolute terms) at 5% level of significance when trend is included but not otherwise. Therefore, these variables are not stationary in level. The PP statistic for levels series of fixed capital is greater in absolute terms than its critical values at 5% level of significance. The presence of a unit root in fixed capital series is partially rejected by the PP test at 5% level of significance. However, both ADF and PP tests statistics exceed their corresponding critical values at 5% level of significance when all the other variables are first differenced. Thus, the null hypothesis of the presence of a unit root in the first differences of fixed capital, labour, human capital and FDI and ICT is rejected, implying that these variables are stationary in first differences.

Table 2: Test of Non-Linear Logarithmic Transformation of the Model

Ordinary Least Squares Estimation. - Dependent variables are DLY, DLK, DLL, DLH DLFDI and DLICT - 53 observations used for estimation from 1953 to 2005

Varia bles	$\hat{\phi}_5$	Standard Error	$T(\hat{\phi}_5)$	Probability $(\hat{\phi}_5)$	R^2	$\overline{R}^2$	DW-Statistic
LY	-2.7565	1.94	-1.4209	0.162	0.3343	0.2788	1.9149
LK	-0.4335	1.1721	-0.3698	0.713	0.0923	0.0165	1.9077
LL	-0.2047	1.2236	-0.1673	0.868	0.0655	-0.0124	2.047
LH	3.0008	1.873	1.6061	0.115	0.1118	0.0378	1.8902
LFDI	0.5144	0.8039	0.6398	0.525	0.0294	-0.0515	2.023
LICT	0.9761	2.6746	0.3649	0.717	0.6485	0.6192	2.021

Notes: Lags order=3 in each regression

The test results suggest that the stationarity assumptions imposed on equations (3.2.10), (3.2.11) and (3.2.12) are not rejected. These results indicate that LY is stationary in levels, whilst LK, LL, LH, LFDI and are difference stationary.

Table 3: Summary of the Augmented Dickey-Fuller and Phillips-Perron Unit Root Tests

Variables	ADF			PP		
	No Trend	Trend	Lags	No Trend	Trend	Lags
Level Series						
LY	-3.9401	-3.8709	1	-5.2728	-6.8717	3
LK	-1.414	-3.0694	1	-3.1214	-5.3491	3
LL	-1.4979	-1.5704	1	-1.5917	-1.4397	3
LH	-1.8695	-0.7481	1	-1.4338	-0.7882	3
LFDI	-0.6847	-2.7556	1	-0.6304	-2.9585	3
LICT	2.1174	0.61351	1	2.63175	1.58139	1
1st Difference Series						
LK	-7.2535	-7.2578	1			
LL	-4.8589	-5.1135	1	-6.3523	-6.4631	3
LH	-4.9526	-5.2994	1	-7.2623	-7.6592	3
LFDI	-5.54	-5.4828	1	-7.913	-7.8304	3
LICT	-2.9454	-3.554	0	-3.1233	-3.7478	5
Critical Values Level Series						
1%	-3.5547	-4.1348		-3.5523	-4.1314	
5%	-2.9157	-3.4435		-2.9146	-3.4919	
10%	-2.5953	-3.1753		-2.5947	-3.1744	
Critical Values 1st Difference						
1%	-3.5572	-4.1383		-3.5547	-4.1348	
5%	-2.9167	-3.4952		-2.9157	-3.4919	
10%	-2.5958	-3.1762		-2.5953	-3.1744	

Notes**:** Critical values from Mackinnon (1991). Figures in the parenthesis represent the optimal lag length determined by Schwartz Information Criterion. The bandwidth is selected following the Newey-West Criterion; and the spectral estimation is based on the Bartlett Kernel method.

The results obtained from estimating equations (4.3.2.10), (4.3.2.11) and (4.3.2.13) taking into consideration structural breaks are reported in Table A2 (Appendix 2). These results indicate that the Perron test does not reject the unit root hypothesis at 5% level of significance and provide further evidence of the existence of a unit root even when structural breaks are allowed. The plausible breaks in the series occur in 1976, 1973, 1998, 2002, 1961 and 2002 for model A, respectively, for series LY, LK, LL, LH, LFDI and LICT. For Model B the breaks in the series occur in 1968, 1999, 1992, 2001, 1962 and 1994 and Model C in 1966, 1963, 1969, 1976, 1966 and 1996 for LY, LK, LL, LH, LFDI and LICT respectively. Since structural break occurs in each variable at different time periods, the productivity analysis for Australia in this study ignores the presence of any structural break in the trend stationary process.

In general, the ADF and PP unit root tests results suggest that the time series LY is integrated processes in order of 0; LK, LL, LH, LFDI and LICT are integrated processes of order 1. Since each of these variables are integrated in an order of 1~I(1), we proceed to the next stage, which determines whether these variables are cointegrated, following Johansen and Juselius (1990) approach.

6.3 Cointegration Test for Variables

6.3.1 Introduction

In order to carry out the cointegration test, we first select the order of the VAR model. This is done by the application of the usual selection criterion namely the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), and Maximum Likelihood (LL). The results reported in Tables A3 and A4 for the various regression equations the SBC suggests a VAR of order 1 and the AIC suggests different VAR orders. The Maximum Likelihood statistics in all the various VAR models considered in this study increase with increase in the lag length. The log-likelihood ratio statistics however, reject most of the lag orders suggested by the selection criterion (AIC and SBC) at the 5 percent significant level.

Based on these contradictory results given by the selection criterion and for the fact that the lag length determined by Schwartz Information Criterion for the PP unit root test for most of the variables is 3, we choose a VAR of order 3 for each factor model.

The test results for the order of integration of the basic set of variables have been obtained using the Johansen procedure, which, as noted in Section 4.3, has well-defined limiting distributions. The tests for the orders of integration do not suffer from parameter instability associated with the ADF and PP unit root tests and are consistent with the use of the Johansen procedure to estimate the cointegrating vectors.

6.3.2 Cointegration test for the two-factor model and the three-factor models

The test statistics and the estimated cointegrating vectors from the Johansen procedure are reported in Tables 4A through 4D, where r denotes the number of cointegrating vectors. Panel A in Table 4A reports the maximal eigenvalue test of the null hypothesis that there are at most r cointegrating vectors against the alternative of r + 1 cointegrating vectors. Testing for the null hypothesis that there are no cointegrating vectors (r = 0) against the alternative of one cointegrating vector (r = 1), the test statistic (26.98) is greater than the 95 percent critical value of (22.04). This indicates that there is at least one cointegrating vector. The null hypothesis of r < = 1 against the alternative r = 2, however, cannot be rejected at either level of significance as the test statistic (10.13) is smaller than 15.87 and 13.81, suggesting that there is a unique cointegrating vector.

Panel B (Table 4A) reports the trace test of the null hypothesis that there are at most r cointegrating vectors against the alternative that there are more than r cointegrating vectors. The test statistic (40.08) is greater than the 95 percent critical value of (34.87). The null hypothesis of r < = 1 against the alternative r = 2, cannot be rejected at either level of significance as the test statistic (13.09) is smaller than 20.18 and 17.88, confirming the existence of a unique cointegrating vector.

For the different model selection criteria shown in Panel C (Table 4A), Hannan-Quinn Criterion and Schwarz Bayesian Criterion also favour r =1 cointegrating vector (r = 1). However, the same is not true for Akaike Information Criterion, which selects r=2. We proceed further by assuming r =1 for the two-factor model (Ly, LK and LL) and present the estimates of the cointegrating coefficients normalised on the coefficient of LY.

Table 4A: Testing for Cointegration between LY, LK and LL

53 observations from 1953 to 2005. Order of VAR = 3.

List of variables included in the cointegrating vector: LY LK LL Intercept

List of eigenvalues in descending order: .39896 .17389 .054481 0.00

PANEL A Cointegration with restricted intercepts and no trends in the VAR

Cointegration LR Test Based on Maximal Eigenvalue of the Stochastic Matrix

Null	Alternative	Statistic	95% Critical Value	90% Critical Value
r = 0	r = 1	26.9822	22.0400	19.8600
r<= 1	r = 2	10.1245	15.8700	13.8100
r<= 2	r = 3	2.9691	9.1600	7.5300

PANEL B Cointegration with restricted intercepts and no trends in the VAR

Cointegration LR Test Based on Trace of the Stochastic Matrix

Null	Alternative	Statistic	95% Critical Value	90% Critical Value
r = 0	r>= 1	40.0758	34.8700	31.9300
r<= 1	r>= 2	13.0936	20.1800	17.8800
r<= 2	r = 3	2.9691	9.1600	7.5300

PANEL C Cointegration with restricted intercepts and no trends in the VAR

Choice of the Number of Cointegrating Relations Using Model Selection Criteria

Rank	Maximized LL	AIC	SBC	HQC
r = 0	316.7688	298.7688	281.0362	291.9497
r = 1	330.2599	306.2599	282.6164	297.1678
r = 2	335.3222	307.3222	279.7381	296.7147

Table A5 presents the estimated cointegrating vectors, and the coefficients in parentheses are normalized on LY. The number of error-correction equations in the two-factor model application is 3, corresponding to jointly determined variables of the model, namely LY, LK and LL. The error-correction equations for Y are presented in Tables A6 and it shows that all the two variables are significant in the long run. In the cointegrating vectors, all the estimated coefficients have the expected signs and are of reasonable magnitudes and the normalized coefficients for the two variables are the same in value as their long-run elasticities.

Panel A (Table 4B) reports the maximal eigenvalue test of the null hypothesis that there are at most r cointegrating vectors against the alternative of r + 1 cointegrating vectors. Testing for the null hypothesis that there are no cointegrating vectors (r = 0) against the alternative of one cointegrating vector (r = 1), the test statistic (34.14) is greater than the 95 percent critical value of (28.27). This indicates that there is at least one cointegrating vector. The null hypothesis of r < = 1 against the alternative r = 2, however, cannot be rejected at either level of significance as the test statistic (18.77) is smaller than 22.04 and 19.86, suggesting that the existence of a unique cointegrating vector.

Panel B (Table 4B) reports the trace test of the null hypothesis that there are at most r cointegrating vectors against the alternative that there are more than r vectors. The test statistic (67.82) is greater than the 95 percent critical value of (53.48). The null hypothesis of r < = 1 against r > = 2 is also rejected. However, the null hypothesis of r < =2 against the alternative r = 3, cannot be rejected at 5% level of significance as the test statistic (33.69) is smaller than 34.87 but greater than 31.93, suggesting that there are at most two cointegrating vectors at 10% level of significance but only one cointegrating vector at the 5% level.

For the different model selection criteria shown in Panel C (Table 4B), Schwarz Bayesian Criterion favours r =1 cointegrating vector (r = 1). However, the same is not true for Akaike Information Criterion and Hannan-Quinn Criterion, which select r=4. We proceed further by assuming r =1 for the three-factor model (LY, LK, LL and LH) and present the estimates of the cointegrating coefficients normalised on the coefficient of LY.

Panel A (Table 4C) reports the maximal eigenvalue test of the null hypothesis that there are at most r cointegrating vectors against the alternative of r + 1 cointegrating vectors. Testing for the null hypothesis that there are no cointegrating vectors (r = 0) against the alternative of one cointegrating vector (r = 1), the test statistic (36.95) is greater than the 95 percent critical value of (28.27). This suggests that there is at least one cointegrating vector. The null hypothesis of r < = 1 against the alternative r = 2, however, cannot be rejected at either level of significance as the test statistic (9.92) is smaller than 22.04 and 19.86, suggesting that there is a unique cointegrating vector.

Table 4B: Testing for Cointegration between LY, LK, LL and LH

53 observations from 1953 to 2005. Order of VAR = 3.				
List of variables included in the cointegrating vector: LY LK LL LH Intercept				
List of eigenvalues in descending order: .47487 .29825 .15029 .11180 .0000				
PANEL A Cointegration with restricted intercepts and no trends in the VAR				
Cointegration LR Test Based on Maximal Eigenvalue of the Stochastic Matrix				
Null	Alternative	Statistic	95% Critical Value	90% Critical Value
r = 0	r = 1	34.1377	28.2700	25.8000
r<= 1	r = 2	18.7714	22.0400	19.8600
r<= 2	r = 3	8.6314	15.8700	13.8100
PANEL B Cointegration with restricted intercepts and no trends in the VAR				
Cointegration LR Test Based on Trace of the Stochastic Matrix				
Null	Alternative	Statistic	95% Critical Value	90% Critical Value
r = 0	r>= 1	67.8239	53.4800	49.9500
r<= 1	r>= 2	33.6862	34.8700	31.9300
r<= 2	r>= 3	14.9148	20.1800	17.8800
PANEL C Cointegration with restricted intercepts and no trends in the VAR				
Choice of the Number of Cointegrating Relations Using Model Selection Criteria				
Rank	Maximized LL	AIC	SBC	HQC
r = 0	425.3876	393.3876	361.8629	381.2647
r = 1	442.4564	402.4564	363.0506	387.3028
r = 2	451.8421	405.8421	360.5254	388.4155

Panel B (Table 4C) reports the trace test of the null hypothesis that there are at most r cointegrating vectors against the alternative that there are more than r cointegrating vectors. The test statistic (55.72) is greater than the 95 percent critical value of (53.48) The null hypothesis of r < = 1 against the alternative r = 2, cannot be rejected at either level of significance as the test statistic (18.78) is smaller than 34.87 and 31.93, confirming the existence of a unique cointegrating vector.

For the different model selection criteria shown in Panel C (Table 4C), Hannan-Quinn Criterion, SBC and AIC also favour r =1 cointegrating vector (r = 1). We proceed further by assuming r =1 for the three-factor model (LY, LK, LL and LFDI) and present the estimates of the cointegrating coefficients normalised on the coefficient of LY.

Panel A (Table 4D) reports the maximal eigenvalue test of the null hypothesis that there are at most r cointegrating vectors against the alternative of r + 1 cointegrating vectors. Testing for the null hypothesis that there are no cointegrating vectors (r = 0) against the alternative of one cointegrating vector (r = 1), the test statistic (54.65) is greater than the 95 percent critical value of (28.27). This indicates that there is at least one cointegrating vector. The null hypothesis of r < = 1 against the alternative r = 2, however, the null hypothesis cannot be rejected at 5% level of significance as the test statistic (20.61) is smaller than 22.04 but greater than 19.86. This suggests that there is a unique cointegrating vector at 5% level of significance.

Panel B (Table 4D) reports the trace test of the null hypothesis that there are at most r cointegrating vectors against the alternative that there are more than r vectors. The test statistic (90.22) is greater than the 95 percent critical value of (53.48). The null hypothesis of r < = 1 against the alternative r = 2, cannot be rejected at 5% level of significance as the test statistic (34.87) is smaller than 35.57 but greater than 31.93. This indicates that there exists a unique cointegrating vector at 5% level of significance.

For the different model selection criteria shown in Panel C (Table 4D), Schwarz Bayesian Criterion also favour r =1 cointegrating vector. However, the same is not true for Hannan-Quinn Criterion and Akaike Information Criterion, which selects r = 2 and r=4 respectively. We proceed further by assuming r =1 for the three-factor model (LY, LK, LL and LICT) and present the estimates of the cointegrating coefficients normalised on the coefficient of LY.

Table 4C: Testing for Cointegration between LY, LK, LL and LFDI

53 observations from 1953 to 2005. Order of VAR = 3.				
List of variables included in the cointegrating vector:				
LY LK LL LFDI Intercept				
List of eigenvalues in descending order: .50198 .17063 .087720 .072597 0.00				
PANEL A Cointegration with restricted intercepts and no trends in the VAR				
Cointegration LR Test Based on Maximal Eigenvalue of the Stochastic Matrix				
Null	Alternative	Statistic	95% Critical Value	90% Critical Value
r = 0	r = 1	36.9469	28.2700	25.8000
r<= 1	r = 2	9.9154	22.0400	19.8600
r<= 2	r = 3	4.8659	15.8700	13.8100
PANEL B Cointegration with restricted intercepts and no trends in the VAR				
Cointegration LR Test Based on Trace of the Stochastic Matrix				
Null	Alternative	Statistic	95% Critical Value	90% Critical Value
r = 0	r>= 1	55.7226	53.4800	49.9500
r<= 1	r>= 2	18.7757	34.8700	31.9300
r<= 2	r>= 3	8.8603	20.1800	17.8800
PANEL C Cointegration with restricted intercepts and no trends in the VAR				
Choice of the Number of Cointegrating Relations Using Model Selection Criteria				
Rank	Maximized LL	AIC	SBC	HQC
r = 0	338.6666	306.6666	275.1419	294.5437
r = 1	357.1400	317.1400	277.7342	301.9864
r = 2	362.0977	316.0977	270.7810	298.6711

Table 4D: Testing for Cointegration between LY, LK, LL and LICT

53 observations from 1953 to 2005. Order of VAR = 3.

List of variables included in the cointegrating vector: LY LK LL LICT Intercept

List of eigenvalues in descending order: .64336 .32214 .14235 .12087 0.00

PANEL A Cointegration with restricted intercepts and no trends in the VAR

Cointegration LR Test Based on Maximal Eigenvalue of the Stochastic Matrix

Null	Alternative	Statistic	95% Critical Value	90% Critical Value
r = 0	r = 1	54.6450	28.2700	25.8000
r<= 1	r = 2	20.6068	22.0400	19.8600
r<= 2	r = 3	8.1385	15.8700	13.8100

PANEL B Cointegration with restricted intercepts and no trends in the VAR

Cointegration LR Test Based on Trace of the Stochastic Matrix

Null	Alternative	Statistic	95% Critical Value	90% Critical Value
r = 0	r>= 1	90.2179	53.4800	49.9500
r<= 1	r>= 2	34.8700	35.5729	31.9300
r<= 2	r>= 3	14.9660	20.1800	17.8800

PANEL C Cointegration with restricted intercepts and no trends in the VAR

Choice of the Number of Cointegrating Relations Using Model Selection Criteria

Rank	Maximized LL	AIC	SBC	HQC
r = 0	462.2500	430.2500	398.7253	418.1271
r = 1	489.5725	449.5725	410.1666	434.4189
r = 2	499.8759	453.8759	408.5592	436.4493

Table A7 presents the estimated cointegrating vectors, and the coefficients in parentheses are normalized on LY. The number of error-correction equations in each of the three-factor models application is 4, corresponding to jointly determined variables of the model, namely LY, LK, LL and LX, (X=H, FDI and ICT). The error-correction equations for Y are presented in Tables A8 through A10 (Appendices 8-10) and they show that all the variables are significant in the long run. In the cointegrating vectors, all the estimated coefficients have the expected signs and are of reasonable magnitudes and the normalized coefficients for all the variables are the same in value as their long-run elasticities.

6.3.3 Cointegration Test for the four-factor models and the five-factor model

The test statistics and the estimated cointegrating vectors from the Johansen procedure for the four-factor model (LY, LK, LL, LH and LFDI) are reported in Table 5. Panel A (Table 5) reports the maximal eigenvalue test of the null hypothesis that there are at most r cointegrating vectors against the alternative of r + 1 cointegrating vectors. Testing for the null hypothesis that there are no cointegrating vectors (r = 0) against the alternative of one cointegrating vector (r = 1), the test statistic (34.6) is greater than the 95 percent critical value of (34.4). This suggests that there is at least one cointegrating vector. The null hypothesis of r < = 1 against the alternative r = 2, however, cannot be rejected at either level of significance as the test statistic (23.43) is smaller than 28.27 and 25.8, suggesting that there is a unique cointegrating vector.

Panel B (Table 5) reports the trace test of the null hypothesis that there are at most r cointegrating vectors against the alternative that there are more than r vectors. The test statistic (85.75) is greater than the 95 percent critical value of (75.98). The null hypothesis of r < = 1 against the alternative r = 2, cannot be rejected at 5 percent level of significance as the test statistic (51.15) is smaller than 53.48 but greater than 49.95, confirming the existence of a unique cointegrating vector at 5 percent level of significance.

For the different model selection criteria shown in Panel C (Table 5), Schwarz Bayesian Criterion selects r = 0, indicating the existence of no cointegrating relationship. However, the same is not true for Hannan-Quinn Criterion and Akaike Information Criterion, which selects r = 2 and r = 3 respectively. We proceed further by assuming r =1 for the four-factor model (LY, LK, LL, LH and LFDI) and present the estimates of the cointegrating coefficients normalised on the coefficient of LY in Table A14. The number of error-correction equations in this application is 5, corresponding to jointly determined variables of the model, namely LY, LK, LL, LH and LFDI. The error-correction equation for Y is presented in Table A15.

Table 5 Testing for Cointegration between LY, LK, LL, LH and LFDI

53 observations from 1953 to 2005. Order of VAR = 3.

List of variables included in the cointegrating vector:

LY LK LL LH LFDI Intercept

List of eigenvalues in descending order: .4794 .3573 .2461 .1467 .0787 .0000

PANEL A Cointegration with restricted intercepts and no trends in the VAR

Cointegration LR Test Based on Maximal Eigenvalue of the Stochastic Matrix

Null	Alternative	Statistic	95% Critical Value	90% Critical Value
r = 0	r = 1	34.5993	34.4000	31.7300
r<= 1	r = 2	23.4268	28.2700	25.8000
r<= 2	r = 3	14.9697	22.0400	19.8600

PANEL B Cointegration with restricted intercepts and no trends in the VAR

Cointegration LR Test Based on Trace of the Stochastic Matrix

Null	Alternative	Statistic	95% Critical Value	90% Critical Value
r = 0	r>= 1	85.7514	75.9800	71.8100
r<= 1	r>= 2	51.1521	53.4800	49.9500
r<= 2	r>= 3	27.7253	34.8700	31.9300

PANEL C Cointegration with restricted intercepts and no trends in the VAR

Choice of the Number of Cointegrating Relations Using Model Selection Criteria

Rank	Maximized LL	AIC	SBC	HQC
r = 0	450.5644	400.5644	351.3071	381.6224
r = 1	467.8641	407.8641	348.7553	385.1337
r = 2	479.5774	411.5774	344.5875	385.8163

Table 6 reports a summary of the Johansen test results for the other four-factor models and the five-factor model. The maximal eigenvalue test of the null hypothesis that there are at most r cointegrating vectors against the alternative of r + 1 cointegrating vectors shows a rejection for the null hypothesis of no cointegrating vectors under the trace statistic for the vector LY, LK, LL, LH and LICT.

Testing for the null hypothesis that there are no cointegrating vectors (r = 0) against the alternative of one cointegrating vector (r =1), the test statistic (89.22) is greater than the 1 percent critical value of (76.07), indicating that there is at least one cointegrating vector. The null hypothesis of r < = 1 against the alternative r = 2, however, cannot be rejected at either level of significance as the test statistic (43.13) is smaller than 47.21 and 54.46, suggesting the existence of a unique cointegrating vector between LY, LK, LL, LH and LICT.

The test results further show that the maximal eigenvalue test of the null hypothesis that there are at most r cointegrating vectors against the alternative of r + 1 cointegrating vectors show a rejection for the null hypothesis of no cointegrating vectors under the trace statistic for the vector LY, LK, LL, LFDI and LICT. Testing for the null hypothesis that there are no cointegrating vectors (r = 0) against the alternative of one cointegrating vector (r =1), the test statistic (88.62) is greater than the 1 percent critical value (76.07. This indicates that there is at least one cointegrating vector. The null hypothesis of r < = 1 against the alternative r = 2, however, cannot be rejected at either level of significance as the test statistic (45.26) is smaller than 47.21 and 54.46, suggesting the existence of a unique cointegrating vector between LY, LK, LL, LFDI and LICT.

The maximal eigenvalue test for LY, LK, LL, LH, LFDI and LICT, the five-factor model of the null hypothesis that there are no cointegrating vectors against the alternative of 1 and at most 1 and more than 1 cointegrating vectors is rejected at the 1% level of significance. The maximal eigenvalue test however does not reject the null hypothesis of 2 cointegrating vectors against the alternative of at most 3 cointegrating vectors. Testing for the null hypothesis that there are no cointegrating vectors (r = 0) against the alternative of one cointegrating vector (r =1), the test statistic (136.83) is greater than the 1 percent critical value of (103.18), thus rejecting the null hypothesis at the 1 percent level.

Table 6: Summary of Cointegration Test for the Four-factor Models and Five-factor model

Vector	Null Hypothesis	Alternative Hypothesis	Eigen-value	Trace Statistic	Critical Value	
					5%	1%
LY, LK, LL, LH & LICT	R = 0**	r = 1	0.5877	89.221	68.52	76.07
	r <= 1	r = 2	0.3442	43.1344	47.21	54.46
LY, LK, LL, LFDI & LICT	r = 0*	r = 1	0.5657	88.6221	68.52	76.07
	r <= 1	r = 2	0.3779	45.2529	47.21	54.46
LY, LK, LL, LH, LFDI & LICT	R = 0**	r = 1	0.6755	136.835	94.15	103.2
	r <= 1	r = 2	0.5322	80.5565	68.52	76.07
	r <= 2	r = 3	0.3716	42.57	47.21	54.46

Note: *(**) denotes rejection of the null hypothesis at the 5% (1%) level.

Testing for the null hypothesis for at most one cointegrating vector (r <= 1) against the alternative of 2 cointegrating vectors (r =2), the test statistic (80.56) is greater than the 1 percent critical value (76.07), thus rejecting the null hypothesis at the 1 percent level of significance. This indicates that there are at least two cointegrating vectors. The null hypothesis of r < = 2 against the alternative r = 3, however, cannot be rejected at either level of significance as the test statistic (42.57) is smaller than both 47.21 and 54.46, suggesting the existence of at most two cointegrating vectors between LY, LK, LL, LH, LFDI and LICT. Detailed results of the cointegration test for the four-factor models (LY, LK, LL, LH and LICT; LY, LK, LL, LFDI and LICT) and the five- factor models are reported in Tables A16 through A18.

6.4 Estimation Results

The production function (3.2.2) in log linear form is estimated using annual data for Australia from 1950 to 2005. Engle and Granger (1987) show that if two variables are cointegrated, (that is if an equilibrium relationship exists) then the short-run disequilibrium relationship between the two variables can always be represented by an error-correction model (ECM). For the purpose of estimating the long-run parameters, this study adopts the Johansen procedure based on maximum likelihood estimates of all the cointegrating vectors in a given set of variables and provides two likelihood ratio tests for the number of cointegrating vectors. Estimation results based on different factor models are discussed next.

For the purpose of the empirical analysis, equation (3.2.10) is written as:

$$Y_t = A_t K^{\alpha}{}_t L^{\beta}{}_t X^{\varphi}{}_t, \quad X\text{=H, FDI and ICT)} \tag{6.4.1}$$

The production function (6.4.1) has some novel features. One unusual feature of the production function is that the coefficients of production factors are not necessarily constrained to sum to unity. One reason to freely estimate the coefficients of fixed capital and labour is that human capital, FDI and ICT are included as additional factors of production, and it is not clear how their factor shares would be calculated. We test for this assumption in the later part of this sub-chapter. In addition, endogenous growth theories have questioned the assumption of constant returns to scale. The estimated results obtained using equations (3.2.2) and (3.2.10) are reported in Table 7.

All the estimated long-run elasticities presented in Table 7 have the anticipated sign and all are significant determinants of GDP. All the long-run parameters are inelastic.

Table 8A displays the results of restricting the sum of the parameters to unity and the hypothesis test for constant returns to scale. The log-likelihood ratio statistic for testing constant return to scale ($\hat{\alpha}+\hat{\beta}$ =1), is given by CHSQ (1) = 1.87, which is not statistically significant and hence suggests that the constant returns to scale hypothesis cannot be rejected for the two-factor model.

Table 7: Estimated Long-Run Coefficients based on Cointegrating VAR (3) for the Two-Factor and Three-Factor Models

Dependent Variable LY- 53 Observations 1953 to 2005			
Regression Equation: : Equation (3.2.2) $Y_t = A_t K^{\alpha}{}_t L^{\beta}{}_t$			
Variable	Coefficient	Standard Error	T-Ratio (P-Value)
LK	0.44689	0.25928	1.723581 (0.038)
LL	0.52537	0.35175	1.493589 (0.075)
Intercept	3.4668	1.8172	1.90777 (0.025)
Regression Equation: Equation (3.2.10) $Y_t = A_t K^{\alpha}{}_t L^{\beta}{}_t H^{\varphi}{}_t$			
LK	0.34774	0.13219	2.63061 (0.005)
LL	0.15287	0.16306	0.937508 (0.150)
LH	0.34662	0.097694	3.54802 (0.001)
Intercept	5.3367	1.1756	4.53955 (0.000)
Regression Equation: Equation (3.2.10) $Y_t = A_t K^{\alpha}{}_t L^{\beta}{}_t FDI^{\varphi}{}_t$			
LK	0.017086	0.50969	0.0335 (0.400)
LL	0.52205	0.35562	1.468 (0.075)
LFDI	0.26344	0.19184	1.37323 (0.078)
Intercept	5.5317	3.0593	1.80816 (0.018)
Regression Equation: Equation (3.2.10) $Y_t = A_t K^{\alpha}{}_t L^{\beta}{}_t ICT^{\varphi}{}_t$			
LK	0.13348	0.10369	1.2873 (0.100)
LL	0.62312	0.088593	7.03351 (0.000)
LICT	0.20276	0.030367	6.67699 (0.000)
Intercept	4.4599	0.56796	7.8525 (0.000)

The results of the hypothesis test for constant returns to scale for the three-factor models by restricting the sum of the parameters to unity are reported in Table 8B. The log-likelihood ratio statistic for testing constant return to scale ($\hat{\alpha}+\hat{\beta}+\hat{\varphi}$ =1) for the two of the three-factor models, ((LY, LK, LL and LH) and (LY, LK, LL and LICT)) in Table 8B are given by CHSQ (1) =6.02 and CHSQ (1) =11.62 respectively and are statistically significant, suggesting the rejection of constant returns to scale hypothesis for these models.

Table 8A: Diagnostic Test for Constant Return to Scale for the Two-Factor Model

ML estimates subject to over identifying restriction(s)- Estimates of Restricted Cointegrating Relations (SE's in Brackets)-Converged after 22 iterations Cointegration with restricted intercepts and no trends in the VAR	
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1. List of variables included in the cointegrating vector: LY LK LL Intercept List of imposed restriction(s) on cointegrating vectors: A1=1; A2+A3=1	
	Vector 1
LY	1.0000 (NONE)
LK	1.2148 (3.5595)
LL	-.21478 (3.5595)
Intercept	-27.7093 (10.8417)
LR Test of Restrictions CHSQ (1) = 1.8732[.171] DF=Total no of restrictions (2) - no of just-identifying restrictions (1) LL subject to exactly identifying restrictions= 330.2599 LL subject to over-identifying restrictions= 329.3234	

The log-likelihood ratio statistic for testing constant return to scale ($\hat{\alpha}+\hat{\beta}+\hat{\varphi}$ =1) for the three-factor model (LY, LK, LL and FDI) as shown in Table 8B**,** is given by CHSQ (1) =0 .8115, which is not statistically significant and this suggests that the constant returns to scale hypothesis cannot be rejected.

We now investigate the importance of the additional exogenous factors which are included in the three-factor production functions namely; human capital, FDI and ICT. The result of the diagnostic test for the significance of human capital is presented in Table 9A. The log-likelihood ratio statistic for testing the over-identifying restriction in Table 9A is given by CHSQ (1) = 19.74, which is above the 99 % critical value of the χ^2 distribution with one degree of freedom. The hypothesis that the long-run elasticity of GDP with respect to human capital is zero is firmly rejected.

Table 8B: Summary of the Diagnostic Test Results for Constant Return to Scale for the Three-Factor Models

Factor Model	LR Test (CHSQ (1)	Probability
LY, LK, LL and LH	6.0155	0.014
LY, LK, LL and LFDI	0.81145	0.368
LY, LK, LL and LICT	11.6178	0.001

Notes: Detailed Tests Results for Constant Return to Scale are presented in Tables A11 through A13

The result of the diagnostic test for the significance of foreign direct investment is reported in Table 9B. The log-likelihood ratio statistic for testing the over-identifying restriction in Table 9B is given by CHSQ (1) =34.28, which is above the 99 % critical value of the χ^2 distribution with one degree of freedom. The hypothesis that the long-run elasticity of GDP with respect to foreign direct investment is zero is firmly rejected.

The result of the diagnostic test for the significance of ICT is reported in Table 9C. The log- likelihood ratio statistic for testing the over-identifying restriction in Table 9C is given by CHSQ (1) = 41.54, which is above the 99 % critical value of the χ^2 distribution with one degree of freedom. The hypothesis that the long-run elasticity of GDP with respect to ICT is zero is also firmly rejected.

Table 9A: Diagnostic Test for Significance of Human Capital (LH) in the Three-Factor Model (LY, LK, LL and LH)

ML estimates subject to over identifying restriction(s) - Estimates of Restricted Cointegrating Relations (SE's in Brackets) - Converged after 19 iterations Cointegration with restricted intercepts and no trends in the VAR	
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1. List of variables included in the cointegrating vector: LY LK LL LH Intercept List of imposed restriction(s) on cointegrating vectors: A1=1; A4=0	
	Vector 1
LY	1.0000 (NONE)
LK	-.65371 (.13789)
LL	-.46067 (.23947)
LH	0.00 (NONE)
Intercept	-1.3774 (.53673)
LR Test of Restrictions CHSQ(1) = 19.7383[.000] DF = Total no of restrictions(2) - no of just-identifying restrictions(1) LL subject to exactly identifying restrictions = 442.4564 LL subject to over-identifying restrictions = 432.5873	

The results of these diagnostic tests suggest that human capital, foreign direct investment and ICT in the three-factor models are very important determinants of the long run GDP growth and for that matter economic growth in Australia in the three-factor production functions.

We now examine the results of the estimated long-run elasticities of the four-factor models and the five-factor model. The results reported in Table 10A are estimated from regression equations (3.2.11) and (3.2.12). The sum of the parameters is however not restricted to unity as in the cases of the two-factor and three-factor models.

All the estimated long-run elasticities presented in Table 10A have the anticipated signs. However, the long-run elasticities of GDP with respect to foreign direct investment in all the four-factor models are not significant, suggesting that FDI is a weak determinant of long-run output in equation (3.2.11).

Table 9B: Diagnostic Test for Significant of Foreign Direct Investment (LFDI) in the Three-Factor Model (LY, LK, LL and LFDI)

ML estimates subject to over identifying restriction(s)- Estimates of Restricted Cointegrating Relations (SE's in Brackets)- Converged after 20 iterations	
Cointegration with restricted intercepts and no trends in the VAR	
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1.	
List of variables included in the cointegrating vector:	
LY LK LL LFDI Intercept	
List of imposed restriction(s) on cointegrating vectors: A1=1; A4=0	
	Vector 1
LY	1.0000 (NONE)
LK	-.93407 (NONE)
LL	.032617 (NONE)
LFDI	-.0000 (NONE)
Intercept	-2.5805 (NONE)
LR Test of Restrictions	CHSQ(1) = 34.2777[.000]
DF = Total no of restrictions(2) - no of just-identifying restrictions(1)	
LL subject to exactly identifying restrictions = 376.0534	
LL subject to over-identifying restrictions = 358.9146	

The results of the hypothesis test for constant returns to scale, that is restricting the sum of the estimated parameters to unity in the four-factor models are reported in Table 10B. The log-likelihood ratio statistics for testing constant return to scale ($\hat{\alpha}+\hat{\beta}+\hat{\phi}+\hat{\gamma}$ =1), are given by CHSQ (1) = 12.87 and 9.07 for two of the four-factor models (LY, LK, LL, LH, LICT) and LY, LK, LL, LFDI and LICT) respectively, which are statistically significant, suggesting the rejection of constant returns to scale hypothesis for these four-factor models. However, the log-likelihood ratio statistic for testing constant return to scale ($\hat{\alpha}+\hat{\beta}+\hat{\phi}+\hat{\gamma}=1$) for the four-factor model (LY, LK, LL, LH and LFDI) reported in Table 10B**,** is given by CHSQ (1) = 3.18, which is not statistically significant and this suggests that the constant returns to scale hypothesis cannot be rejected for this model.

Table 9C: Diagnostic Test for Significance of ICT (LICT) in the Three-Factor Model (LY, LK, LL and LICT)

ML estimates subject to over identifying restriction(s)- Estimates of Restricted Cointegrating Relations (SE's in Brackets)- Converged after 19 iterations Cointegration with restricted intercepts and no trends in the VAR	
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1. List of variables included in the cointegrating vector: LY LK LL LICT Intercept List of imposed restriction(s) on cointegrating vectors: A1=1; A4=0	
	Vector 1
LY	1.0000 (NONE)
LK	-.29937 (.41021)
LL	-1.1368 (.68772)
LICT	0.00 (NONE)
Intercept	.62583 (1.4376)
LR Test of Restrictions	CHSQ (1)= 41.5412[.000]
DF=Total no of restrictions (2) - no of just-identifying restrictions (1) LL subject to exactly identifying restrictions= 491.7553 LL subject to over-identifying restrictions= 470.9847	

Table 10A: Estimated Long-Run Coefficients based on Cointegrating VAR (3) for the Four-Factor and Five-Factor Models

Dependent Variable LY- 53 Observations 1953 to 2005			
Variable	Coefficient	Standard Error	T-Ratio (P-Value)
Regression Equation: Equation (3.2.11) $Y_t = A_t K^{\alpha}{}_t L^{\beta}{}_t H_t^{\varphi} FDI_t^{\gamma}$			
LK	0.32754	0.17249	1.8989 (0.038)
LL	0.15985	0.18585	0.8601 (0.200)
LH	0.32907	0.12664	2.5985 (0.005)
LFDI	0.022429	0.071738	0.3127 (0.325)
Intercept	5.3798		
Regression Equation: Equation (3.2.11) $Y_t = A_t K^{\alpha}{}_t L^{\beta}{}_t H_t^{\varphi} ICT_t^{\gamma}$			
LK	0.276471	0.06819	4.0538 (0.000)
LL	0.546815	0.08404	6.5074 (0.000)
LH	0.106577	0.06223	1.7115 (0.038)
LICT	0.144692	0.03887	3.7233 (0.000)
Intercept	3.118708		
Regression Equation: Equation (3.2.11) $Y_t = A_t K^{\alpha}{}_t L^{\beta}{}_t FDI_t^{\varphi} ICT_t^{\gamma}$			
LK	0.212579	0.08395	2.53221 (0.010)
LL	0.673246	0.08378	8.03588 (0.000)
LFDI	0.044425	0.02211	2.0093 (0.025)
LICT	0.175026	0.03028	5.7803 (0.000)
Intercept	2.742423		
Regression Equation: Equation (3.2.12) $Y_t = A_t K^{\alpha}{}_t L^{\beta}{}_t H_t^{\varphi} FDI_t^{\gamma} ICT_t^{\delta}$			
LK	0.198908	0.08785	2.2641 (0.018)
LL	0.46357	0.08708	5.3237 (0.000)
LH	0.083548	0.04139	2.0187 (0.025)
LFDI	0.074928	0.02529	2.9628 (0.005)
LICT	0.162564	0.03665	4.4356 (0.000)
Intercept	3.8895641		

Table 10B: Summary of the Diagnostic Test Results for Constant Return to Scale for the Four-Factor Models

Factor Model	LR Test (CHSQ (1)	Probability
LY, LK, LL, LH and LFDI	3.1801	0.075
LY, LK, LL, LH and LICT	12.8690	0.000
LY, LK, LL, LFDI and LICT	9.0658	0.003

Notes: Detailed Tests Results for Constant Return to Scale are presented in Tables A19 through A21

The results of the diagnostic tests for the significance of human capital in the four-factor model are presented in Tables 11A and 11B. The log-likelihood ratio statistic for testing the over- identifying restriction in Tables 11A and 11B are given by CHSQ (1) =18.25 and 15.13 respectively, and are above the 99 % critical values of the χ^2 distribution with one degree of freedom. The hypothesis that the long-run elasticity of GDP with respect to human capital in the four-factor models is zero is firmly rejected in each case.

The results of the diagnostic tests for the significance of ICT in the four-factor models are reported in Tables 11C and 11D. The log-likelihood ratio statistic for testing the over- identifying restrictions in Tables 11C and 11D are given by CHSQ (1) =12.53 and 25.20 respectively, which are above the 99 % critical values of the χ^2 distribution with one degree of freedom. The hypothesis that the long-run elasticity of GDP with respect to ICT in the two models is zero each is firmly rejected.

The results of the diagnostic tests for the significance of FDI in the four-factor models are reported in Tables 11E and 11F. The log-likelihood ratio statistic for testing the over-identifying restrictions in Tables 11E and 11F are given by CHSQ (1) = 0.3371 and 0.1215 respectively, which are below the 99 % critical values of the χ^2 distribution with one degree of freedom. The hypothesis that the long-run elasticity of GDP with respect to FDI in the four-factor production function is zero cannot be rejected in each case.

Table 11A: Diagnostic Test for Significance of Human Capital (LH) in the Four-Factor Model (LY, LK, LL, LH and LICT)

ML estimates subject to over identifying restriction(s)-Estimates of Restricted Cointegrating Relations (SE's in Brackets)- Converged after 19 iterations	
Cointegration with restricted intercepts and no trends in the VAR	
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1.	
List of variables included in the cointegrating vector:	
LY LK LL LH LICT Intercept	
List of imposed restriction(s) on cointegrating vectors: A1=1; A4=0	
	Vector 1
LY	1.0000 (NONE)
LK	-.088909 (.12726)
LL	-.68964 (.11185)
LH	-.0000 (NONE)
LICT	-.21456 (.036397)
Intercept	-4.3036 (.63469)
LR Test of Restrictions	CHSQ(1)= 18.2513[.0001]
DF=Total no of restrictions(2) - no of just-identifying restrictions(1)	
LL subject to exactly identifying restrictions= 591.1295	
LL subject to over-identifying restrictions= 590.1669	

The estimated results of equation (3.2.11) and the results of the diagnostic tests suggest that in addition to fixed capital and labour, human capital and ICT are also important determinants of long-run GDP in Australia. However, the results indicate that FDI is not a significant determinant of GDP in the four-factor production models. We now examine causality relationships between GDP and production factors which are discussed next.

Table 11B: Diagnostic Test for Significance of Human Capital (LH) in the Four-Factor Model (LY, LK, LL, LH and LFDI)

ML estimates subject to over identifying restriction(s)-Estimates of Restricted Cointegrating Relations (SE's in Brackets)-Converged after 21 iterations Cointegration with restricted intercepts and no trends in the VAR	
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1. List of variables included in the cointegrating vector: LY LK LL LH LFDI Intercept List of imposed restriction(s) on cointegrating vectors: A1=1; A4=0	
	Vector 1
LY	1.0000 (NONE)
LK	.011672 (.63999)
LL	-.52488 (.41451)
LH	-.0000 (NONE)
LFDI	-.27248 (.22769)
Intercept	-5.7674 (3.8137)
LR Test of Restrictions	CHSQ(1)= 15.1333[.0004]
DF=Total no of restrictions(2) - no of just-identifying restrictions(1) LL subject to exactly identifying restrictions= 467.8641 LL subject to over-identifying restrictions= 466.7974	

6.5 Granger Causality Test

A causal link between production factors and GDP is found based on the values of the F-statistics on chosen lag orders of the independent variable, and the t-statistics on the lag value of the error correction term. Granger (1988) argues that the independent variables Granger cause the dependent variable in the long run if the error correction term in cointegration vector is statistically significant. The results of the standard pair-wise Granger causality tests are reported in Table 12. The F-statistics, which denote the statistical significance of the short-run causation between variables, are reported columns 3 and 4. The t-statistics on the one-period lag of error correction term, which denote the statistical significance of the long-run causation between variables, are reported in columns 5 and 6.

Table 11C: Diagnostic Test for Significance of ICT (LICT) in the Four-Factor Model (LY, LK, LL, LH and LICT)

ML estimates subject to over identifying restriction(s)-Estimates of Restricted Cointegrating Relations (SE's in Brackets)- Converged after 26 iterations	
Cointegration with restricted intercepts and no trends in the VAR	
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1.	
List of variables included in the cointegrating vector:	
LY LK LL LH LICT Intercept	
List of imposed restriction(s) on cointegrating vectors: A1=1; A5=0	
	Vector 1
LY	1.0000 (NONE)
LK	-.13668 (.26412)
LL	-.46233 (.23719)
LH	-.28789 (.10815)
LICT	-.0000 (NONE)
Intercept	-5.3771 (1.6772)
LR Test of Restrictions	CHSQ(1)= 12.5278[.000]
DF=Total no of restrictions(2) - no of just-identifying restrictions(1)	
LL subject to exactly identifying restrictions= 591.1295	
LL subject to over-identifying restrictions= 584.8656	

The F-statistics reported in Table 12 indicate that labour, human capital, FDI, and ICT Granger cause GDP in the short run, as the null hypotheses for these variables are each rejected at the 5% level of significance. The test results indicate a non-rejection of the null hypothesis at 5% level of significance in the case of fixed capital, suggesting that fixed capital does not Granger cause GDP in the short run. The test results further indicates that GDP Granger causes fixed capital, labour, human capital and ICT in the short run, as the null hypotheses are rejected at the 5% level of significance in each of these cases. Furthermore, the test results show a non-rejection of the null hypothesis at 5% level of significance for GDP with regard to FDI, suggesting that GDP does not Granger cause FDI in the short run.

Table 11D: Diagnostic Test for Significance of ICT (LICT) in the Four-Factor Model (LY, LK, LL, LFDI and LICT)

ML estimates subject to exactly identifying restriction(s)-Estimates of Restricted Cointegrating Relations (SE's in Brackets)-Converged after 22 iterations Cointegration with restricted intercepts and no trends in the VAR	
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1. List of variables included in the cointegrating vector: LY LK LL LFDI LICT Intercept List of imposed restriction(s) on cointegrating vectors: A1=1; A5=0	
	Vector 1
LY	1.0000 (NONE)
LK	-.87114 (.24222)
LL	-.029296 .48185)
LFDI	-.099855 (.058704)
LICT	0.00 (NONE)
Intercept	-2.3341 (1.2270)
LR Test of Restrictions	CHSQ(1)= 25.1959[.000]
DF=Total no of restrictions(2) - no of just-identifying restrictions(1) LL subject to exactly identifying restrictions= 529.4611 LL subject to over-identifying restrictions= 516.8631	

The Granger causality test results reported in Table 12 suggest that causality between GDP and each of the following production factors labour, human capital and ICT are bi-directional in the short run. However, causality between GDP and FDI is uni-directional and it runs from FDI to GDP in the short run. The results further suggest that causality between GDP and fixed capital in the short run is also uni-directional and it runs from GDP to fixed capital.

Table 11E: Diagnostic Test for Significant of Foreign Direct Investment (FDI) in the Four- Factor Model (LY, LK, LL, LFDI and LICT

ML estimates subject to over identifying restriction(s)-Estimates of Restricted Cointegrating Relations (SE's in Brackets)- Converged after 19 iterations Cointegration with restricted intercepts and no trends in the VAR	
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1. List of variables included in the cointegrating vector: LY LK LL LFDI LICT Intercept List of imposed restriction(s) on cointegrating vectors: A1=1; A4=0	
	Vector 1
LY	1.0000 (NONE)
LK	.0088628 (.15717)
LL	-.75987 (.13189)
LFDI	0.00 (NONE)
LICT	-.23316 (.044486)
Intercept	-4.6682 (.80568)
LR Test of Restrictions CHSQ(1)= .33709[.562] DF=Total no of restrictions(2) - no of just-identifying restrictions(1) LL subject to exactly identifying restrictions= 529.4611 LL subject to over-identifying restrictions= 529.2925	

Table 11F: Diagnostic Test for Significance of FDI in the Four-Factor Model (LY, LK, LL, LH and LFDI)

ML estimates subject to over identifying restriction(s)-Estimates of Restricted Cointegrating Relations (SE's in Brackets)-Converged after 20 iterations Cointegration with restricted intercepts and no trends in the VAR	
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1. List of variables included in the cointegrating vector: LY LK LL LH LFDI Intercept List of imposed restriction(s) on cointegrating vectors: A1=1; A5=0	
	Vector 1
LY	1.0000 (NONE)
LK	-.35636 (.12611)
LL	-.13538 (.15353)
LH	-.35305 (.095463)
LFDI	-.0000 (NONE)
Intercept	-5.3352 (1.1287)
LR Test of Restrictions	CHSQ(1)= .12147[.727]
DF=Total no of restrictions(2) - no of just-identifying restrictions(1)	
LL subject to exactly identifying restrictions= 467.8641	
LL subject to over-identifying restrictions= 467.8033	

The t-statistics reported in Table 12 suggest that, in the long run, in exception of causality between GDP and FDI, there is evidence of bi-directional causality between GDP and production factors. FDI, Granger causes GDP in the long run, as the null hypothesis that the lag value of the error term in the VECM is zero is strongly rejected at the 5% level of significance. The test results provide further evidence that GDP does not Granger cause FDI in the log run as the null hypothesis that the lag value of the error term in the VECM with FDI as the dependent variable is zero cannot be rejected at the

5% level of significance. In the long run, causality between GDP and FDI is uni-directional and it runs from FDI to GDP.

Table 12: Granger Causality Tests Based on VECM for LY, LK, LL, LH, LFDI and LICT

Null Hypothesis:	F-Statistic	Prob.	T-Statistic	Prob.
LK does not Granger Cause LY	0.75112	0.39010	-9.390	0.0000
LY does not Granger Cause LK	5.85253	0.0191	-6.405	0.0000
LL does not Granger Cause LY	5.886	0.0188	-9.390	0.0000
LY does not Granger Cause LL	10.9453	0.0017	-3.839	0.0000
LH does not Granger Cause LY	37.2984	0 .0000	-9.390	0.0000
LY does not Granger Cause LH	7.51958	0.0084	-7.268	0.0000
LFDI does not Granger Cause LY	15.1612	0.0031	-9.390	0.0000
LY does not Granger Cause LFDI	2.7808	0.1014	-1.673	0.1000
LICT does not Granger Cause LY	23.0711	0.0002	-9.390	0.0000
LY does not Granger Cause LICT	19.4883	0.000 4	-26.954	0.0000

Notes: Lag order =1

The results of the Granger causality test suggest that human capital, FDI and ICT have significant impacts on GDP in both the short and long run periods. However, the *F*-statistics for these variables fail to explain the sign of the relationship between these variables and GDP or how long these effects are persistent in GDP. In other words, *F*-test results do not reveal whether the change in any given variable has a positive or negative impact on other variables in the system. Neither do the *F*-test results indicate how long it would take for the effect of a particular variable to work through the system. The Granger causality is a within sample test and can only be used to discern the plausible Granger exogeneity or endogeneity of each of the variables in the sample period. It cannot be used to ascertain the degree of exogeneity of the variables beyond the sample period. The impulse response functions and forecast error variance decomposition which are discussed next provide such information.

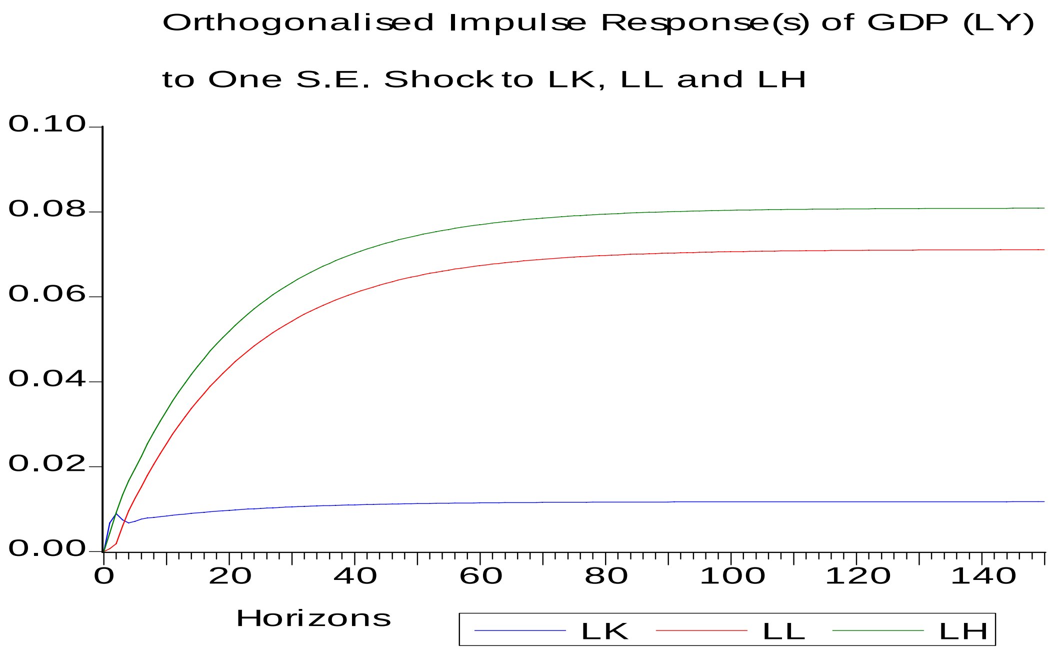
6.6 Impulse Response Functions and Forecast Error Variance Decomposition

This sub-section investigates the interrelationships between GDP and fixed capital, labour, human capital, FDI and ICT. The section examines how GDP responds to a unit standard error (S.E.) shock in each of these factors and determines the proportion of the forecast error variance of GDP due to innovations of each production factor at different forecast horizons. The variance decomposition measures the contribution of each innovation in the vector error correction model (VECM) to k-step ahead forecast error variance of the dependent variables. The variance decomposition is a useful tool for determining the relative quantitative importance of shocks to the variables in the system. These analyses are carried out to determine the dynamic interrelation between GDP and production factors.

The results of the orthogonalised impulse response(s) of GDP to a unit standard error shock of each factor based on the three-factor, the four-factor and the five-factor models are presented graphically in Figures 4 through 10. These results suggest that GDP's response to a unit standard error shock to each production factor has persistence effects and do not generally die out. As can be seen from Figure 4, for a unit standard error shock to fixed capital, GDP responds positively. The effect of the shock is persistent and never dies out even when the number of forecast horizons is increased. GDP's response to a unit standard error shock to labour units is also positive and has persistent effect on output in Figures 4, 5 and 7.

Figure 5 shows that GDP responds negatively to a unit standard error shock to fixed capital but the shock has a persistent negative effect on GDP. The responses of GDP to a unit standard error shock to labour units in Figures 6-8 are also negative but persistent and never die out.

Figure 4: Orthogonalised Impulse Response(s) of GDP (LY) to One S.E. Shock in the Equation for the Variables Fixed Capital, Labour and Human Capital



Figures 4 through 10 show that the responses of GDP to a unit standard error shock to human capital, FDI and ICT have persistent effects and increase as the number of forecast horizons is increased. The results of the impulse response functions suggest that the responses of GDP to a unit standard error shock to each production factor have persistence effects and do not generally die out even with increase in the number of forecast horizons.

Figures 11 through 17 display graphically the proportion of the forecast error variance of GDP due to innovations of each production factor for the three-factor, four-factor and five-factor models for a 50-year forecast period. The results reported in Figure 11 (Table A22a) indicate that after five years, 59.72% of the variation in the forecast error for GDP is explained by its own innovations, while at the end of the 50 years, the forecast error variance for GDP explained by its own innovations is 20.14%. About 10.41%, 7.73% and 22.14% of the variation in the forecast error for GDP is explained by innovations of fixed capital, labour and human capital respectively after five years. At the end of the 50 years, about 5.41%, 32.02% and 42.44% of the variation in the forecast error for GDP is explained by innovations of fixed capital, labour and human capital respectively.

Figure 5: Orthogonalised Impulse Response(s) of GDP (LY) to One S.E. Shock in the Equation for the Variables Fixed Capital, Labour and FDI

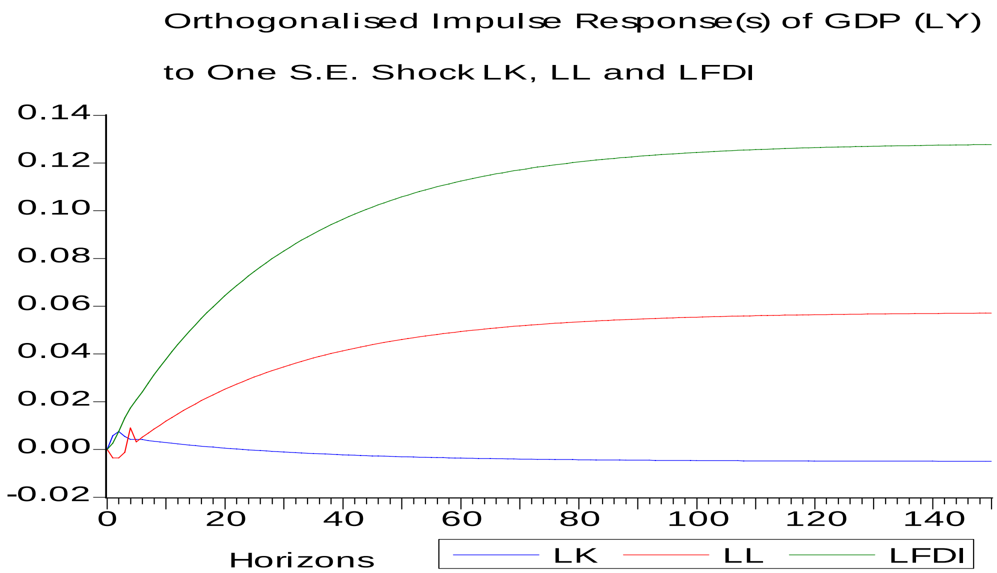


Figure 6: Orthogonalised Impulse Response(s) of GDP (LY) to One S.E. Shock in the Equation for the Variables Fixed Capital, Labour and ICT

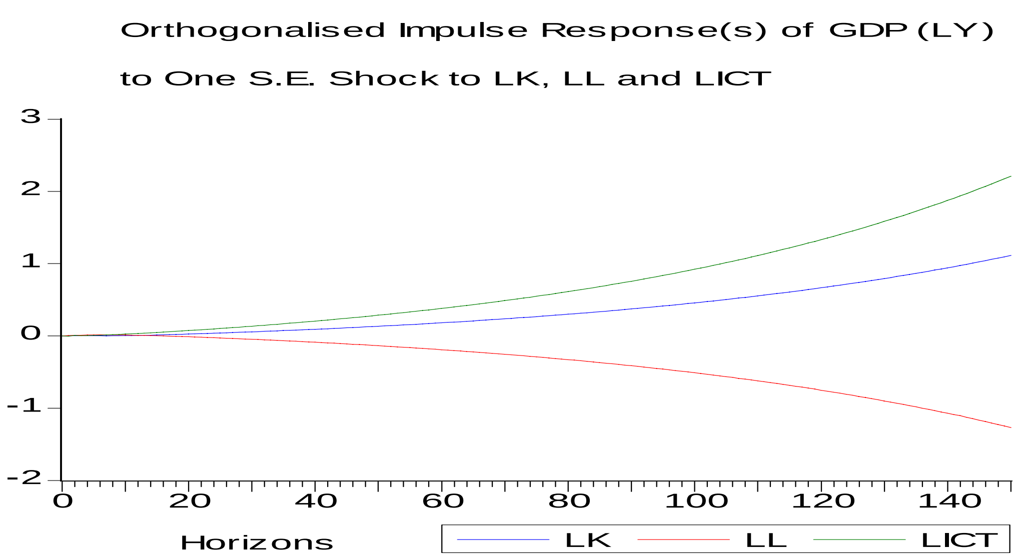


Figure 7: Orthogonalised Impulse Response(s) of GDP (LY) to One S.E. Shock in the Equation for the Variables Fixed Capital, Labour, Human Capital and FDI

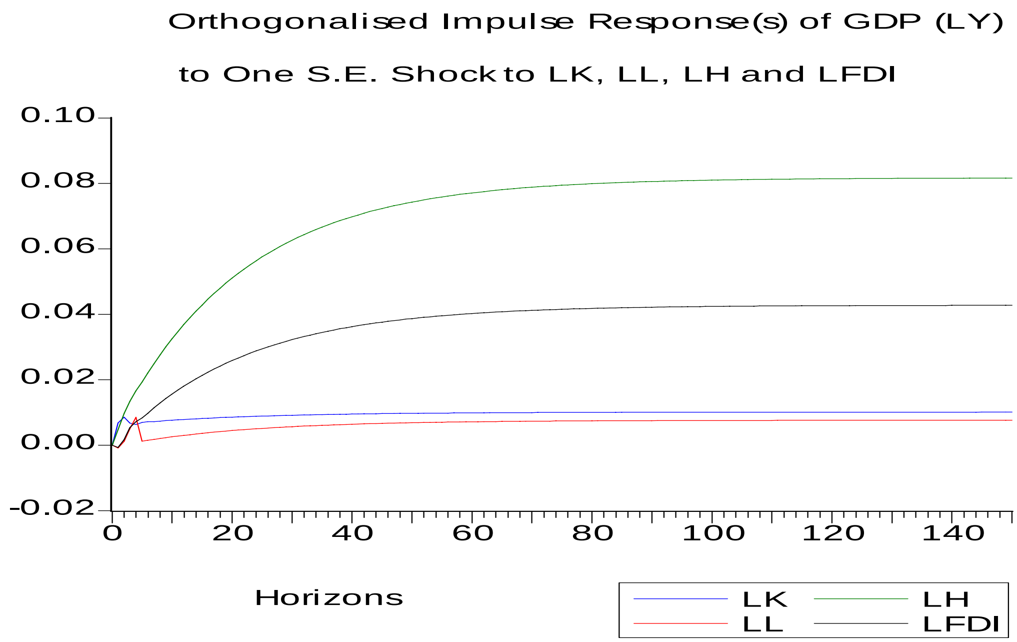


Figure 8: Orthogonalised Impulse Response(s) of GDP (LY) to One S.E. Shock in the Equation for the Variables Fixed Capital, Labour, Human Capital and ICT

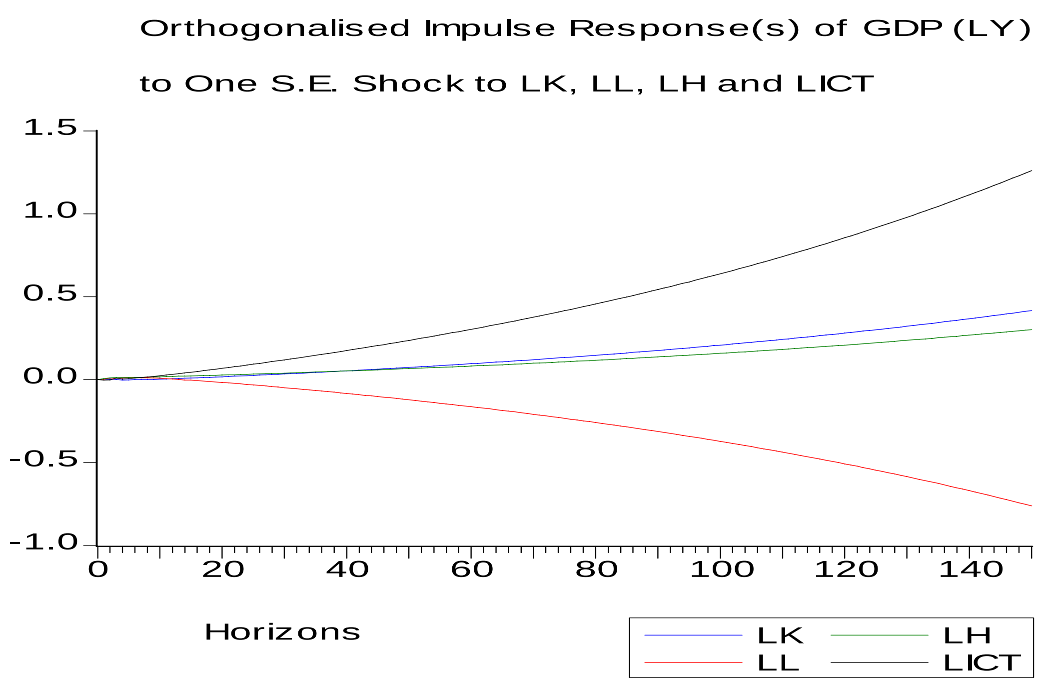


Figure 9: Orthogonalised Impulse Response(s) of GDP (LY) to One S.E. Shock in the Equation for the Variables Fixed Capital, Labour, FDI and ICT

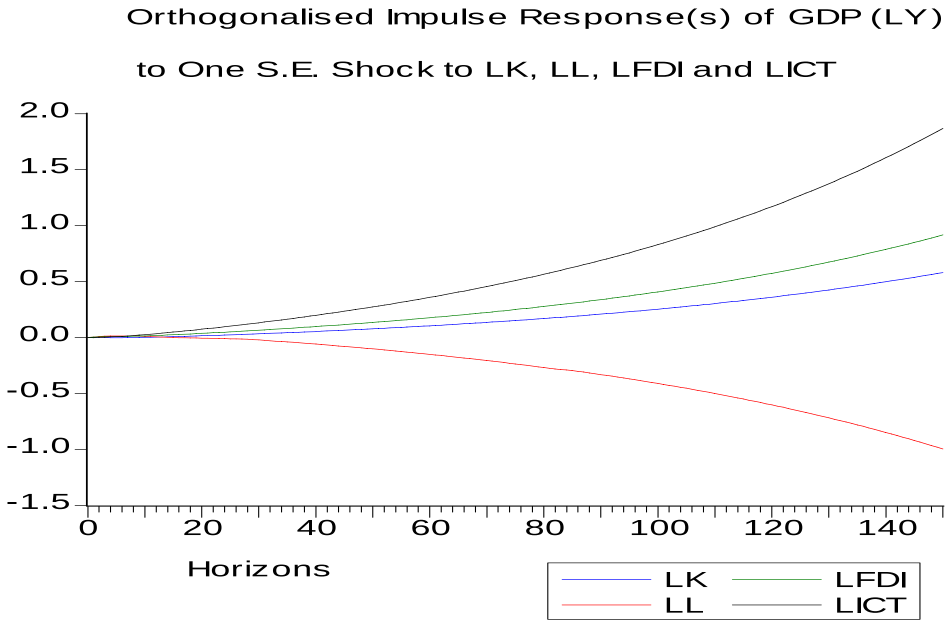


Figure 10: Orthogonalised Impulse Response(s) of GDP (LY) to One S.E. Shock in the Equation for the Variables Fixed Capital, Labour, Human Capital, FDI and ICT

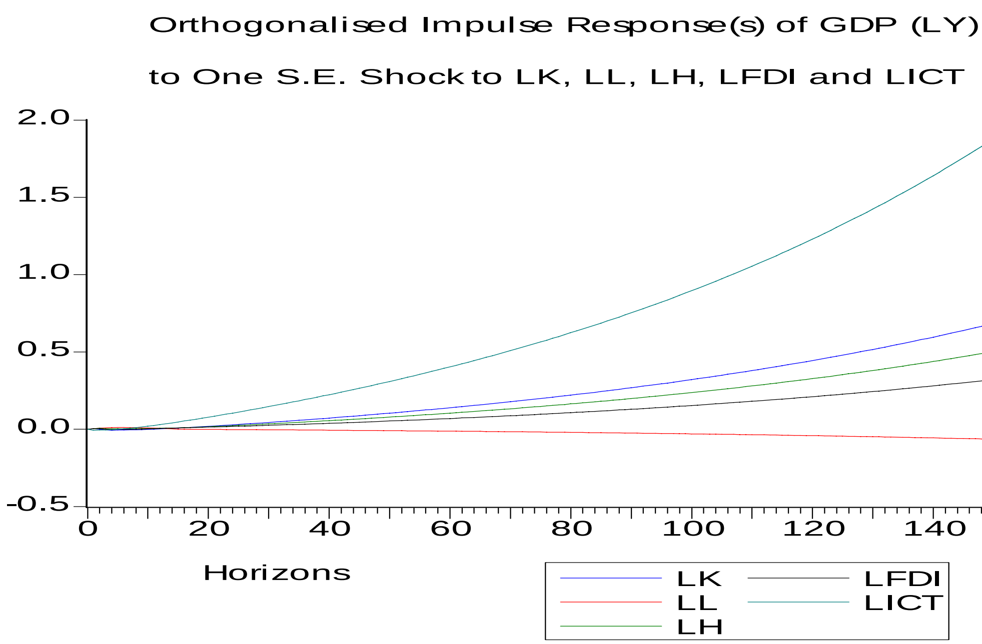
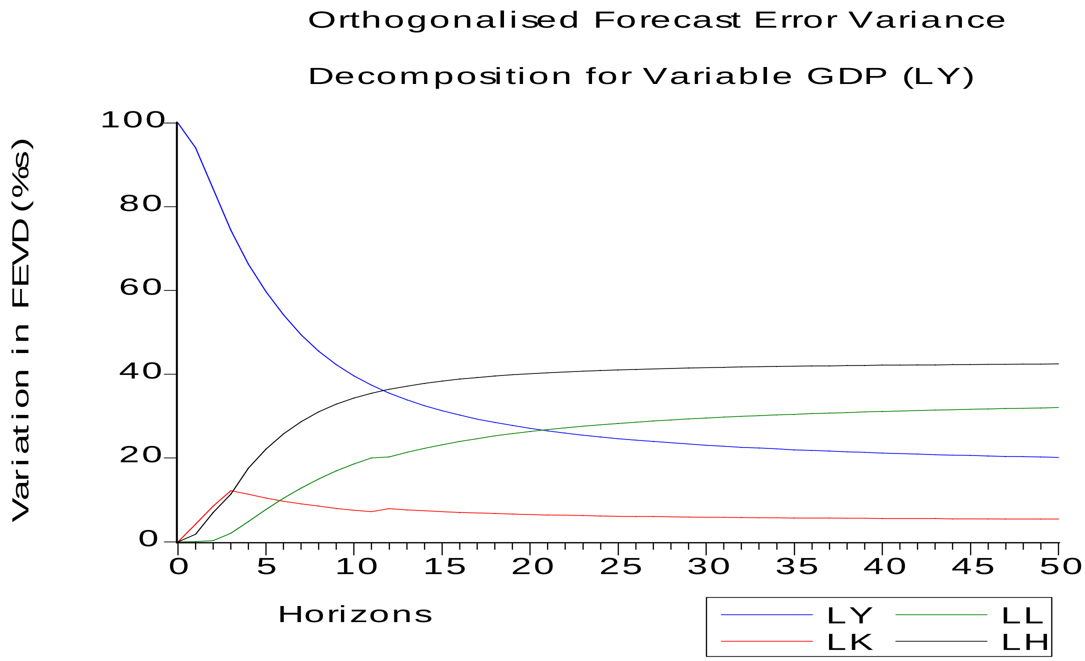


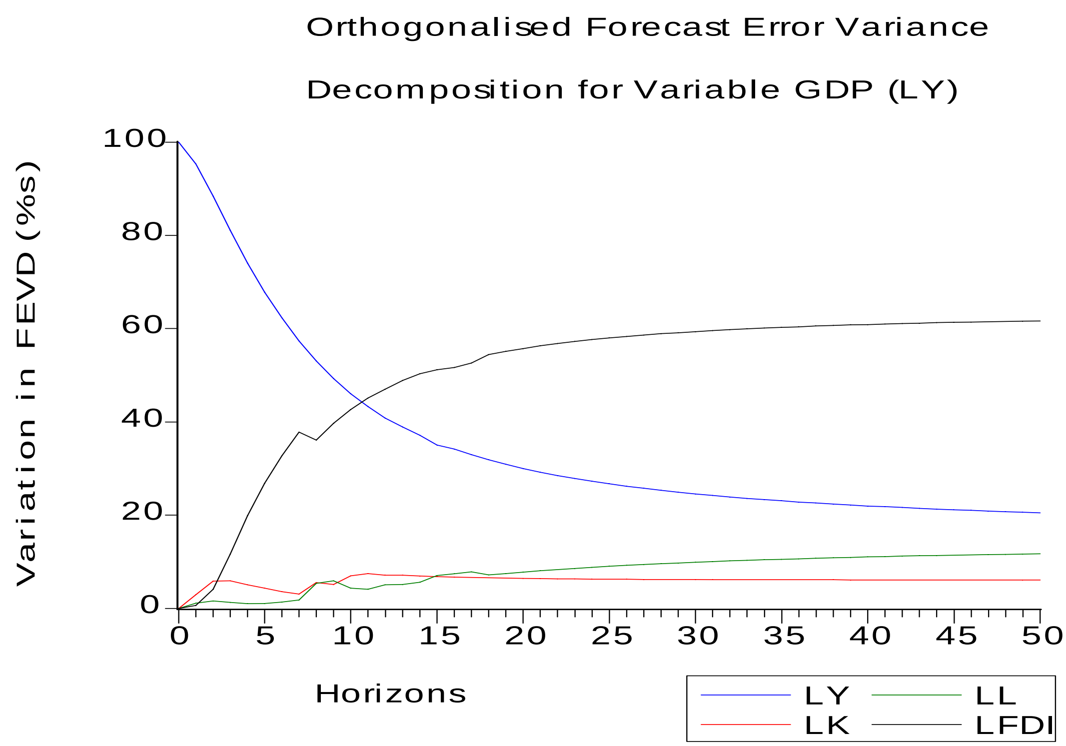
Figure 11: Orthogonalised Forecast Error Variance Decomposition for Variable GDP (LY) Three-Factor Model (LY, LK, LL and LH)



The results reported in Figure 12 (Table A22b) suggest that after five years, 67.62% of the variation in the forecast error for GDP is explained by its own innovations, while at the end of the 50 years the forecast error variance for GDP explained by its own innovations is 20.51%. After five years about 4.3%, 1.04% and 26.84% of the variation in the forecast error for GDP is explained by innovations of fixed capital, labour and FDI respectively. However, at the end of the 50 years, about 6.09%, 11.72% and 61.68% of the variation in the forecast error for GDP is explained by innovations of fixed capital, labour and FDI respectively.

The results reported in Figure 13 (Table A22c) reveal that after five years, 87.16% of the variation in the forecast error for GDP is explained by its own innovations, while at the end of the 50 years the forecast error variance for GDP explained by its own innovations is 36.9%. After five years about 0.61%, 10.99% and 1.24% of the variation in the forecast error for GDP is explained by innovations of fixed capital, labour and ICT respectively. At the end of the 50 years, about 8.17%, 10.02% and 44.91% of the variation in the forecast error for GDP is explained by innovations of fixed capital, labour and ICT respectively.

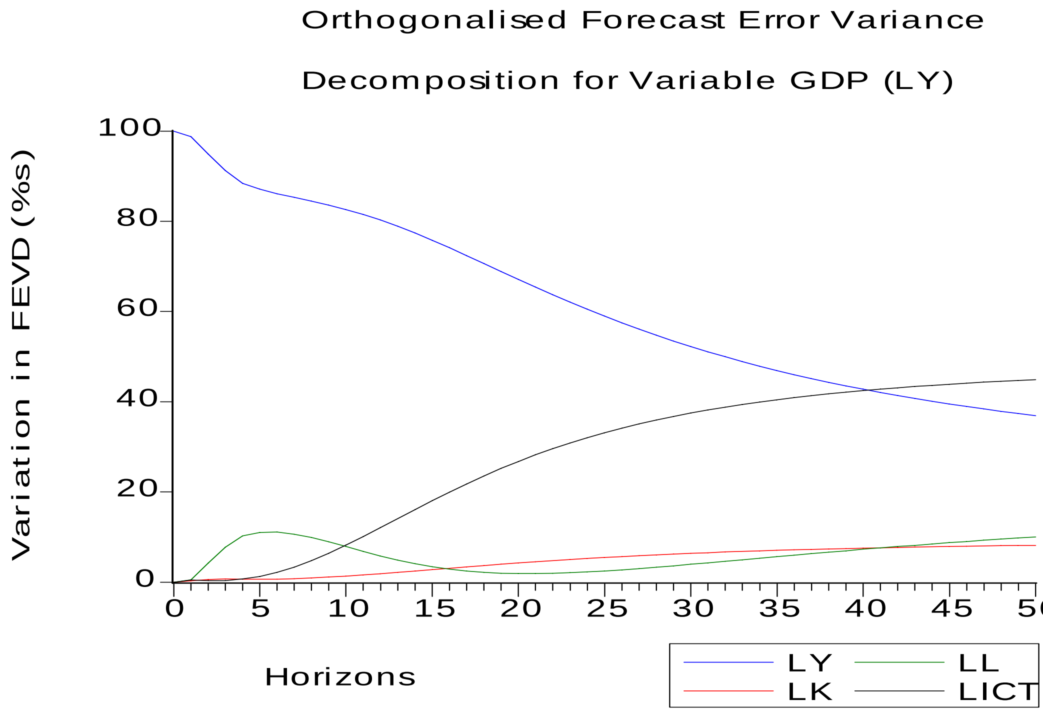
Figure 12: Orthogonalised Forecast Error Variance Decomposition for Variable GDP (LY) Three-Factor Model (LY, LK, LL and LFDI)



The results reported in Figure 14 (Table A22d) indicate that after five years, 60.34% of the variation in the forecast error for GDP is explained by its own innovations, while at the end of the 50 years the forecast error variance for GDP explained by its own innovations is 21.23%. After five years about 6.31%, 6.06%, 18.46% and 8.84% of the variation in the forecast error for GDP is explained by innovations of fixed capital, labour, human capital and FDI respectively. By the end of the 50 years, about 4.42%, 26.82%, 32.62% and 14.91% of the variation in the forecast error for GDP is explained by innovations of fixed capital, labour, human capital and FDI respectively.

Figure 13: Orthogonalised Forecast Error Variance Decomposition for Variable

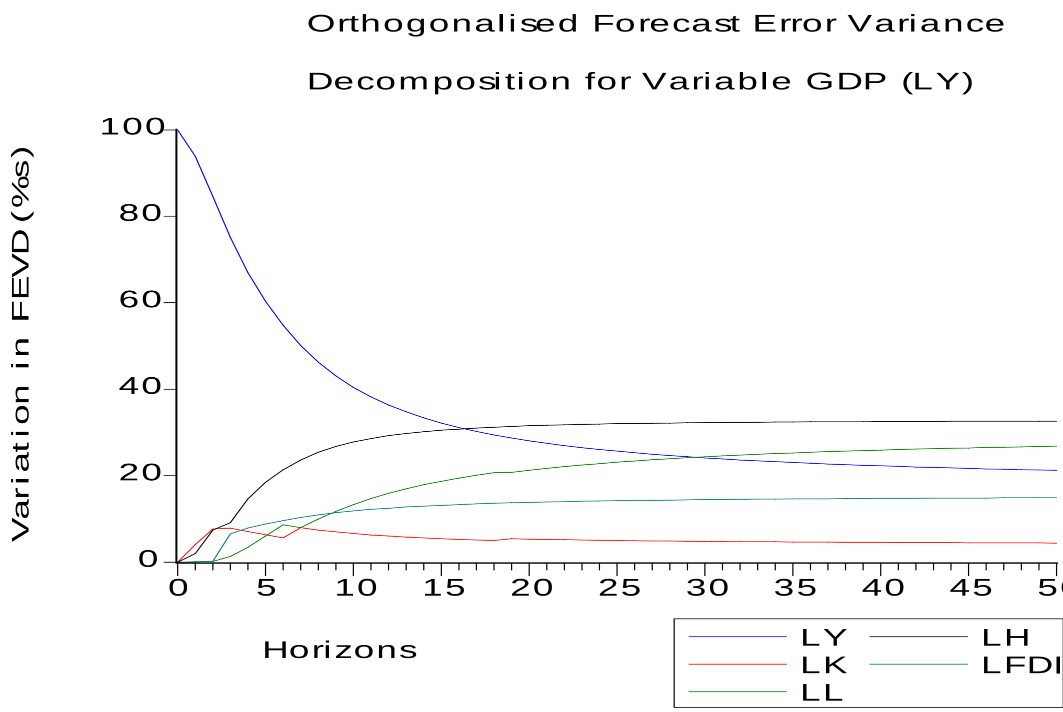
GDP (LY) Three-Factor Model (LY, LK, LL and LICT)



The results presented in Figure 15 (Table A23a) indicate that after five years, 75.03% of the variation in the forecast error for GDP is explained by its own innovations, while at the end of the 50 years the forecast error variance for GDP explained by its own innovations is only 8.99%. After five years about 0.58%, 7.98%, 12.3% and 4.11% of the variation in the forecast error for GDP is explained by innovations of fixed capital, labour, human capital and ICT respectively. By the end of the 50 years, about 5.24%, 25.44%, 10.58% and 49.75% of the variation in the forecast error for GDP is explained by innovations of fixed capital, labour, human capital and ICT respectively.

The results reported in Figure 16 (Table A23b) indicate that after five years, 82.84% of the variation in the forecast error for GDP is explained by its own innovations, while at the end of the 50 years the forecast error variance for GDP explained by its own innovations is only 2.43%. After five years about 3.64%, 5.27%, 4.15% and 4.1% of the variation in the forecast error for GDP is explained by innovations of fixed capital, labour, FDI and ICT respectively. By the end of the 50 years, about 7.92%, 29.86%, 18.35% and 41.44% of the variation in the forecast error for GDP is explained by innovations of fixed capital, labour, FDI and ICT respectively.

Figure 14: Orthogonalised Forecast Error Variance Decomposition for Variable GDP (LY) Four-Factor Model (LY, LK, LL, LH and LFDI)



The results presented in Figure 17 (Table A24) indicate that after five years, 84.2% of the variation in the forecast error for GDP is explained by its own innovations, while at the end of the 50 years the forecast error variance for GDP explained by its own innovations is 35.13%. After five years about 4.96%, 6.89%, 4.95%, 8.96% and 5.18% of the variation in the forecast error for GDP is explained by innovations of fixed capital, labour, human capital, FDI and ICT respectively. By the end of the 50 years, about 6.52%, 5.89%, 7.11%, 5.95% and 39.4% of the variation in the forecast error for GDP is explained by innovations of fixed capital, labour, human capital, FDI and ICT respectively.

Figure 15: Orthogonalised Forecast Error Variance Decomposition for Variable GDP (LY) Four-Factor Model (LY, LK, LL, LH and LICT)

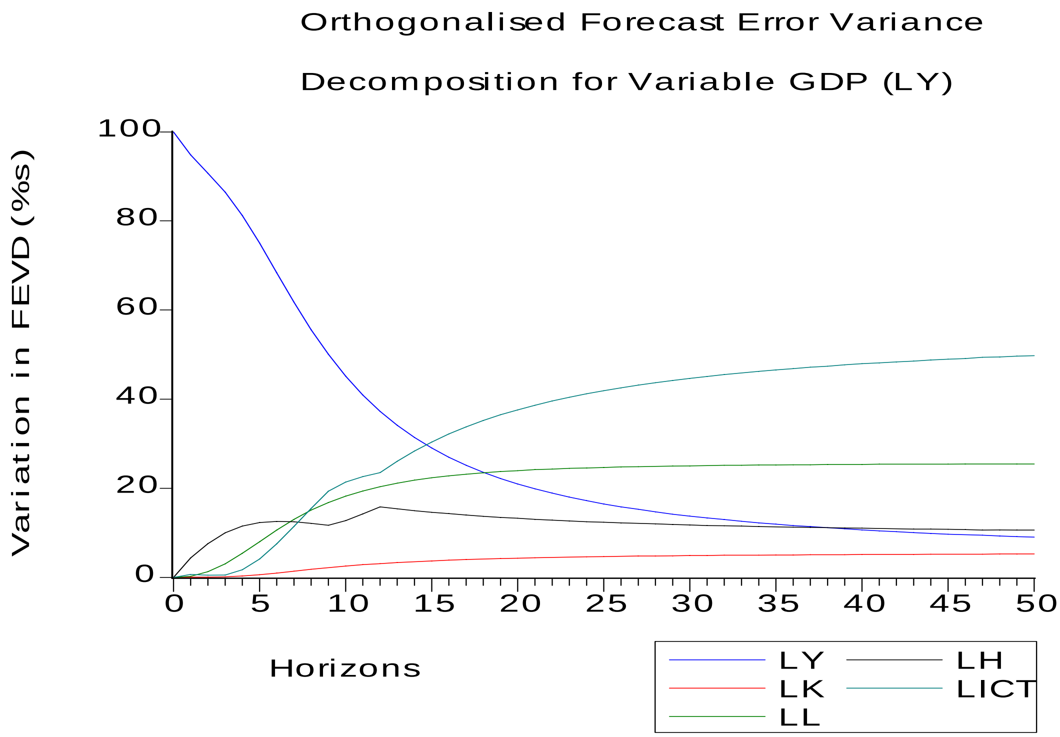


Figure 16: Orthogonalised Forecast Error Variance Decomposition for Variable GDP (LY) Four-Factor Model (LY, LK, LL, LFDI and LICT)

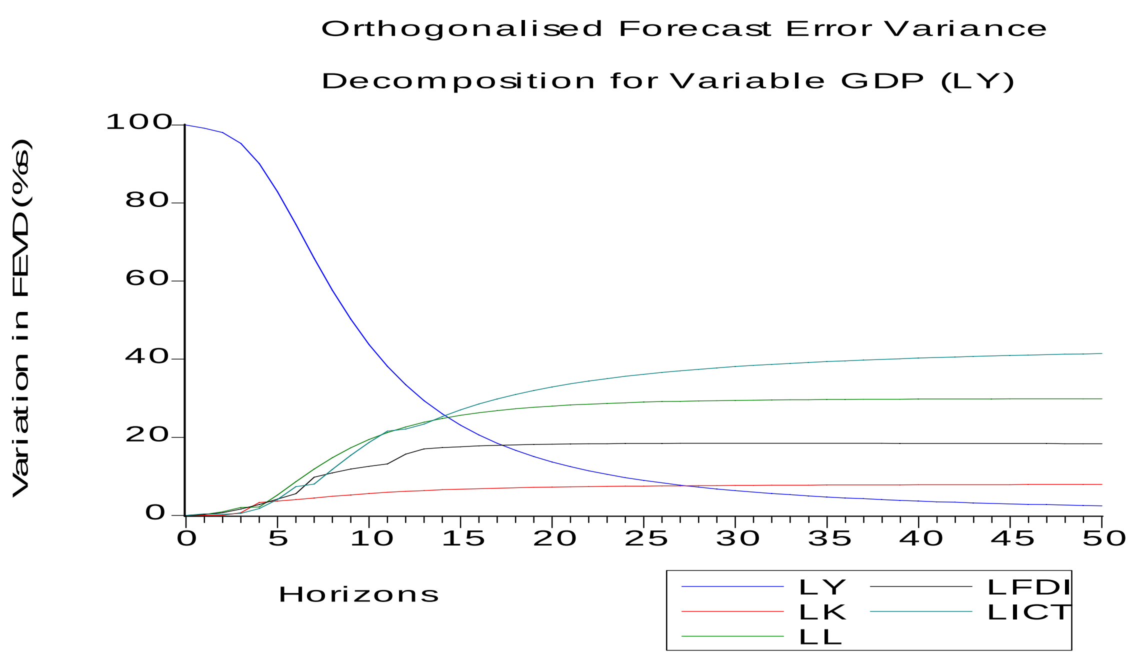
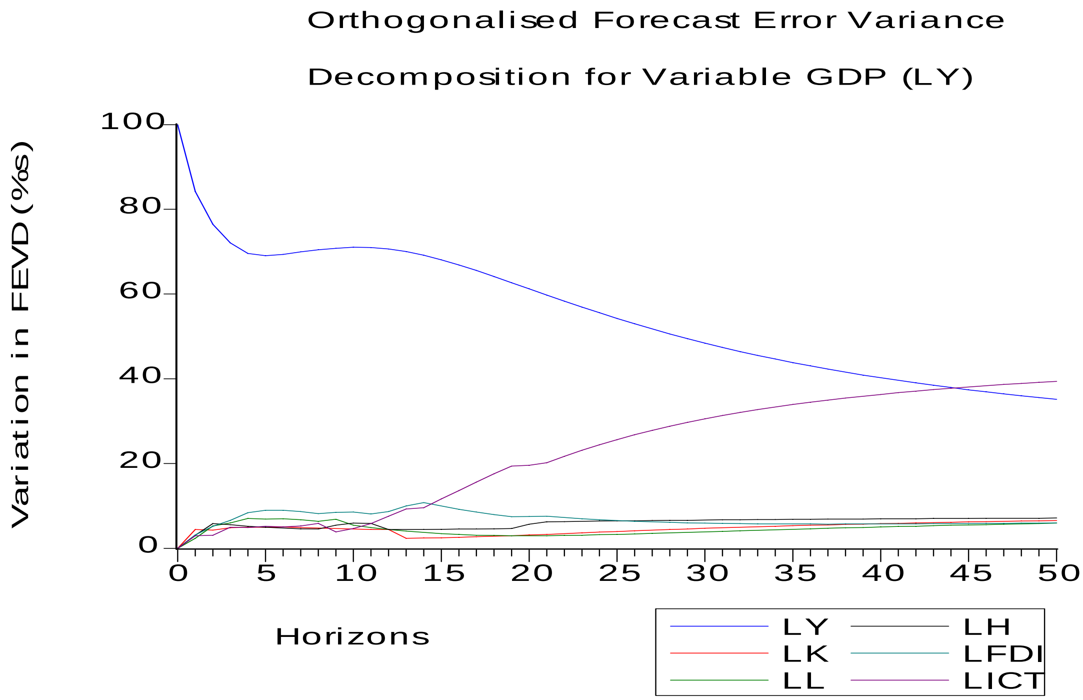


Figure 17: Orthogonalised Forecast Error Variance Decomposition for Variable GDP (LY) Five-Factor Model (LY, LK, LL, LH, LFDI and LICT)



The variance decomposition analysis suggests that the forecast error variance of GDP accounted for by the innovations of fixed capital, labour, human capital, FDI and ICT are all substantial at the end of the 50 years forecast period. The analysis further suggests that capital, labour, human capital, FDI and ICT innovations account for the most of the variability of GDP in the long run in all the various factor models. For the three-factor models, the forecast error variance of GDP explained by the innovations of human capital, FDI and ICT in the long run are each greater than the variability in the forecast error of GDP explained by innovations of fixed capital and labour. For the four-factor model (LY, LK, LL, LH and LFDI), the innovations of human capital has the greatest impact on variability of GDP's forecast error in the long run. The innovations of ICT have the biggest impact on the variability of GDP's forecast error in the long run for the four-factor models (LY, LK, LL, LH and LICT) and (LY, LK, LL, LFDI and LICT). For the five-factor model, the innovations of fixed capital have the biggest impact on the variability of GDP,s forecast error in the long run. These findings suggest that fixed capital, labour, human capital, FDI and ICT contribute to a significant proportion of GDP's forecast error in the long run. However, the analysis suggests that, in the short run, over 54% of the variation in the forecast error for GDP is explained by its own innovations.

The results of the diagnostic tests, the Granger causality test and the impulse response analysis provide very strong evidence that the measurement of GDP growth in Australia demands the consideration of not only capital and labour inputs, but also other factors such as human capital, FDI and ICT which are equally important in determining GDP growth. Failure to take into account all factors may produce inaccurate productivity estimates that may mislead policy decisions.

6.7 Measurement of Productivity in Australia

6.7.1 Measurement of Labour Productivity

This sub-section measures the performance of labour productivity and capital per unit labour in Australia's economy by elaborating on their growth rates over the period 1950-2005. The dynamics of labour productivity and its growth rates are presented graphically and discussed. The section further presents graphically the dynamics of capital per unit labour and its growth rates in Australia within the study period with accompanying discussion.

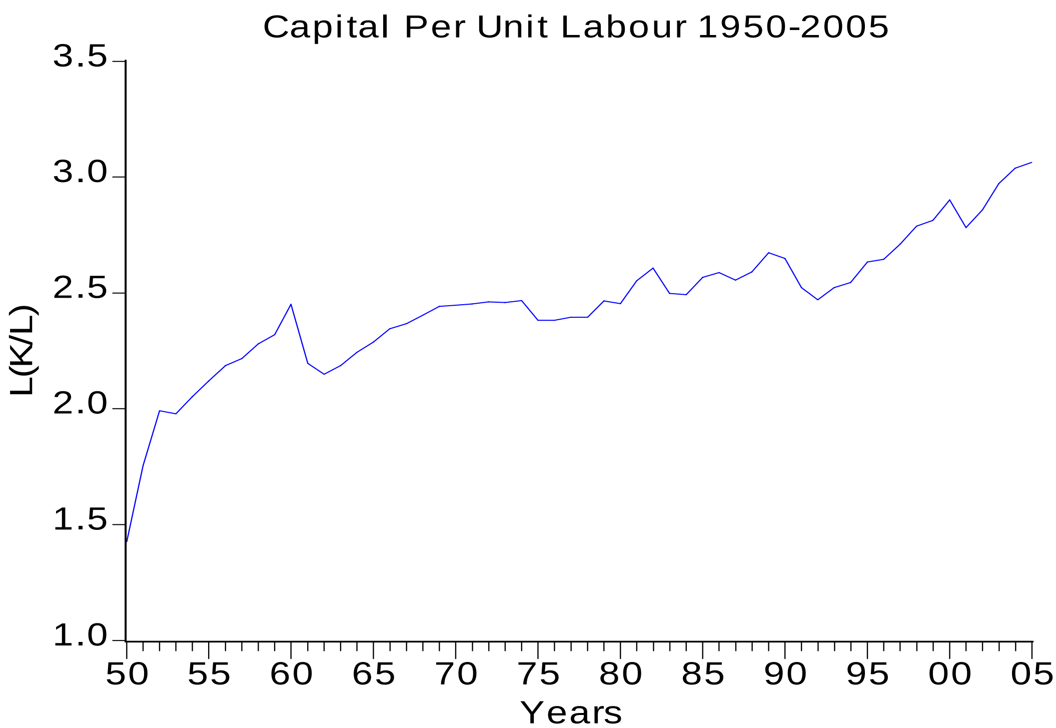
The dynamics of labour productivity are presented graphically in Figure 18 and that of its growth rates in Figure 19. The dynamics of capital per unit labour are presented in Figure 20 and that of its growth rates are in Figure 21. Labour productivity increases on average by 2.55% per annum over the period 1950-2005. However, as can be seen from Figures 18 and 19, the graphs of the dynamics suggest that the growth rate of labour productivity before 1960 was faster than those from 1960 onwards. The highest labour productivity growth rate within the period 1950-2005 of 2.86% was achieved in 1951 and the lowest growth rate of -2.44% was achieved in 1961. The graph in Figure 19 further indicates a structural break in labour productivity growth in 1961. The studies of Madden and Savage (1998), ABS (2001, 2003-2004), Valadkhani (2003) and Commonwealth of Australia (2005a, 2005b) all find positive growth trend for labour productivity.

Figure 18: Dynamics of Labour Productivity in Australia (1950-2005)

Figure 19: Dynamics of Labour Productivity Growth Rate in Australia (1950-2005)

Figure 20 presents the dynamics of capital intensity which increases on average by 3.37% yearly over the period 1950-2005. The highest capital intensity growth rate of 3.88% is achieved in 1951 and the lowest of -2.26% is achieved in 1961. As in the case of labour productivity, the graphs in Figures 20 and 21 also indicate a structural break in the growth rate of capital per unit labour in 1961.

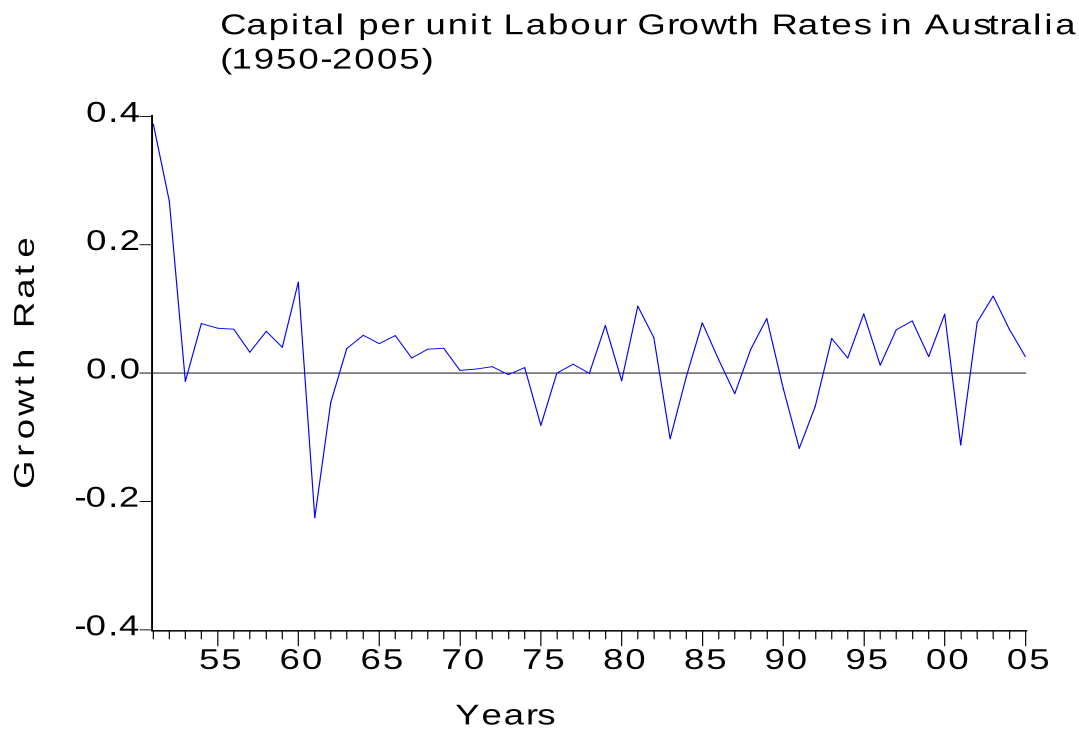
Figure 20: Dynamics of Capital per Unit Labour in Australia (1950-2005)



6.7.2 Measurement of TFP in Australia

This section uses the formulae derived in Chapter 4, Section 6.2 (Equations 4.6.2.5 and 4.6.2.6) to compute the indices of TFP in Australia for the period 1950–2005. Based on the long-run parameters of the various factor production functions estimated in Section 6.4 of this chapter (Tables 7 and 10A), estimates of TFP and its growth rates for Australia's economy are computed. The results of TFP estimates and TFP growth rates for the different factor models are presented graphically in Figures 22 through 29 and 30 through 37 respectively.

Figure 21: Dynamics of Capital per Unit Labour Growth Rates in Australia (1950-2005)



With exception of TFP estimates reported in Figures 24 and 27, all the rest increased steadily up to the year 1957, decreased for a while and increased then after. TFP estimates reported in Figure 22 increased steadily up to the year 1977, decreased and then picked up strongly in the early 1990s. The indices of TFP estimates reported in this study (Figures 22 through 29) for the various factor models have tendencies of growth and they increase on average at different rates per annum over the period 1950-2005. TFP estimates for the two-factor model (Figure 22) increases on average by 0.01091, annually for the period 1950-2005.

TFP estimates for the three-factor models reported in Figures 23, 24 and 25 increase on average by 0.00932, 0.01975 and 0.0098 per annum respectively over the period 1950-2005. The TFP estimates for the four-factor models reported in this study increase on average by 0.0096, 0.0055 and 0.0068 per annum for Figures 26, 27 and 28 respectively over the period 1950-2005. The TFP estimates for the five-factor model reported in Figure 29 increase on average by 0.0069 per annum over the period 1950-2005.

Figure 22: Indices of TFP in Australia (1950-2005) Two-Factor Model (LY, LK and LL)

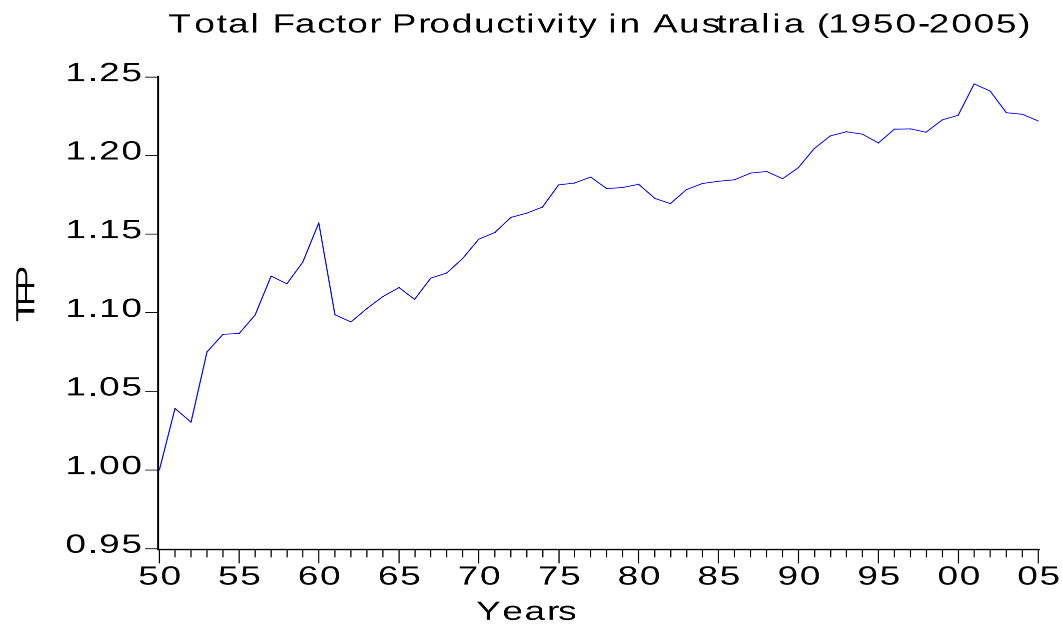


Figure 23: Indices of TFP in Australia (1950-2005) for the Three-Factor Model (LY, LK, LL and LH)

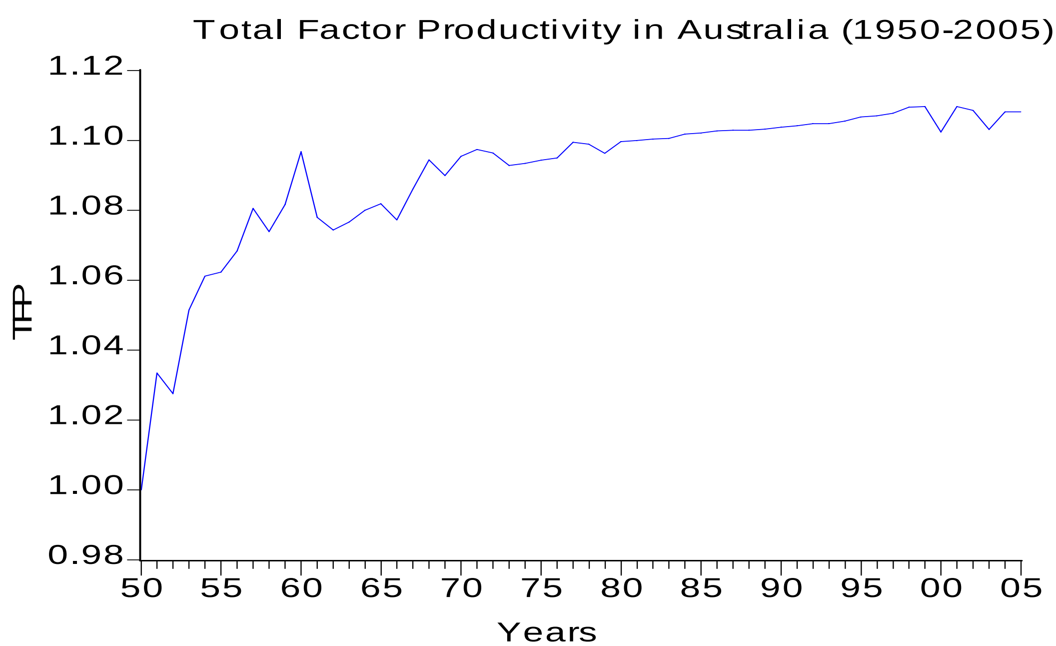


Figure 24: Indices of TFP in Australia (1950-2005) for the Three-Factor Model (LY, LK, LL and LFDI)

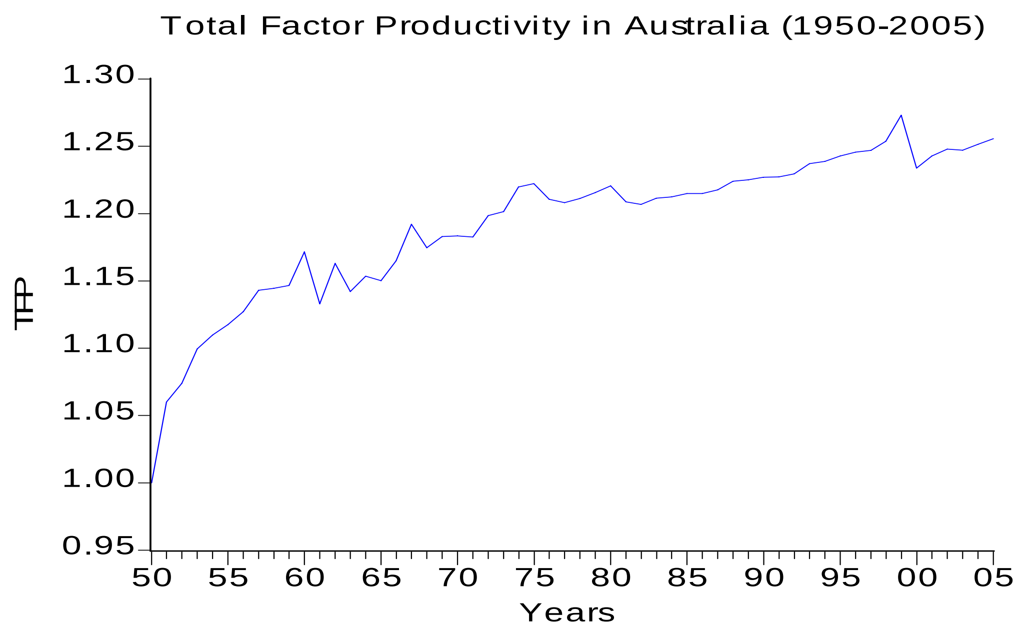


Figure 25: Indices of TFP in Australia (1950-2005) for the Three-Factor Model (LY, LK, LL and LICT)

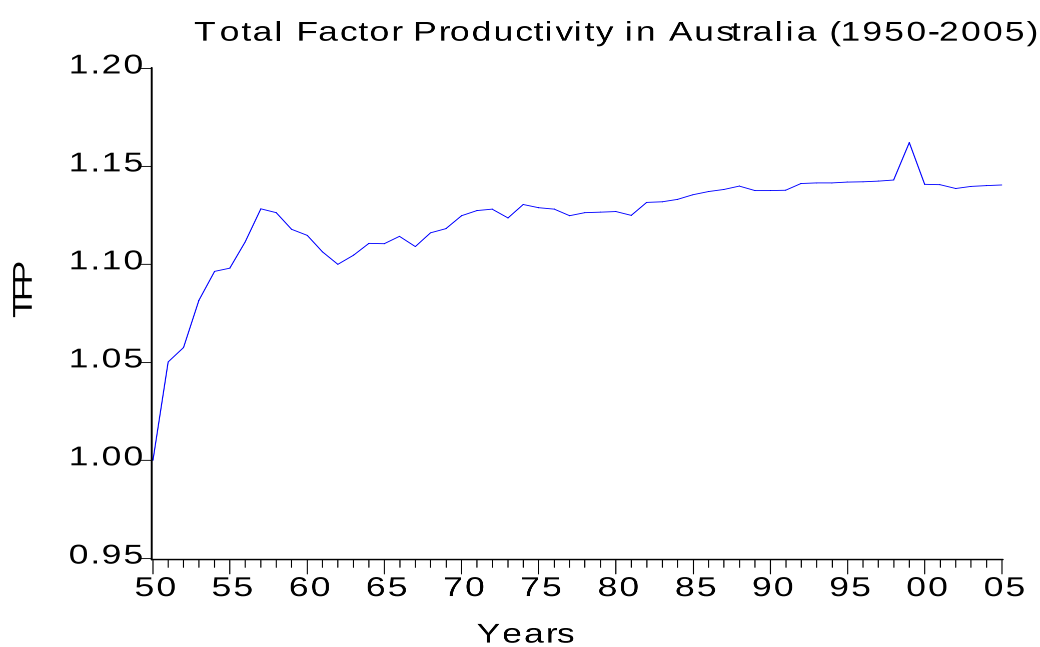


Figure 26: Indices of TFP in Australia (1950-2005) for the Four-Factor Model (LY, LK, LL, LH and LFDI)

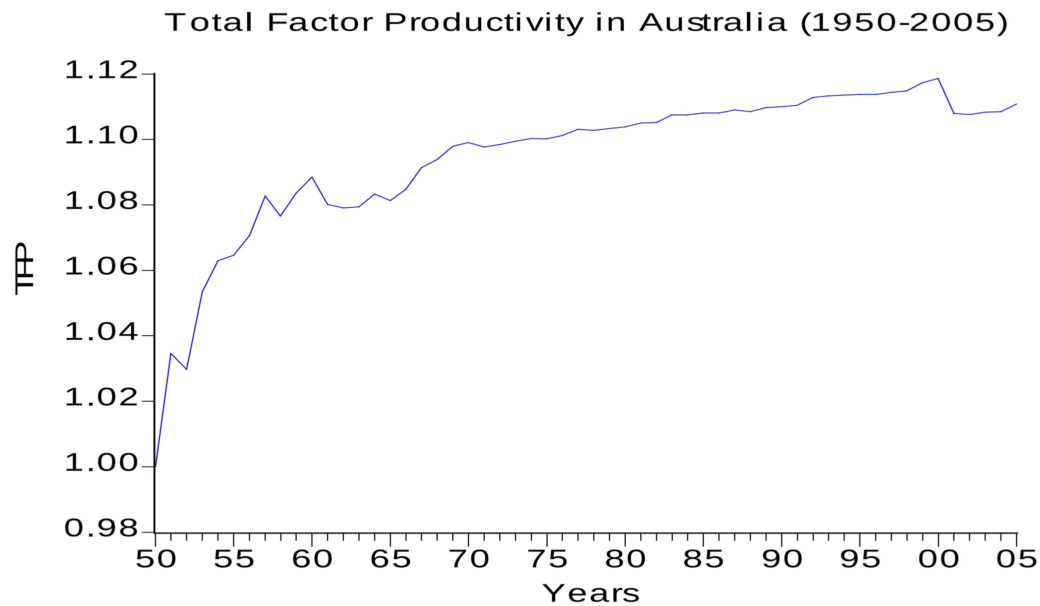


Figure 27: Indices of TFP in Australia (1950-2005) for the Four-Factor Model (LY, LK, LL, LH and LICT)

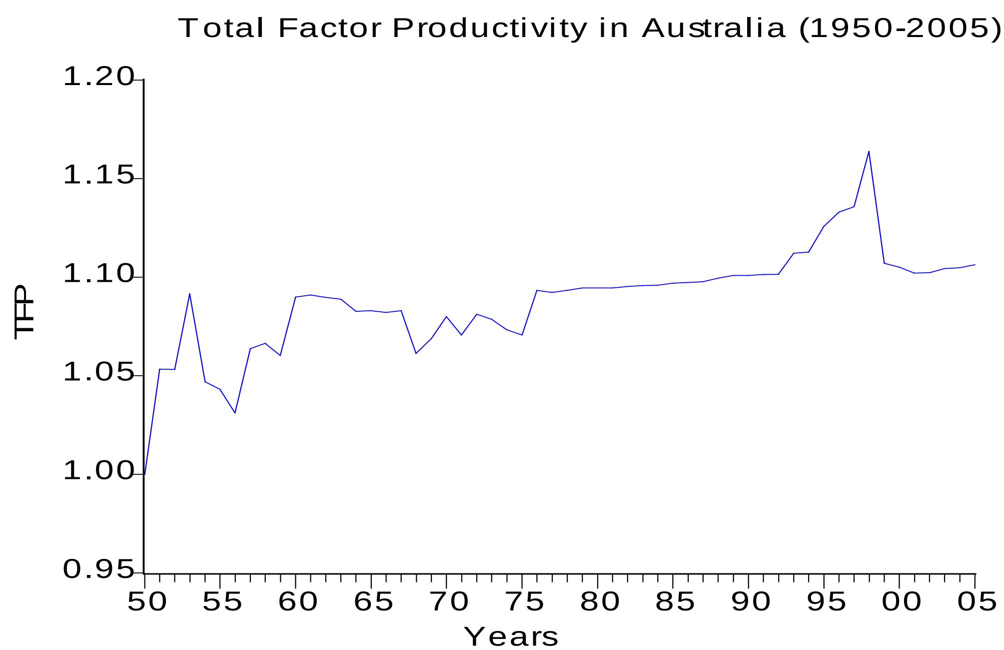


Figure 28: Indices of TFP in Australia (1950-2005) for the Four-Factor Model
(LY, LK, LL, LFDI and LICT)

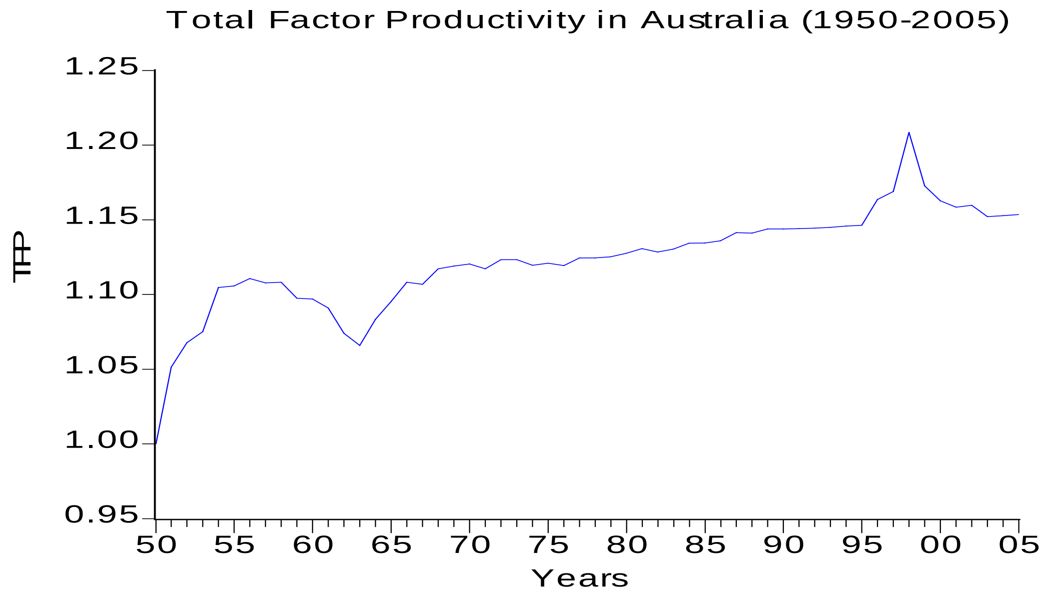
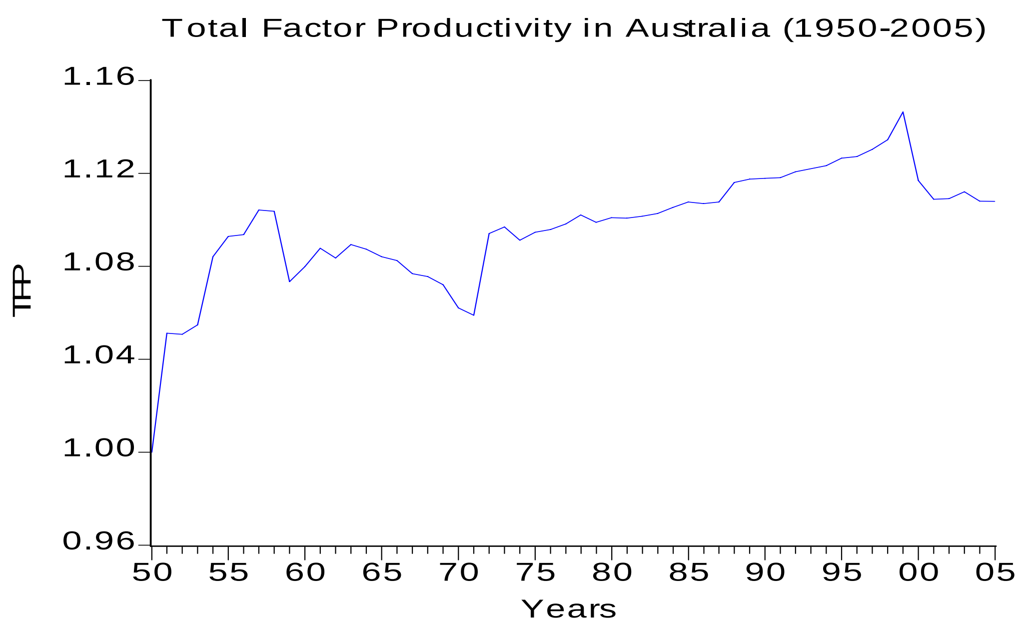


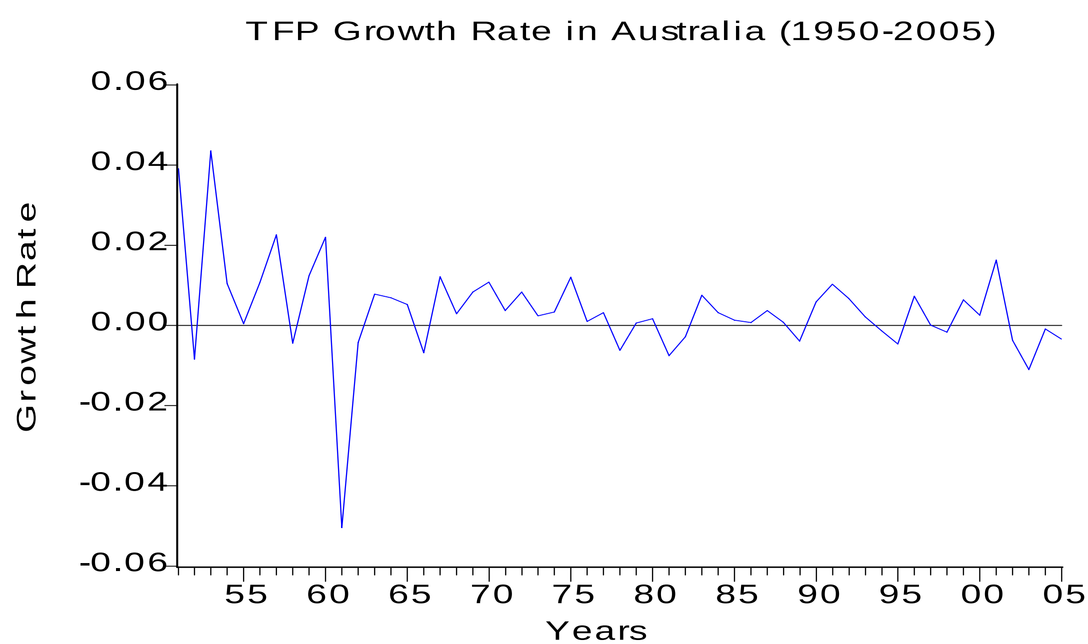
Figure 29: Indices of TFP in Australia (1950-2005) for the Five-Factor Model
(LY, LK, LL, LH, LFDI and LICT)



Figures 30 through 37 display the dynamics of TFP growth rates with fluctuating trends through out the period 1950-2005 for the various factor models. The TFP growth rate graphs show that Australia experienced the highest TFP growth rate for most of the factor models in the early 1950s. In exception of TFP growth rates obtained using the two-factor model (Figure 30), which has the highest TFP growth rate in 1953, all the others which are presented in Figures 31 through 37 experience their highest TFP growth rates in 1951.

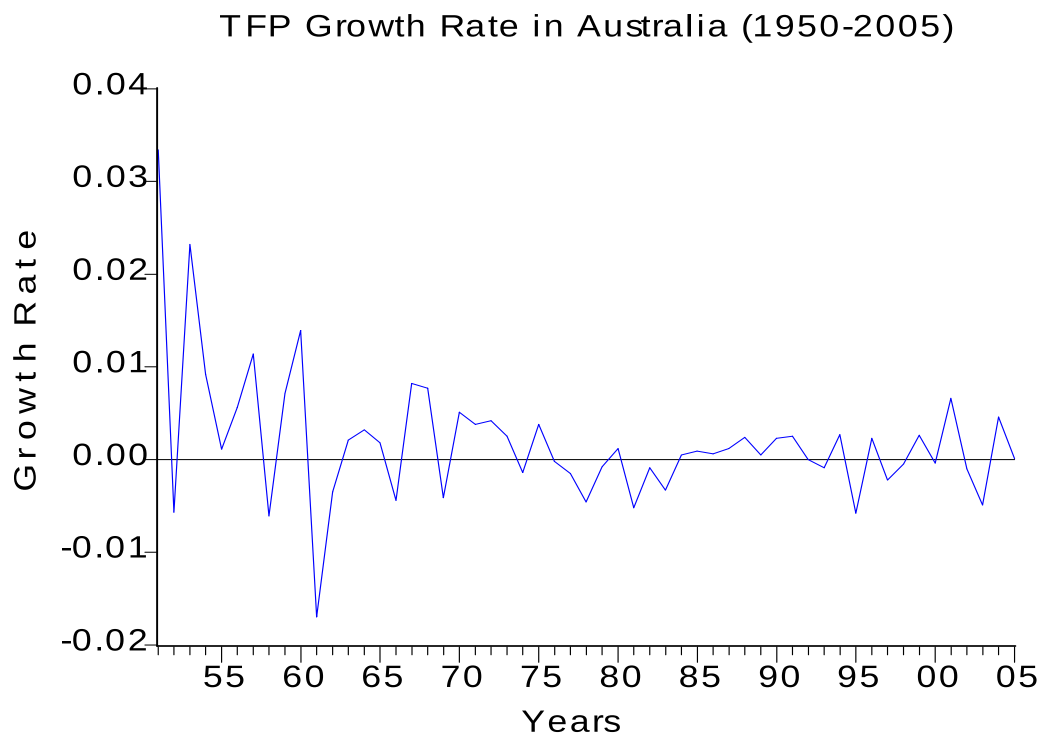
TFP growth rates estimates obtained using the two-factor model are presented graphically in Figure 30. The graph shows that the highest TFP growth rate of 5.04% is achieved in 1953 and the lowest TFP growth rate of -4.35% is achieved in 1961. The annual average growth rate of TFP estimates obtained based on the two-factor model over the 56 years period (1950-2005) is 0.3727% (Table A25).

Figure 30: Dynamics of TFP Growth Rate in Australia (1950-2005) for the Two-Factor Model (LY, LK and LL)



Figures 31 through 33 report the TFP growth rates obtained using the three-factor models. The graph in Figure 31 shows that the highest TFP growth rate achieved over the 56 years period is 3.34% (1951) and the lowest TFP growth rate of -1.7% is achieved in 1961. The annual average growth rate of TFP estimates obtained using the three-factor model (LY, LK, LL and LH) for the period considered in this study is 0.1889% (Table A25).

Figure 31: Dynamics of TFP Growth Rate in Australia (1950-2005) for the Three-Factor Model (LY, LK, LL and LH)



The graph in Figure 32 suggests that the highest TFP growth rate achieved over the period 1950-2005 is 6.0% (1951) and the lowest TFP growth rate of -3.3% is achieved in 1961. The annual average growth rate of TFP estimates obtained based on the three-factor model (LY, LK, LL and LFDI) for the period 1950-2005 is 0.4235% (Table A25).

The graph in Figure 33 shows that the highest TFP growth rate achieved over the 56 years period was 5.02% (1951) and the lowest TFP growth rate of -1.84% was achieved in 2000. The annual average growth rate of TFP estimates obtained using the three-factor model (LY, LK, LL and LICT) for the 56 years period is 0.2425% (Table A25).

Figure 32: Dynamics of TFP Growth Rate in Australia (1950-2005) for the Three-Factor Model (LY, LK, LL and LFDI)

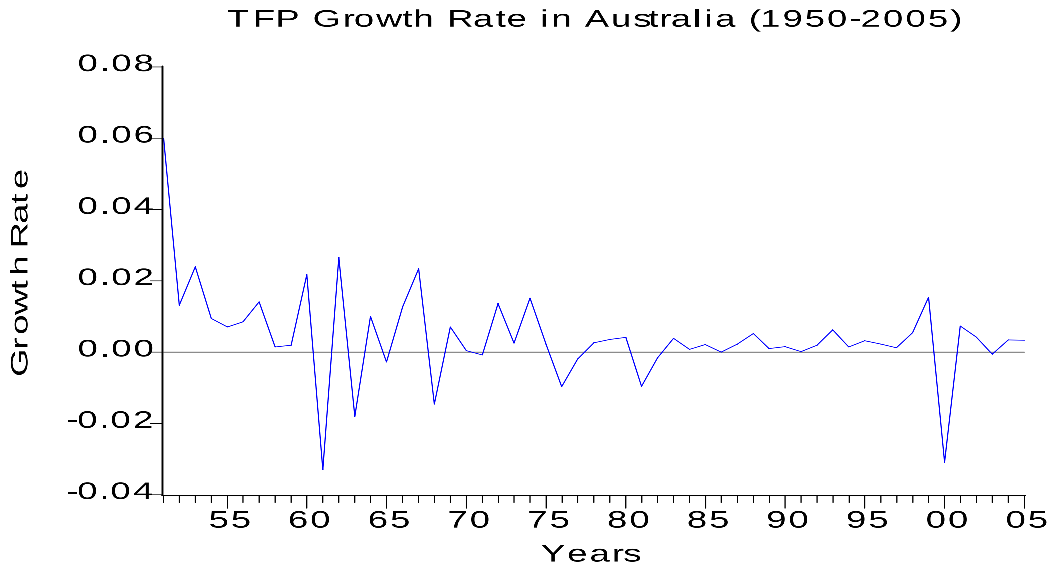
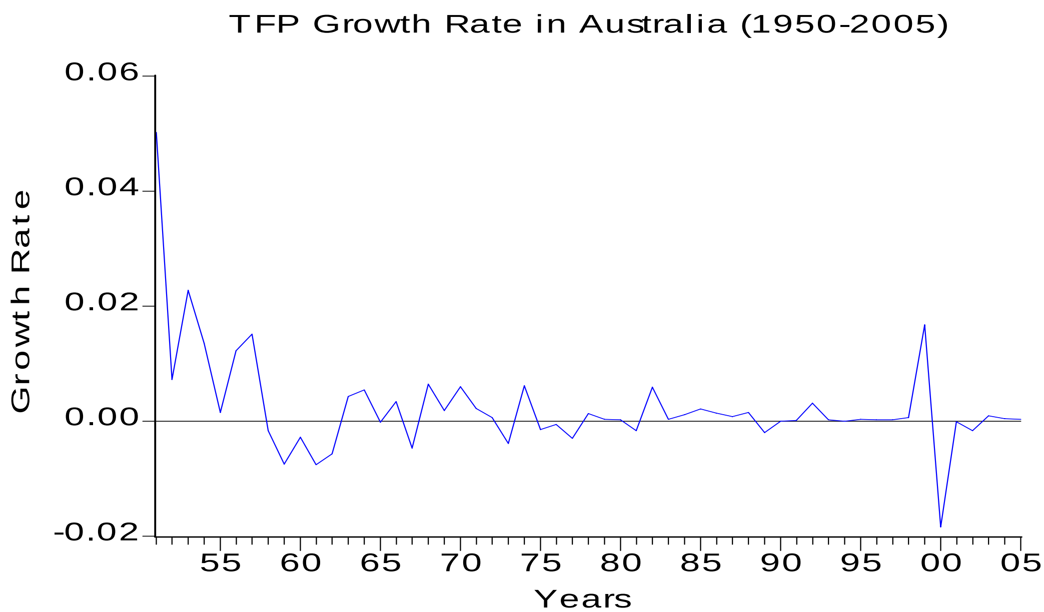


Figure 33: Dynamics of TFP Growth Rate in Australia (1950-2005) for the Three-Factor Model (LY, LK, LL and LICT)

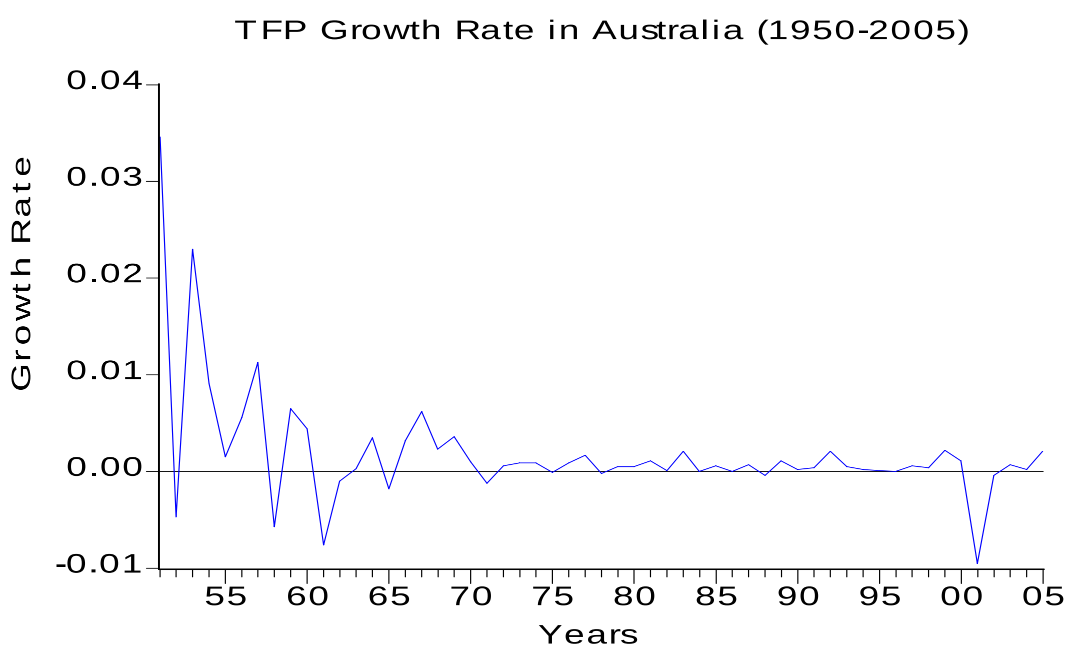


Figures 34, 35 and 36 report the TFP growth rates obtained using the four-factor models. The graph in Figure 34 reveals that the highest TFP growth rate achieved over the period

1950-2005 is 3.46% (1951) and the lowest TFP growth rate of -0.95% is achieved in 2001. The annual average TFP growth rate estimates obtained using the four-factor model (LY, LK, LL, LH and LFDI) for the period considered in this study is 0.1927% (Table A25) .

The graph in Figure 35 shows that the highest TFP growth rate achieved over the period 1950-2005 is 5.34% (1951) and the lowest TFP growth rate of -4.88% is achieved in 1999. The annual average growth rate of TFP estimates obtained based on the four-factor model (LY, LK, LL, LH and LICT) for the period 1950-2005 is 0.1949% (Table A25).

Figure 34: Dynamics of Total Factor Productivity Growth Rate in Australia (1950-2005) Four-Factor Model (LY, LK, LL, LH and LFDI)



The graph in Figure 36 shows that the highest TFP growth rate achieved over the period 1950-2005 is 5.14% (1951) and the lowest TFP growth rate of -2.96% is achieved in 1999. The annual average growth rate of TFP estimates obtained based on the four-factor model (LY, LK, LL, LFDI and LICT) for the period 1950-2005 is 0.2758% (Table A25).

Figure 35: Dynamics of TFP Growth Rate in Australia (1950-2005) for the Four-Factor Model (LY, LK, LL, LH and LICT)

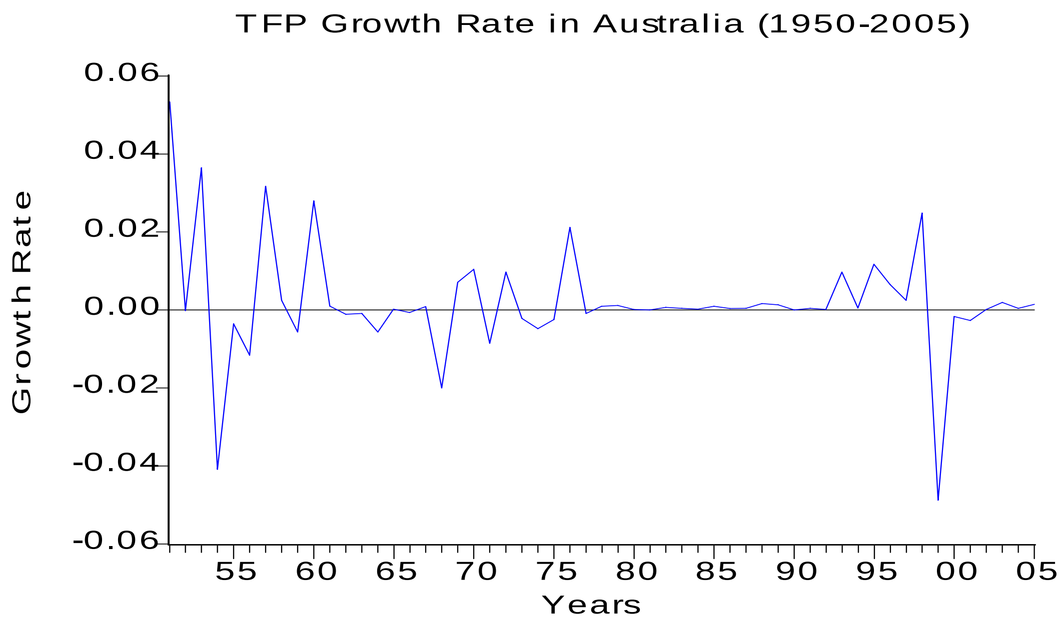
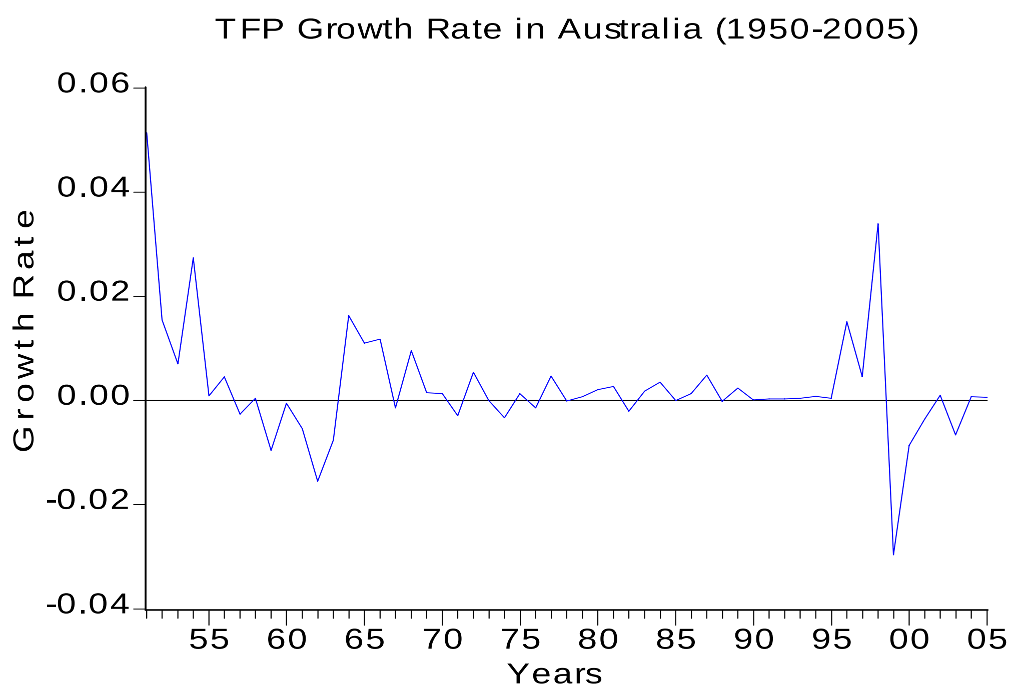


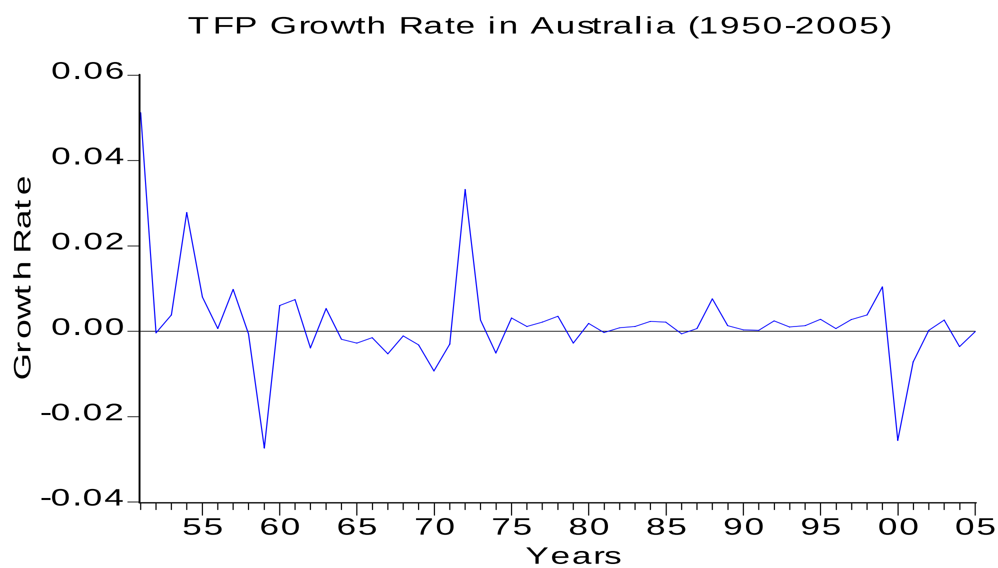
Figure 36: Dynamics of TFP Growth Rate in Australia (1950-2005) for the Four-Factor Model (LY, LK, LL, LFDI and LICT)



Figures 37 reports the TFP growth rates obtained using the five-factor models. The graph shows that the highest TFP growth rate achieved over the period 1950 -2005 is 5.12% in 1951 and the lowest TFP growth rate of -2.74% is achieved in 1959. The annual average growth rate of TFP for this factor model over the 56 years is 0.1922% (Table A25).

In general, the results of the productivity analysis provide evidence that Australia has experienced a very strong productivity growth in the 1950s, a slow down in the mid 1960s and a pick up strongly in the 1990s. The results of the productivity analysis suggest that Australia has experienced a continuous productivity growth within the period 1990-1999. These findings are consistent with earlier productivity studies such as (ABS (2001, 2003-2004), Parham (2004), Commonwealth of Australia (2005a, 2005b) in Australia. However, this continuous productivity growth could not be sustained for long and Australia started to experience a slowdown in productivity growth in 2000.

Figure 37: Dynamics of TFP Growth Rate in Australia (1950-2005) for the Five-Factor Model (LY, LK, LL, LH, LFDI and LICT)



As noted in Chapter 3, Section 3.5 of this study, a string of policy reviews in the 1960s attributed the poor performance of productivity in the mid 1960s to highly regulated product, capital and labour markets and the inefficient provision of economic infrastructure, which were dominated by government-owned enterprises operating without clear commercial imperative or performance regulation.

The results of the productivity analysis suggest that productivity estimates obtained using different factor models produce the same pattern of productivity performance in Australia. Although there are some small differences in the productivity results obtained using different factor models, in exception of the three-factor model (LY, LK, LL and LFDI), all the other factor models have average productivity growth rates lower than that of the two-factor model over the 56 years period (Table A25).

6.7.3 Determinants of Productivity in Australia

This section investigates and identifies the contributing production factors to productivity growth in Australia. Based on the productivity estimates obtained using the various factor models developed in Section 7.2 of this chapter, the Granger causality test and impulse response analysis are used to determine the importance of fixed capital, labour, human capital, FDI and ICT in productivity growth in Australia. The main objective of this sub-section is to assess the impact of production factors on the unexplained output growth (productivity). As a result, all factors which take place in the various production processes are regressed against the respective productivity estimates. This study argues that, since fixed capital, labour, human capital, FDI and ICT are identified as separate factors of production which take part in the production process, it is likely that all the drivers behind TFP growth are associated with these factors in one way or the other. Hence, we regress TFP estimates on the production factors namely capital, labour, human capital, FDI and ICT in order to assess the impact of each of these factors on TFP growth in Australia. As stated in Chapter 4 Section 2, all variables are converted into natural logarithms.

We first test for the stationary of TFP estimates by conducting unit root tests. The results of a unit root test by applying both the ADF and the PP tests to the TFP estimates of the different factor models are presented in Table 13. The ADF and PP statistics for levels series of TFP estimates of the three-factor model (LY, LK, LL and LH) and the four-factor model (LY, LK, LL, LH and LFDI) are greater in absolute terms than their critical values at 5% level of significance. The null hypothesis of the presence of a unit root in TFP estimates of the three-factor model (LY, LK, LL and LH) and the four-factor model (LY, LK, LL, LH and LFDI) is each rejected and this implies TFP estimates for these

Table 13: Summary of the ADF and PP Unit Root Tests of TFP Estimates of the Different Factor Production Models

TFP Estimates of the Factor Models	ADF No Trend	ADF Trend	ADF Lags	PP No Trend	PP Trend	PP Lags
Level Series						
LPKLH	-4.4335	-3.8672	1	-6.4417	-5.9177	3
LPKLF	-3.0544	-2.9476	1	-4.2425	-4.3027	3
LPKLT	-3.9353	-3.2664	1	-6.4587	-5.3926	3
LPKLHF	-4.553	-3.7921	1	-6.3409	-5.7328	3
LPKLHT	-2.2602	-3.4268	1	-3.942	-5.5731	3
LPKLFT	-2.3321	-3.5823	1	-3.9644	-5.4476	3
LPKLHFT	-2.4658	-2.9068	1	-4.496	-5.0852	3
1st Difference Series						
LPKLH						
LPKLF	-5.0019	-5.0293	1	-8.9261	-9.1456	3
LPKLT		-5.4175	1			3
LPKLHF			1			3
LPKLHT	-5.7597	-5.7003	1			3
LPKLFT	-5.1772	-5.087	1			3
LPKLHFT	-6.1868	-6.3605	1			3
Critical Values Level Series						
1%	-3.5547	-4.1348		-3.5523	-4.1314	
5%	-2.9157	-3.4935		-2.9146	-3.4919	
10%	-2.5953	-3.1753		-2.5947	-3.1744	
Critical Values 1st Difference						
1%	-3.5572	-4.1383		-3.5523	-4.1314	
5%	-2.9167	3.4952		-2.9146	-3.4919	
10%	-2.5958	-3.1762		-2.5947	-3.1744	

factor models are stationary in levels. The ADF and PP statistics for levels series of TFP estimates of the three-factor models (LY, LK, LL and LFDI) and (LY, LK, LL and

LICT), the four-factor models (LY, LK, LL, LH and LICT) and (LY, LK, LL, LFDI and LICT) and the five-factor model do not exceed their critical values (in absolute terms) at 5% level of significance. Therefore, TFP estimates of these factor models are not stationary in levels. However, both ADF and PP tests statistics exceed their corresponding critical values at 5% level of significance when TFP estimates obtained for all the other factor models are first differenced. Thus, the null hypothesis of the presence of a unit root in TFP estimates of the three-factor models (LY, LK, LL and LFDI) and (LY, LK, LL and LICT), the four-factor models (LY, LK, LL, LH and LICT) and (LY, LK, LL, LFDI and LICT) and the five-factor model is rejected in each case, implying that TFP estimates for these factor models are stationary in first differences.

These results indicate that TFP estimates of the three-factor model (LY, LK, LL and LH) and the four-factor model (LY, LK, LL, LH and LF) are stationary levels, whilst TFP estimates of the three-factor models (LY, LK, LL and LFDI) and (LY, LK, LL and LICT), the four-factor models (LY, LK, LL, LH and LICT) and (LY, LK, LL, LFDI and LICT) and the five-factor model are difference stationary.

To achieve the objective of this sub-section, vector error correction models (VECMs) are derived from the following regression equations:

$$LTFP_t = A + \alpha\, LK_t + \beta\, LL_t + \phi\, L(X_t = H, \text{FDI and ICT}) \qquad (6.7.3.1)$$

$$LTFP_t = A + \alpha\, LK_t + \beta\, LL_t + \phi\, LX_{it} + \gamma\, LX_{jt} \qquad (6.7.3.2)$$

where:

$Xi \neq X\, j)$ =H, FDI and ICT,

$$LTFP_t = A + \alpha\, LK_t + \beta\, LL_t + \phi\, LH_t + \gamma\, LFDI_{t\,+}\ \delta\, LICT_t, \qquad (6.7.3.3)$$

which are used to carry out the Granger causality test and the impulse response analysis.

The results of the standard pair-wise Granger causality tests for the three-factor models are reported in Table 14 and those of the four-factor and five-factor models are presented in Table 15. The F-statistics, which denote the statistical significance of the short-run causation between variables, are reported Columns 3 and 4 of each table. The t-statistics on the one-period lag of error correction term that denote the statistical significance of the long-run causation between variables are reported Columns 5 and 6 of each table.

The F-statistics reported in Table 14 suggest that fixed capital, labour, human capital, FDI, and ICT Granger cause TFP in the three-factor models in the short run, as the null hypotheses for these variables are each rejected at the 5% level of significance. The results further show that TFP Granger causes fixed capital, labour and human capital in the three-factor model (LY, LK, LL and LH) in the short run as the null hypothesis in respect to each of the variables is rejected at the 5% level of significance. However, the results indicate that TFP does not Granger cause fixed capital and FDI in the three-factor model (LY, LK, LL and LFDI) and labour in the three-factor model (LY, LK, LL and LICT) in the short run as the null hypothesis in each case can not be rejected at the 5% level of significance.

The Granger causality test results reported in Table 14 suggest that causality between TFP estimates obtained using the three-factor model (LY, LK, LL and LH) and each of the production factors in the short run is bi-directional. However, causality between TFP based on the three-factor model (LY, LK, LL and LFDI) is only bi-directional with labour and are uni-directional with fixed capital and FDI in the short run, running from fixed capital and FDI to TFP. The results further suggest that causal relationship between TFP estimates based on the three-factor model (LY, LK, LL and LICT) and labour in the short run is uni-directional and it runs from labour to TFP.

The test results reported in Table 14 suggest that in the long run, with the exception of causality between TFP and FDI in the three-factor (LY, LK, LL and LFDI), there is evidence of bi-directional causality between TFP and production factors in the remaining three-factor models. FDI, Granger causes TFP in the three-factor model (LY, LK, LL and LFDI) in the long run, as the null hypothesis that the lag value of the error term in the VECM is zero is strongly rejected at the 5% level of significance. The test results provide further evidence that TFP does not Granger cause FDI in the log run in this factor model as the null hypothesis that the lag value of the error term in the VECM with FDI as the dependent variable is zero cannot be rejected at the 5% level of significance. In the long run, causality between TFP and FDI is uni-directional and it runs from FDI to TFP.

The results reported in Table 15 indicate that fixed capital, labour, human capital, FDI, and ICT Granger-cause TFP in the short run in the four-factor models, as the null hypotheses for these variables are each rejected at the 5% level of significance. The results suggest that TFP Granger causes ICT in the short run in only the four-factor model (LY, LK, LL, LFDI and LICT) as the null hypothesis is rejected at the 5% level of significance. For all the other variables, TFP does not Granger cause any in the short run as the test results show a non-rejection of the null hypotheses at 5% level of significance for all the variables in the case of the four-factor models.

In the case of the five-factor model, it is only human capital, FDI and ICT which do Granger cause TFP in the short run as the null hypotheses for these variables are each rejected at the 5% level of significance. Fixed capital and labour do not Granger cause TFP as each of the null hypotheses can not be rejected at 5% level of significance. The test results for the five- factor model indicate that TFP does not Granger cause any of the production factors as the null hypothesis in each case can not be rejected at 5% level of significance.

The test results reported in Table 15 suggest that causality between TFP estimates obtained using the four-factor model (LY, LK, LL, LFDI and LICT) and LICT in the short run is the only bi-directional. The causal relationships between TFP and all the production factors in the short run in the four-factor and five-factor models are uni-directional, each running from the respective production factor to TFP. However, causality between TFP and human capital, FDI and ICT based on the five-factor model in the short run are uni-directional with causalities running from human capital, FDI and ICT to TFP.

Table 14: Granger Causality Tests Based on VECM for TFP, LK, LL, LH, LFDI and LICT (Three-Factor Model)

Null Hypothesis	F-Statistic	Prob.	T-Statistic	Prob.
Equation (6.7.3.1) $LTFP_t = A + \alpha LK_t + \beta LL_t + \phi LH_t$				
LK does not Granger Cause LTFP	13.0034	0.0007	-3.656	0.001
LTFP does not Granger Cause LK	5.65760	0.0211	-8.277	0.000
LL does not Granger Cause LTFP	11.0620	0.0016	-3.656	0.001
LTFP does not Granger Cause LL	10.1400	0.0025	-4.26	0.000
LH does not Granger Cause LTFP	11.6954	0.0012	-3.656	0.001
LTFP does not Granger Cause LH	12.5162	0.0009	-7.470	0.000
Equation (6.7.3.1) $LTFP_t = A + \alpha LK_t + \beta LL_t + \phi LFDI_t$				
LK does not Granger Cause LTFP	22.6052	0.0000	-6.000	0.000
LTFP does not Granger Cause LK	3.30280	0.0749	-8.132	0.000
LL does not Granger Cause LTFP	24.6199	0.0008	-6.000	0.000
LTFP does not Granger Cause LL	6.11777	0.0167	-3.011	0.004
LFDI does not Granger Cause TFP	12.8279	0.0008	-6.000	0.000
LTFP does not Granger Cause LFDI	2.63837	0.11036	-1.042	0.302
Equation (6.7.3.1) $LTFP_t = A + \alpha LK_t + \beta LL_t + \phi LICT_t$				
LK does not Granger Cause LTFP	12.4924	0.0009	-3.743	0.000
LTFP does not Granger Cause LK	9.89052	0.0028	-7.294	0.000
LL does not Granger Cause LTFP	12.8869	0.0007	-3.743	0.000
LTFP does not Granger Cause LL	1.44530	0.2347	-4.076	0.000
LICT does not Granger Cause LTFP	13.3154	0.0006	-3.743	0.000
LTFP does not Granger Cause LICT	10.4452	0.0021	-19.516	0.000

Notes: Lag order = 1

The t-statistics reported in Table 15 suggest that, in the long run, in exception of causality between TFP and FDI in the four factor models and ICT in the four-factor model (LY, LK, LL, LH and LICT), there is evidence of bi-directional causality between TFP and production factors considered for the other four-factor models. FDI and ICT Granger cause TFP in the long run in the respective factor models, as the null hypotheses that the lag values of the error term in the VECM are zero in each case is strongly rejected at the 5% level of significance. The test results provide further evidence that TFP does not Granger cause FDI and ICT in these factor models in the log run as the null hypothesis that the lag values of the error term in the VECM with FDI and ICT as the dependent variables are each zero cannot be rejected at the 5% level of significance. In the long run, causality between TFP and production factors (FDI and ICT) is uni-directional for each factor model and run from FDI and ICT to TFP for each factor model in the long run.

Table 15: Granger Causality Tests Based on VECM for LTFP, LK, LL, LH, LFDI and LICT (Four and Five-Factor Models)

Null Hypothesis	F-Statistic	Prob.	T-Statistic	Prob.
Equation (6.7.3.2) $LTFP_t = A + \alpha\, LK_t + \beta\, LL_t + \phi\, LH_t + \gamma\, LFDI_t$				
LK does not Granger Cause LTFP	11.0551	0.0016	-5.159	0.000
LTFP does not Granger Cause LK	9.64793	0.0031	-8.817	0.000
LL does not Granger Cause LTFP	13.8094	0.0005	-5.159	0.000
LTFP does not Granger Cause LL	5.08110	0.0284	-3.617	0.000
LH does not Granger Cause LTFP	12.3147	0.0009	-5.159	0.000
LTFP does not Granger Cause LH	10.9001	0.0017	-6.552	0.000
LFDI does not Granger Cause LTFP	6.30836	0.0152	-5.159	0.000
LTFP does not Granger Cause LFDI	1.26033	0.2668	-1.907	0.062
Equation (6.7.3.2) $LTFP_t = A + \alpha\, LK_t + \beta\, LL_t + \phi\, LH_t + \gamma\, LICT_t$				
LK does not Granger Cause LTFP	7.38463	0.0089	-2.733	0.009
LTFP does not Granger Cause LK	0.05454	0.8163	1.96	0.057

Table 15 Continues

Null Hypothesis	F-Statistic	Prob.	T-Statistic	Prob.
LL does not Granger Cause LTFP	10.1047	0.0025	-2.733	0.009
LTFP does not Granger Cause LL	3.88245	0.0541	3.291	0.002
LH does not Granger Cause LTFP	13.2495	0.0006	-2.733	0.009
LTFP does not Granger Cause LH	2.90511	0.0943	3.558	0.001
LICT does not Granger Cause LTFP	9.86440	0.0028	-2.733	0.009
LTFP does not Granger Cause LICT	0.92603	0.3404	0.557	0.581
Equation (6.7.3.2) $LTFP_t = A + \alpha LK_t + \beta LL_t + \phi LFDI_t + \gamma LICT_t$				
LK does not Granger Cause LTFP	4.94061	0.0306	-2.665	0.010
LTFP does not Granger Cause LK	1.47116	0.2306	-6.884	0.000
LL does not Granger Cause LTFP	7.44600	0.0086	-2.665	0.010
LTFP does not Granger Cause LL	0.53327	0.4685	-4.129	0.000
LFDI does not Granger Cause LTFP	10.0724	0.0025	-2.665	0.010
LTFP does not Granger Cause LFDI	0.83189	0.3659	1.799	0.078
LICT does not Granger Cause LTFP	12.7714	0.0008	-2.665	0.010
LTFP does not Granger Cause LICT	7.82707	0.0072	-25.18	0.000
Equation (6.7.3.3) $LTFP_t = A + \alpha LK_t + \beta LL_t + \phi LH_t + \gamma LFDI_{t} + \delta LICT_t$				
LK does not Granger Cause LTFP	1.98764	0.1645	-4.542	0.000
LTFP does not Granger Cause LK	1.59042	0.2129	-2.169	0.036
LL does not Granger Cause LTFP	3.61575	0.0628	-4.542	0.000
LTFP does not Granger Cause LL	0.19957	0.6569	0.767	0.447
LH does not Granger Cause LTFP	6.79199	0.0119	-4.542	0.000
LTFP does not Granger Cause LH	2.52936	0.1178	1.1624	0.252
LFDI does not Granger Cause LTFP	5.89731	0.0187	-4.542	0.000
LTFP does not Granger Cause LFDI	1.00578	0.3206	0.024	0.981
LICT does not Granger Cause LTFP	4.91257	0.0311	-4.542	0.000
LTFP does not Granger Cause LICT	2.56007	0.1157	1.216	0.231

Notes: Lag order = 1

In the case of the five-factor model, in exception of causality between TFP and fixed capital which is bi-directional in the long run, there is evidence of uni-directional causality between TFP and production factors. Labour, human capital FDI and ICT each Granger-causes TFP in the long run, as the null hypotheses that the lag value of the error term in the VECM is zero is strongly rejected at the 5% level of significance. However, there is evidence that TFP does not Granger cause any of these factors in the log run as the null hypotheses that the lag value of the error term in the VECM with each factor as the dependent variable is zero cannot be rejected at the 5% level of significance. In the long run, causality between TFP and each of these production factors is uni-directional in each case and it runs from the factors to TFP. As mentioned earlier, the *F*-statistics for the variables fail to explain the sign of the relationship between these variables and TFP or how long these effects are persistent in TFP. The impulse response analysis provides such information and is discussed next.

The impulse response analysis is carried out to determine the dynamic interrelation between TFP and production factors. The results of the orthogonalised impulse response(s) of TFP to a unit standard error shock to each production factor based on the three-factor, the four-factor and the five-factor models are presented graphically in Figures 38 through 44. These results indicate that TFP's response to a unit standard error shock to each production factor has persistence effects and do not generally die out.

As demonstrated by the graphs for the various factor models, for a unit standard error shock to labour, human capital, FDI and ICT, TFP responds positively as the number of horizons become larger. The effects of the shocks to these variables are persistent in TFP and never die out. It is only in the case of a unit standard error shock to fixed capital that TFP responds negatively as it is shown in Figures 38, 39 and 41. However these effects are also persistent in TFP even at larger numbers of forecast horizons.

Figures 45 through 51 report graphically the results of the variance decomposition analysis, which measure the proportion of the forecast error variance of TFP due to innovations of each production factor included in the three-factor, four-factor and five

Figure 38: Orthogonalised Impulse Response(s) of TFP to One S.E. Shock in the Equation for the Variables Fixed Capital, Labour and Human Capital

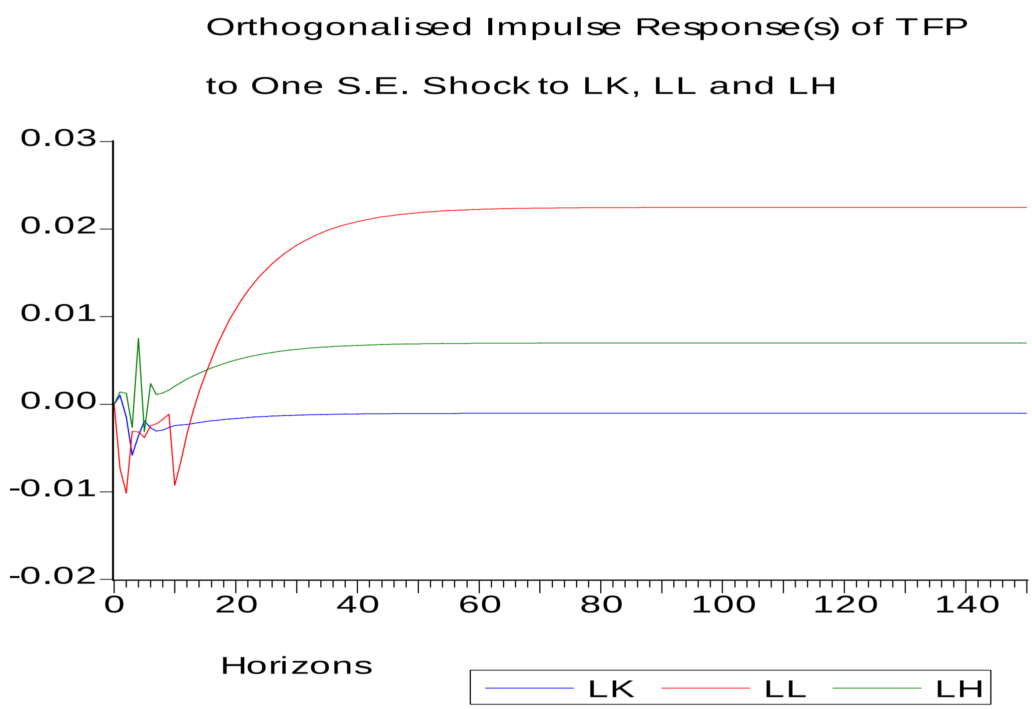
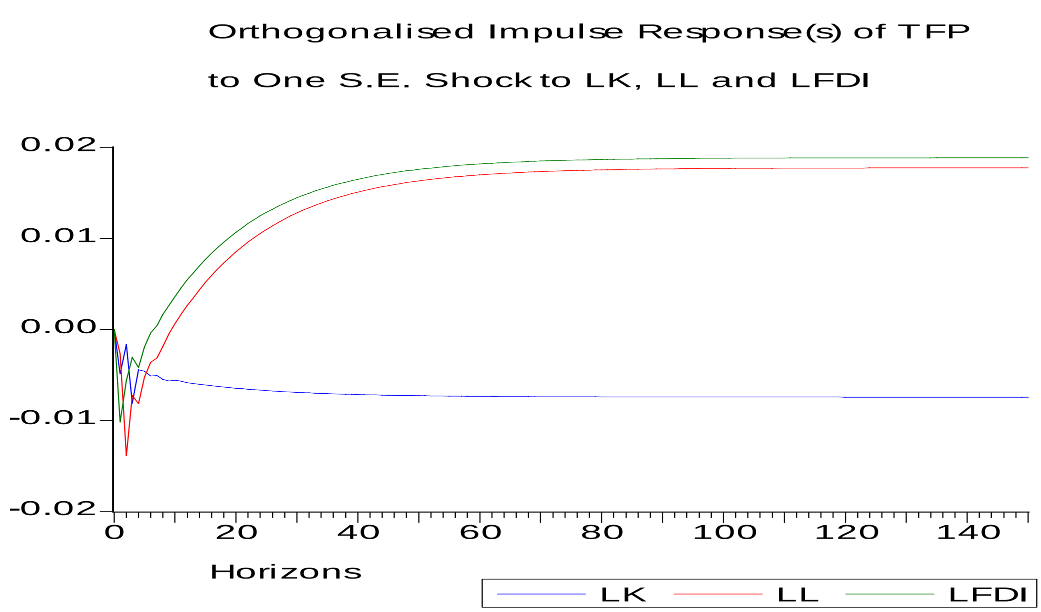
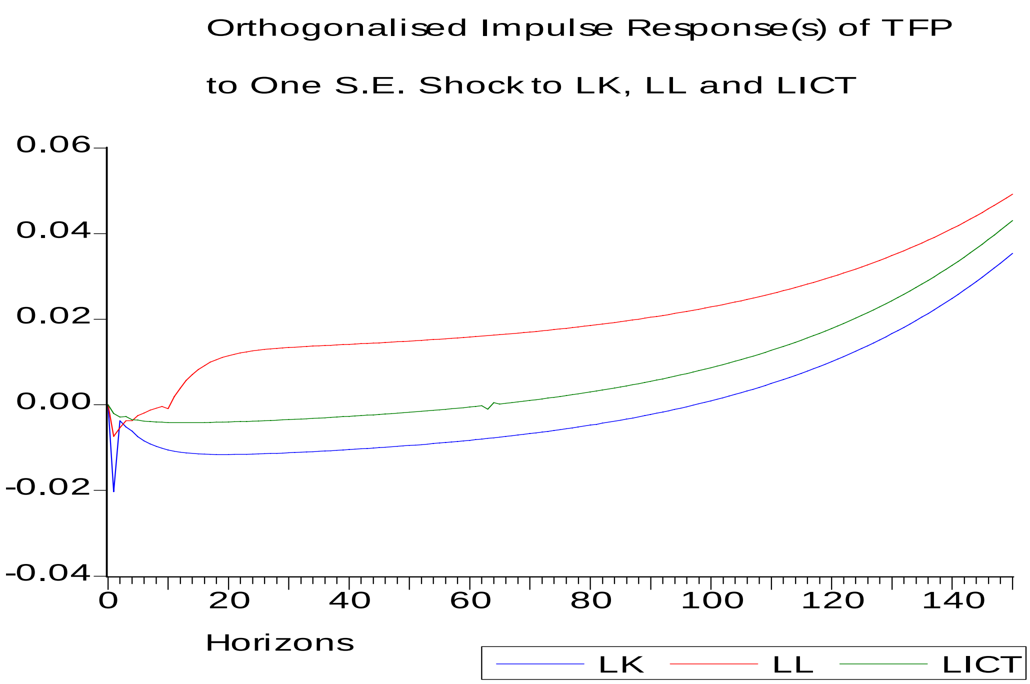


Figure 39: Orthogonalised Impulse Response(s) of TFP to One S.E. Shock in the Equation for the Variables Fixed capital, Labour and FDI



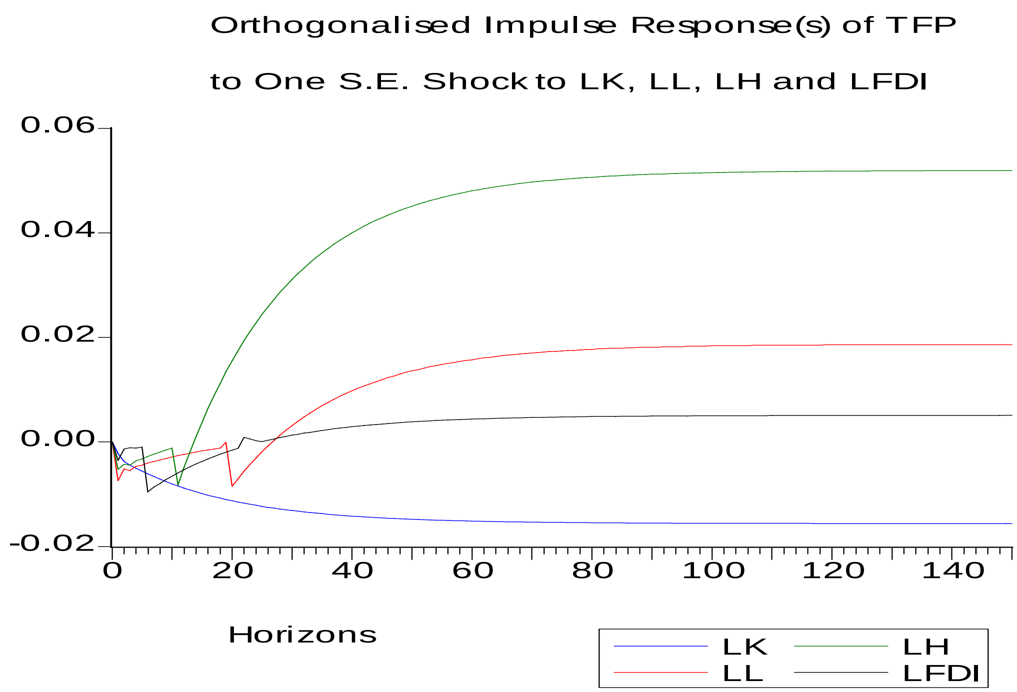
factor models for a 50-year forecast period. The results reported in Figure 45 (Table A26a) indicate that after five years, 55.67% of the variation in the forecast error for TFP is explained by its own innovations, while at the end of the 50 years, the forecast error variance for TFP explained by its own innovations is 21.29%. After five years, about 9.54%, 34.06% and 0.74% of the variation in the forecast error for TFP is explained by the innovations of fixed capital, labour and human capital respectively. However, at the end of the 50 years forecast period, about 7.35%, 13.32% and 58.04% of the variation in the forecast error for TFP is explained by the innovations of fixed capital, labour and human capital respectively.

Figure 40: Orthogonalised Impulse Response(s) of TFP to One S.E. Shock in the Equation for the Variables Fixed Capital, Labour and ICT



The results reported in Figure 46 (Table A26b) suggest that at the end of the five year, about 87.49% of the variation in the forecast error for TFP is explained by its own innovations, and at the end of the 50 years the forecast error variance for TFP explained by its own innovations is 41.21%. About 2.58%, 6.71% and 3.22% of the variation in the forecast error for TFP is explained by the innovations of fixed capital, labour and FDI respectively after five years. However, at the end of the 50 years, about 7.59%, 22.99% and 28.22% of the variation in the forecast error for TFP is explained by the innovations of fixed capital, labour and FDI respectively.

Figure 41: Orthogonalised Impulse Response(s) of TFP to One S.E. Shock in the Equation for the Variables Fixed Capital, Labour, Human Capital and FDI



The results reported in Figure 47 (Table A26c) reveal that after five years, 60.83% of the variation in the forecast error for TFP is explained by its own innovations, while at the end of the 50 years the forecast error variance for TFP explained by its own innovations is 22.83%. After five years about 15.7%, 4.06% and 19.41% of the variation in the forecast error for TFP is explained by the innovations of fixed capital, labour and ICT respectively. At the end of the 50 years, about 12.29%, 6.22% and 58.67% of the variation in the forecast error for TFP is explained by the innovations of fixed capital, labour and ICT respectively.

The results reported in Figure 48 (Table A26d) indicate that 85.3% of the variation in the forecast error for TFP is explained by its own innovations after five years, while at the end of the 50 years the forecast error variance for TFP explained by its own

Figure 42: Orthogonalised Impulse Response(s) of TFP to One S.E. Shock in the Equation for the Variables Fixed Capital, Labour, Human Capital and LICT

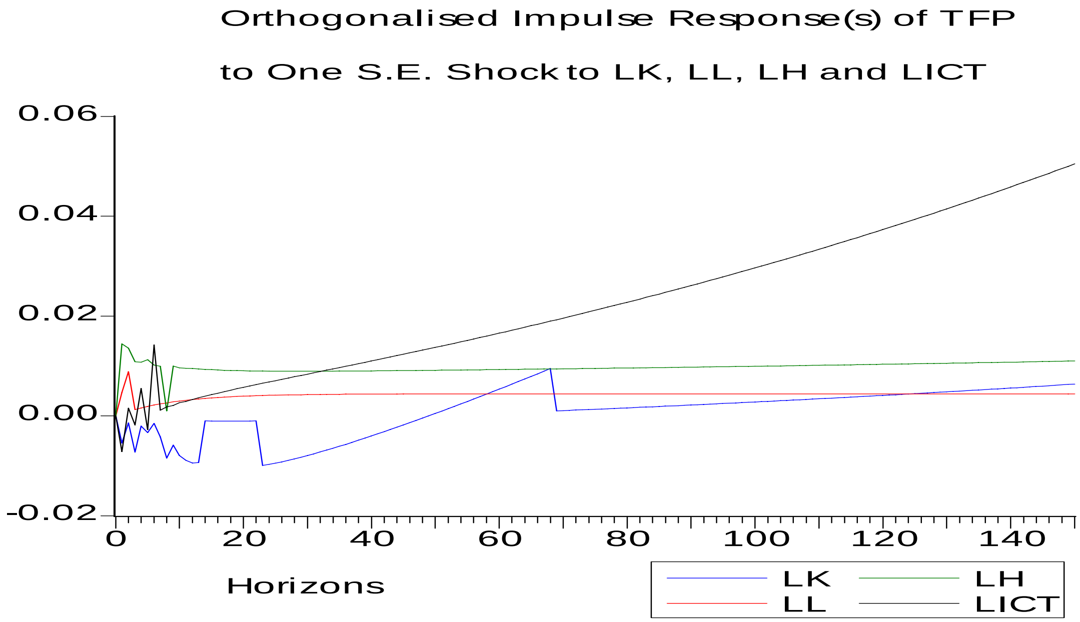


Figure 43: Orthogonalised Impulse Response(s) of TFP to One S.E. Shock in the Equation for the Variables Fixed Capital, Labour, FDI and ICT

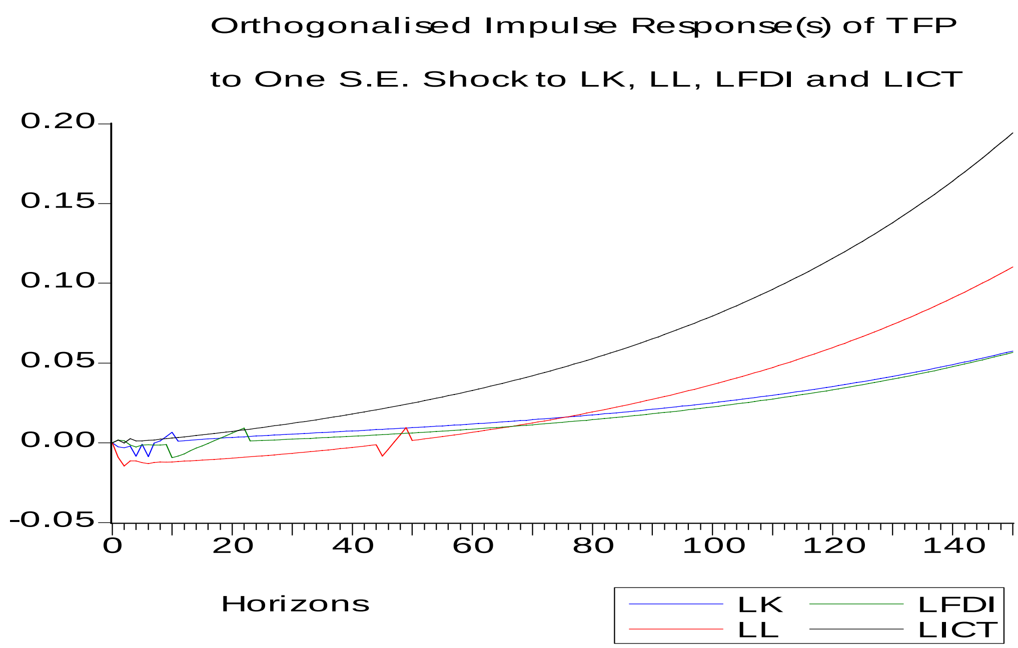


Figure 44: Orthogonalised Impulse Response(s) of TFP to One S.E. Shock in the Equation for the Variables Fixed Capital, Labour, Human Capital, FDI and ICT

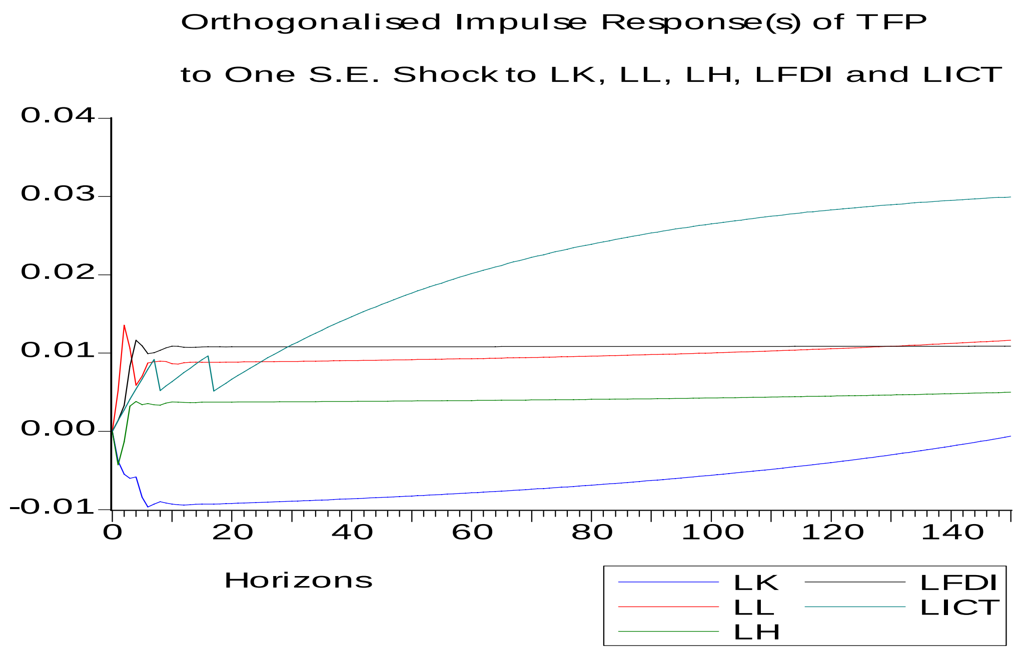
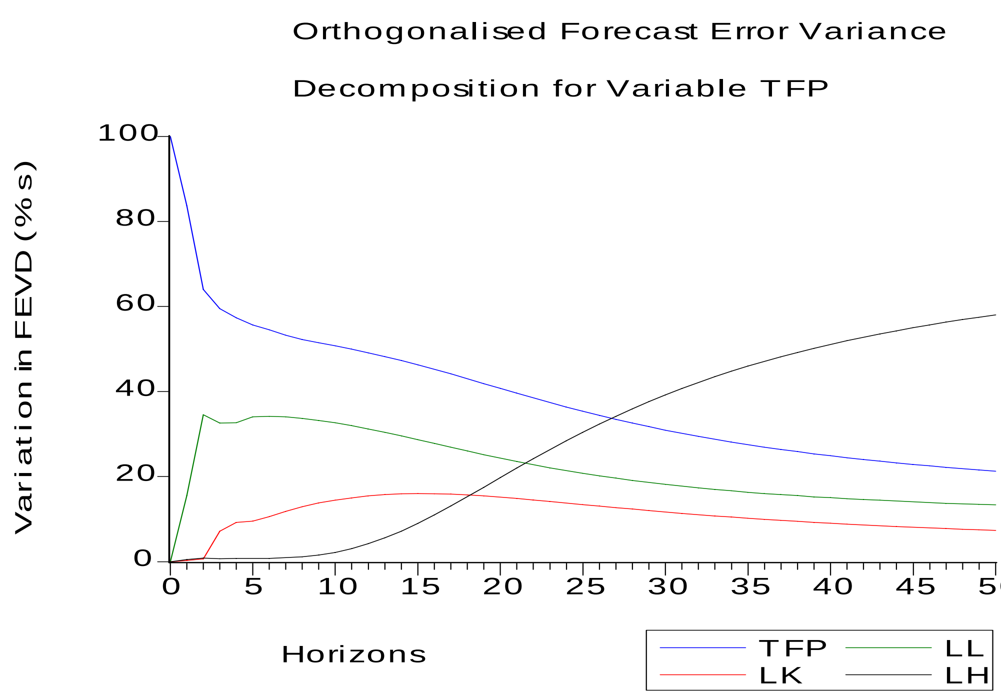


Figure 45: Orthogonalised Forecast Error Variance Decomposition for Variable TFP Three-Factor Model (LY, LK, LL and LH)



innovations is 32.53%. After five years about 2.83%, 2.24%, 4.92% and 4.71% of the variation in the forecast error for TFP is explained by the innovations of fixed capital, labour, human capital and FDI respectively. By the end of the 50 years, about 40.35%, 4.95%, 12.13% and 10.04% of the variation in the forecast error for TFP is explained by the innovations of fixed capital, labour, human capital and FDI respectively.

The results reported graphically in Figure 49 (Table A27a) indicate that after five years, 74.72% of the variation in the forecast error for TFP is explained by its own innovations, while at the end of the 50 years the forecast error variance for TFP explained by its own innovation is 54.11%. After five years about 2.56%, 2.14%, 13.68% and 6.9% of the variations in the forecast error for TFP is explained by the innovations of fixed capital, labour, human capital and ICT respectively. By the end of the 50 years, about 5.13%, 7.51%, 16.96% and 16.29% of the variation in the forecast error for TFP is explained by the innovations of fixed capital, labour, human capital and ICT respectively.

The results presented in Figure 50 (Table A27b) indicate that after five years, 68.69% of the variation in the forecast error for TFP is explained by its own innovations and at the end of the 50 years the forecast error variance for TFP explained by its own innovations is 32.31%. After five years about 3.49%, 11.39%, 10.3% and 6.13% of the variation in the forecast error for TFP is explained by the innovations of fixed capital, labour, FDI and ICT respectively. By the end of the 50 years, about 8.92%, 10.61%, 17.17% and 30.99% of the variation in the forecast error for TFP is explained by the innovations of fixed capital, labour, FDI and ICT respectively.

The results reported in Figure 51 (Table A28) reveal that after five years, 53.88% of the variation in the forecast error for TFP is explained by its own innovations, while at the end of the 50 years the forecast error variance for TFP explained by its own innovations is 38.09%. After five years about 11.39%, 7.64%, 7.73%, 7.3% and 12.06% of the variation in the forecast error for TFP is explained by the innovations of fixed capital, labour, human capital, FDI and ICT respectively. However, by the end of the 50 years, about 21.09%, 7.49%, 9.71%, 11.39% and 12.24% of the variation in the forecast error

Figure 46: Orthogonalised Forecast Error Variance Decomposition for Variable TFP Three-Factor Model (LY, LK, LL and LFDI)

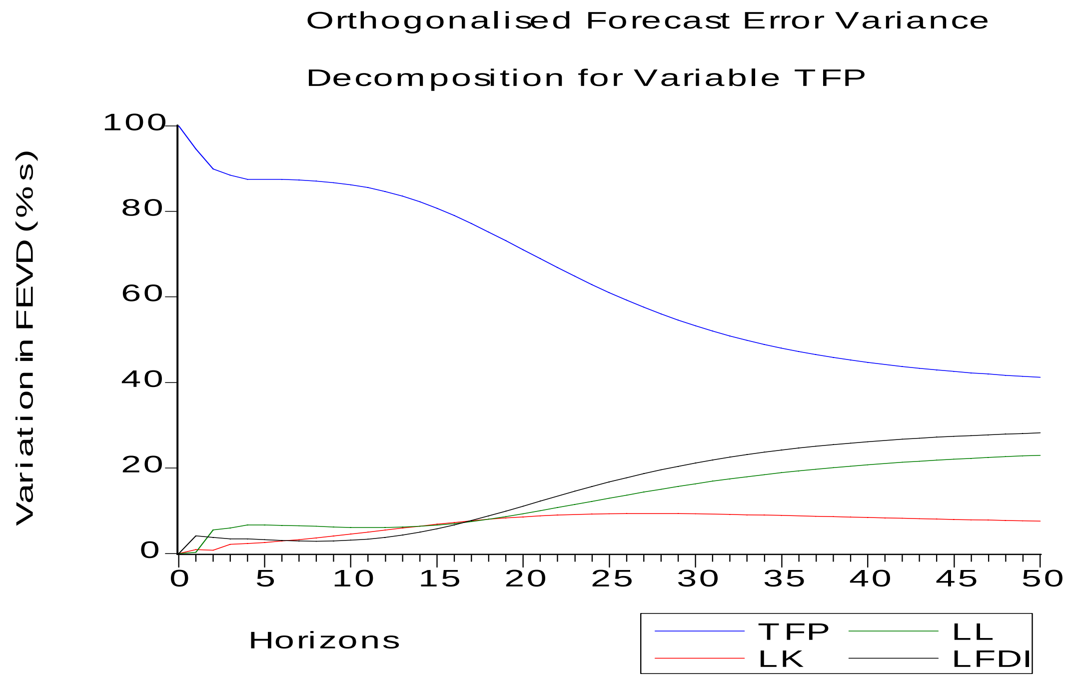


Figure 47: Orthogonalised Forecast Error Variance Decomposition for Variable TFP Three-Factor Model (LY, LK, LL and LICT)

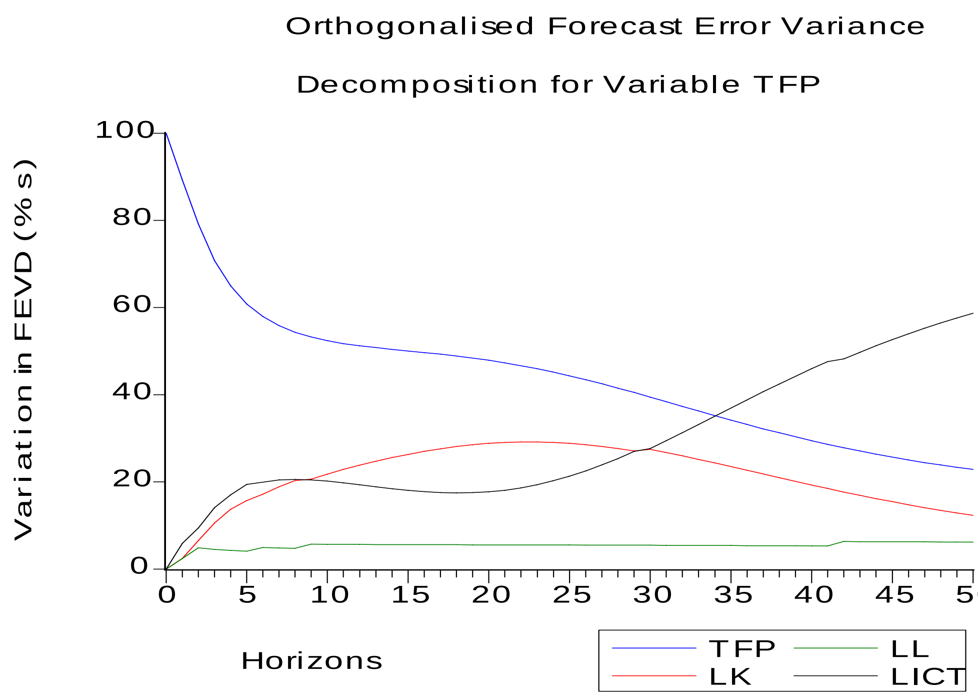


Figure 48: Orthogonalised Forecast Error Variance Decomposition for Variable TFP

Four-Factor Model (LY, LK, LL, LH and LFDI)

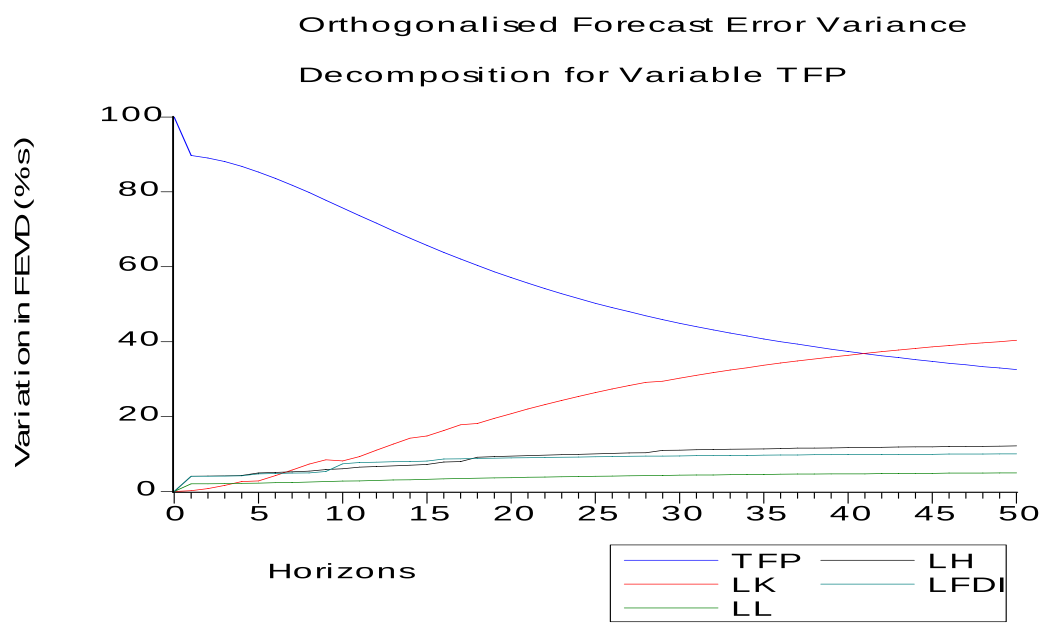


Figure 49: Orthogonalised Forecast Error Variance Decomposition for Variable TFP

Four-Factor Model (LY, LK, LL, LH and LICT)

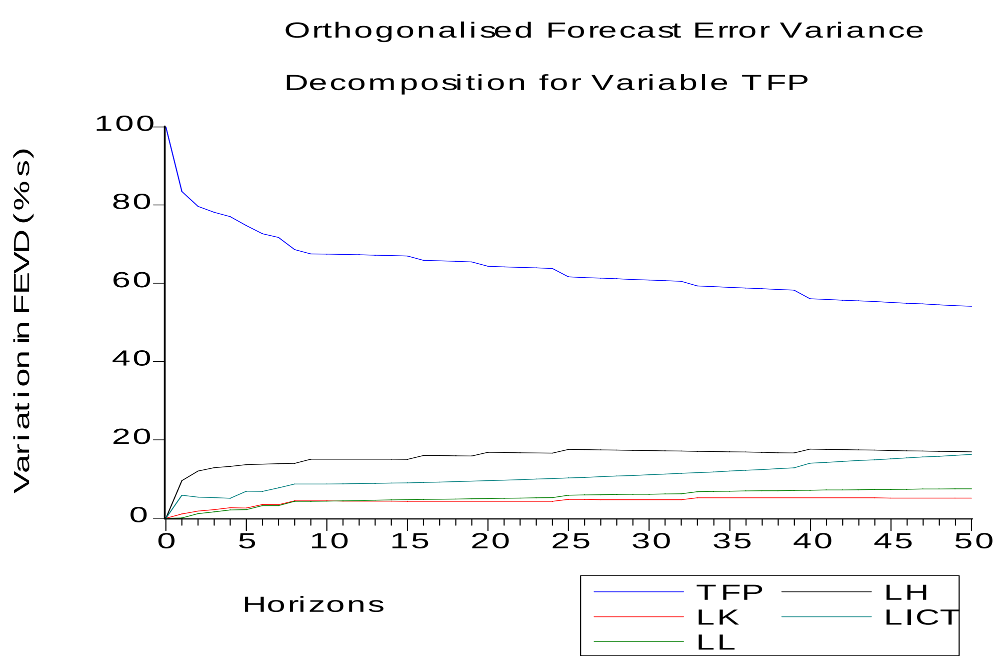


Figure 50: Orthogonalised Forecast Error Variance Decomposition for Variable TFP Four-Factor Model (LY, LK, LL, LFDI and LICT)

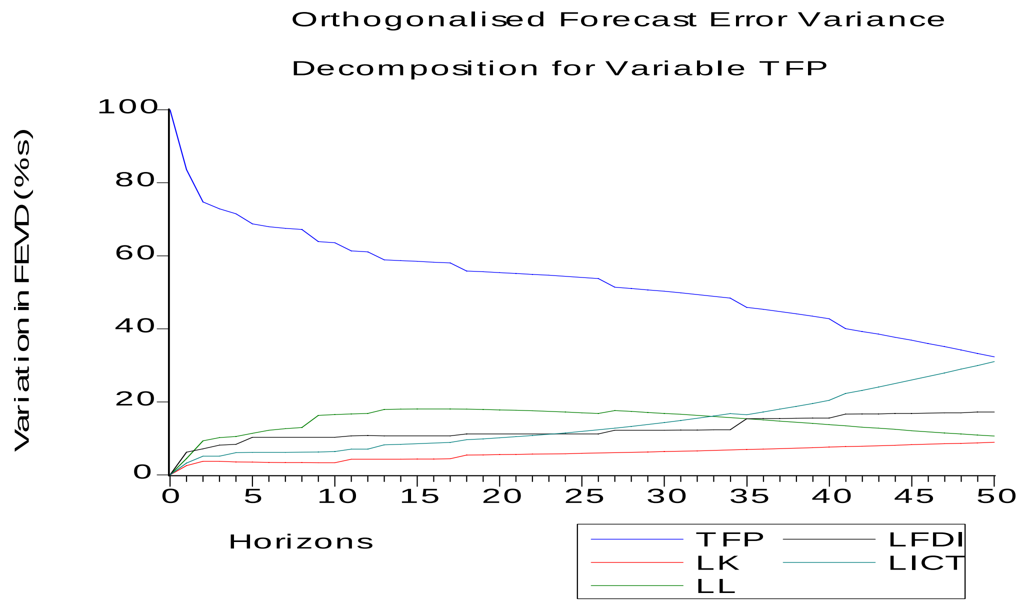
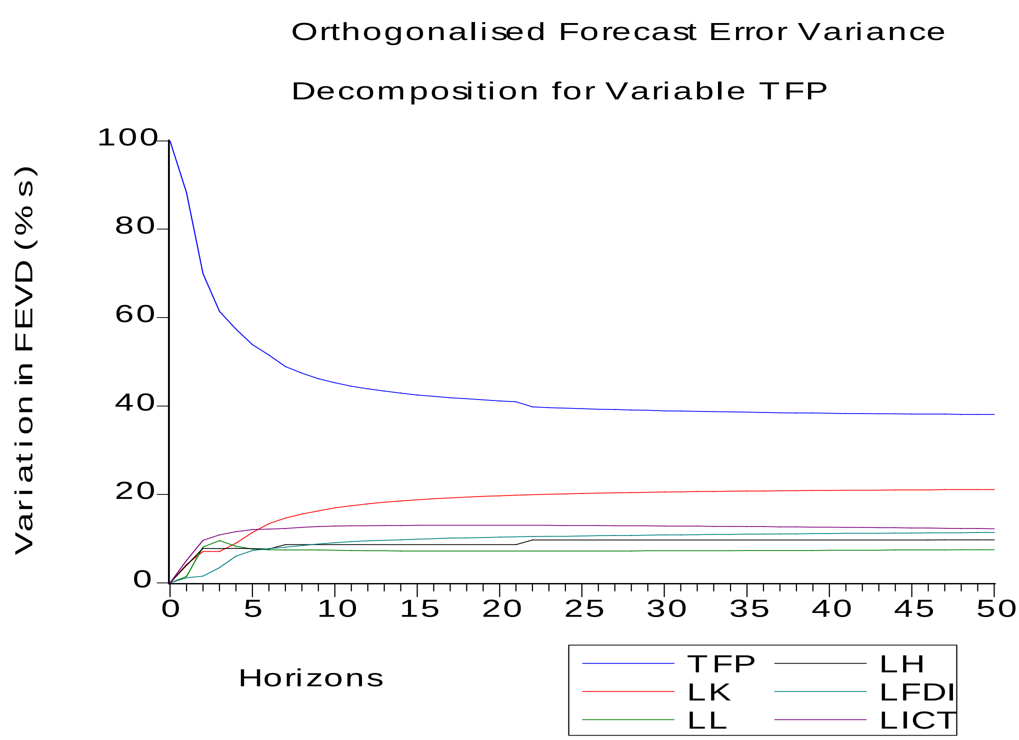


Figure 51: Orthogonalised Forecast Error Variance Decomposition for Variable TFP Five-Factor Model (LY, LK, LL, LH, LFDI and LICT)



for TFP is explained by the innovations of fixed capital, labour, human capital, FDI and ICT respectively.

The results of the variance decomposition analysis suggest that the forecast error variance of TFP accounted for by the innovations of fixed capital, labour, human capital, FDI and ICT are all substantial at the end of the 50 years forecast period. The analysis provide evidence that capital, labour, human capital, FDI and ICT innovations account for reasonable proportion of the variabilities of TFP in the long run in all the three, four and five factor models. For the three-factor models, the forecast error variance of TFP accounted the innovations of human capital, FDI and ICT are each greater than the variability in the forecast error of TFP explained by innovations of fixed capital and labour. For the four-factor model (LY, LK, LL, LH and LFDI), the innovations of fixed capital has the greatest impact on variability of TFP's forecast error in the long run.

In the case of the four-factor model (LY, LK, LL, LH and LICT), the innovations of human capital and ICT each has a bigger impact on variability of TFP's forecast error in the long run than the innovations of fixed capital and labour. The innovations of ICT have the biggest impact on the variability of TFP's forecast error in the long run for the four-factor model (LY, LK, LL, LFDI and LICT). For the five-factor model, the innovations of fixed capital have the biggest impact on the variability of TFP's forecast error in the long run. These findings suggest that fixed capital, labour, human capital, FDI and ICT contribute to a significant proportion of TFP's forecast error variance in the long run**.** However, over 54% of the variation in the forecast error variance of TFP in the short run is accounted for by its own innovations.

In general, the results of the Granger causality test and the impulse response analysis suggest that fixed capital, labour, human capital, FDI and ICT are all significant determinants of long-run productivity in Australia. These findings provide strong evidence that the production functions that include human capital, FDI and ICT as additional exogenous variables are likely to better explain productivity performance in

Australia than the two-factor production function that ignores these variables. The extra factors are clearly very strong determinants of long-run productivity in Australia.

6.8 Chapter Summary

This chapter describes the estimation procedures used to achieve the objectives of this research. Diagnostic tests, unit root, structural break and cointegration tests for all variables are conducted. The ADF and PP tests results suggest that each variable is integrated in an order of 1~I(1). The results of the cointegration tests for all the factor models suggest that there exist at least one cointegrating vector between variables selected for each factor model. Estimates of the long-run elacticities of the different factor production functions are presented and discussed in this chapter. The estimated elasticities and factors of production are analysed to determine the contribution of each production factor to the growth of GDP for the period 1950-2005.

Various factor production functions namely two-factor, three-factor, four-factor and five-factor models are developed, estimated and analysed in this chapter. The Granger causality tests, impulse response functions and the forecast error variance decomposition tests are carried out to determine the importance of production factors to GDP growth in Australia. The analysis suggests that in addition to physical capital and labour units, human capital, FDI and ICT are each important determinants of long run GDP growth in Australia.

Estimates of labour productivity and its growth rate as well as capital per unit labour and its growth rate are presented graphically and analysed in this chapter. The chapter further reports graphically estimates of comprehensive measure of productivity known as TFP and its growth rate for all the factor models that are analysed. The results of the productivity analysis provide evidence that Australia experienced very strong productivity growth in the 1950s, a slow down in the mid 60s and a pick up very strongly in the 1990s. The results of the productivity analysis further suggest that Australia experienced continuous productivity growth in the 1990s. However, this continuous productivity growth could not be sustained for long and Australia started to experience a slowdown in productivity growth in 2000.

In general, the three-factor production function that recognises FDI as additional exogenous variable and includes it in the production function accordingly better explains productivity performance in Australia than any other factor model.

Finally, the chapter investigates the contributing production factors to productivity growth in Australia. Unit root tests are conducted for the TFP estimates and the ADF and PP tests results suggest that TFP variable is integrated in an order of 1~I(1). The Granger causality test and impulse response analysis are used to determine the importance of fixed capital, labour, human capital, FDI and ICT in productivity growth. The results of the Granger causality test and the impulse response analysis suggest that in addition to fixed capital and labour, human capital, FDI and ICT are also very important determinants of productivity in Australia in both the short and long run.

This study finds that in addition to fixed capital and labour, human capital, FDI and ICT are also very important determinants of productivity in Australia and should be included in the production function as additional exogenous variables for a better productivity analysis in Australia. The study suggests that productivity estimates obtained using the production functions that recognise and include human capital, FDI and ICT as additional exogenous variables are better measures of productivity performance in Australia than the two-factor production function that ignores these variables.

CHAPTER SEVEN

CONCLUSIONS AND RECOMMENDATIONS

7.1 Introduction

This chapter summarises the main empirical findings of this research and discusses how to improve upon future productivity measurement in Australia. The chapter further highlights the contributions of this study to knowledge and discuses some of the problems encountered by this research which are beyond the scope of the study and are likely to affect the outcomes this research. Furthermore, the chapter discusses policy implications arising from the findings of this research and also some directions for future productivity analysis in Australia. The research ends with a concluding remark.

7.2 Thesis Summary

This research empirically measures the performance of productivity in Australia's economy from 1950 to 2005. The factors responsible for output growth in Australia within this period are identified. Time-series data based on the aggregate economy are used to estimate a Cobb-Douglas type of production function capturing the dynamic inter-action between GDP and fixed capital, labour units, human capital FDI and ICT. Various production factor models such as a two-factor, three-factor, four-factor and five-factor models are developed, estimated and analysed. Based on the estimated long-run elasticities, TFP estimates of Australia are computed, presented graphically and analysed for the various factor models developed in this study.

The ADF and PP unit root and Perron's structural break tests are carried out on the variables selected for this study. Unit root tests results suggested that GDP series are stationary in levels, fixed capital, labour, human capital, FDI and ICT series are stationary at first differences. The results of the Perron test provide further evidence of the existence of a unit root even when structural breaks are allowed. However, plausible breaks in the series occur in 1976, 1973, 1998, 2002, 1961 and 2002 for Model A (Equation 4.3.2.10), respectively, for series LY, LK, LL, LH, LFDI and LICT. For

Model B (Equation 4.3.2.11) the breaks in the series occur in 1968, 1999, 1992, 2001, 1962 and 1994 and Model C (Equation 4.3.2.13) in 1966, 1963, 1969, 1976, 1966 and 1996 for LY, LK, LL, LH, LFDI and LICT respectively. The results of the unit root tests suggest that in exception of GDP, which is integrated processes in order of 0, the rest of the variables are integrated processes of order 1. Diagnostic test results suggest that the logarithmic transformation of equation (3.2.12) is appropriate for testing a single unit root in all ADF auxiliary and Perron ADF equations.

Tests for cointegration for the different factor models suggest the existence of a unique cointegrating relationship between the variables selected for each factor model in exception of the five-factor model that has two cointegrating relationships between the variables.

The VAR methodology is used to estimate the long-run elasticities of the different factor production functions. Based on the VAR models, vector error correction models (VECM) are derived and used to estimate both the short-run and the long-run elasticities. The long-run elasticities estimates obtained using the two and the three factor models all have the expected signs and are all significant determinants of long-run output growth in Australia.

Diagnostic tests carried out on the sum of the elasticities suggest that the constant return to scale assumption imposed on the two-factor production function and the three-factor production function (LY, LK, LL and LFDI) cannot be rejected at 5% level of significance. However, this assumption is strongly rejected for the other three-factor production functions which recognise (LY, LK, LL and LH) and (LY, LK, LL and LICT) as the only factors of production. Diagnostic tests are carried out on the significance of human capital, FDI and ICT in the tree-factor production functions. The test results suggest that these variables are very strong determinants of long-run GDP growth in Australia.

All the long-run elasticities obtained using the four-factor models have the anticipated signs. In exception of the long run elasticities of GDP with respect to foreign direct investment in all the four-factor models are significant determinants of long GDP growth. Diagnostic tests carried out on the sum of the elasticities of the four-factor models (LY, LK, LL, LH and LICT) and (LY, LK, LL, LFDI and LICT) suggest a rejection of the constant return to scale assumption imposed on these four-factor production functions at 5% level of significance in favour of increasing returns to scale. However the results of the diagnostic tests carried out on the sum of the elasticities of the four-factor model (LY, LK, LL, LH and LFDI) suggest a non-rejection of the constant return to scale assumption imposed on this four-factor production function at 5% level of significance.

Diagnostic tests are carried out on the significance of human capital, FDI and ICT in the four-factor production models as well. The test results reveal that, in exception of FDI, the other two exogenous additional variables, human capital and ICT are very strong determinants of long-run output growth in Australia.

The standard pair-wise Granger causality tests are carried out in order to examine the causal interactions between GDP and factors of production. The results of the Granger causality test suggest that human capital, FDI and ICT have significant impacts on GDP. The orthogonalised impulse response function is used to determine the response of GDP to a unit standard error shock to production factors. The impulse response(s) indicate that GDP's response to a unit standard error shock to each of the production factors namely human capital, FDI and ICT are permanent and positive for all the number of forecast horizons considered in this study.

Furthermore, the impulse response(s) show that GDP's response to a unit standard error shock to fixed capital is also permanent and positive for all the number of horizons, except for the three-factor model (LY, LK, LL and LFDI) which is negative. GDP's response to a unit standard error shock to labour on the other hand is permanent and positive only for the three-factor model (LY, LK, LL and LFDI). GDP's response to a unit standard error shock to labour is persistently negative for the other three-factor models, four and five-factor models for all the number of forecast horizons considered in this study. The forecast error variance decomposition analysis reveals that the innovations of each production factor considered for this research contribute to a significant proportion of the variation of GDP's forecast error variance in all the various factor models in the long run. The forecast error variance decomposition analysis provides evidence that in the short run, a greater proportion of the variation of the forecast error variance of GDP is due to its own innovations for all the factor models developed in this study.

The results of the diagnostic tests, the pair-wise Granger causality tests, the impulse response functions and the forecast error variance decomposition analysis suggest that human capital, FDI and ICT are highly significant determinants of long run GDP growth in Australia.

Measurement of the partial productivities indicates that labour productivity has a tendency of growth. Measurement of total factor productivity (TFP) performance reveals that Australia experienced productivity growth in the 1950s, a slow down in the mid 1960s and a very strong productivity growth in the mid 1990s. Granger causality test and the impulse response analysis suggest that fixed capital, labour, human capital, FDI and ICT are all significant determinants of productivity in Australia in both the short and long-run periods.

Total factor productivity analysis suggests that the three, four and the five factor models are likely to give better measures of productivity performance in Australia as these models recognise human capital, FDI and ICT and include them as separate factors in the production function, The omission of these factors, which are very strong determinants of long run productivity growth in Australia, from the productivity analysis will produce inaccurate productivity measures that may mislead policy formulation, planning and budgeting decisions.

7.3 Contributions of the Research to Knowledge

This sub-section highlights the main contributions of this study to the economic literature. The first contribution of this study to knowledge is that it is the first study to use aggregate data to develop different factor production models namely, three-factor, four-factor and five-factor models for Australia's economy and use them to obtain different productivity measures for Australia.

A possible contribution to knowledge by this study is that it represents the first attempt at putting the analysis of productivity, fixed capital, labour, human capital, FDI and ICT in Australia in a temporal 'causal' framework by binding the variables in a multivariate cointegrated system. It is the first study to use the standard Granger causality test and the impulse response function analysis to investigate the important of production factors in productivity growth in Australia.

Another contribution of this study to the economic literature is that the study is the first to use aggregate data, which in addition to fixed capital and labour units, recognises human capital, FDI and ICT as additional exogenous factors of production and includes them in the production function accordingly to measure productivity performance in Australia.

7.4 Research Limitations

This study has some limitations. Firstly, the measurement errors associated with the data used for the analysis, which are beyond the scope of this study. To get a reliable result from any empirical analysis, accurate data without measurement error is needed. But achieving this is not an easy task and data for empirical analysis continues to be saddled with measurement related problems. Several economists have argued that measured output and productivity growth may be biased downward, particularly in the service industries, where output is often intangible and difficult to measure.

The usual way to handle the heterogeneity of output for example is to construct an index that weights the physical units of output by their "real value", that is, their market prices, adjusted for inflation. However, in a diverse modern economy, it is difficult to keep track of the prices of all products because of changes in product quality, product innovation, and product and outlet substitution. Therefore, various price indices are used to deflate nominal prices. The GDP deflator and its components, for example, are used to deflate the final purchases of consumer goods and services, which are large components of GDP. Any index of real output needs to account for quality changes. Normally market prices in the base year period are often used to reflect relative values that capture quality differences. However, if quality changes are not associated with increases in production costs (market prices), productivity can be biased downwards.

Another difficulty in measuring output is associated with products that do not have market prices. Examples are goods and services produced by governments and non-profit making institutions, services of owner-occupied dwellings, and goods produced for individual consumption. In general, the prices of these products are computed based on the cost of their inputs or are imputed from prices of similar products. For example, services of owner-occupied dwellings are valued at their estimated rental prices. However, using the cost of inputs to measure real output, which is how government output is generally measured, implies that productivity growth is zero.

The estimates of comprehensive productivity (TFP) obtained in this study using different factor production functions can be inaccurate. Total tertiary students enrolment is used as a proxy to measure human capital. One major limitation of this approach is that it does not necessarily include the portion of human capital attributable to on-the-job training. A second limitation is that the annual enrolment measure is used to represent a stock of human capital.

Another major limitation is the use of aggregate data for the productivity analysis. The study is unable to measure the performance of productivity in the various sectors of the economy due to unavailability of reliable sectoral data for the period considered for this analysis. Annual data are also not available for most of the variables selected for the study for most of the sectors by mid 1970s. For instance, annual data for two of the variables, namely human capital and FDI are not available at all on sectoral basis for the entire period considered for this study. Furthermore, some of the sectors were non-existing at the earlier periods of the sample period considered for this study. As a result, the measurement of sectoral productivity performance is impossible and omitted in this study. It is therefore impossible to assess the contributions of each sector to aggregate productivity growth in Australia. This limits suggestions on how to improve upon future productivity growth in Australia.

Finally, the constant returns to scale assumption imposed on equations (3.2.2) and (4.6.2.6) are rejected for all the factor models, except for the two-factor production function, the three-factor production function (LY, LK, LL and LFDI) and four-factor production function (LY, LK, LL, LH and LFDI). This could bias the estimates of productivity measures presented in this study for these factor models in which the constant to scale assumptions are rejected in favour of increasing returns to scale downwards.

7.5 Suggestions for future research

The results and limitations of this study, suggest some avenues for further research to deepen the understanding of productivity performance in Australia. Some of the recommendations are directed to policy makers in Australia and others to the academics. First, to reduce the measurement error associated with the data, we suggest that if possible, future research measures GDP, fixed capital, FDI and ICT in output units rather than monetary terms. This would avoid the biases which are normally associated with GDP, fixed capital, FDI and ICT when measured in monetary terms. Although these variables are measured in units of constant 2004 dollar prices, all the inflationary problems associated with the prices of these variables have still not been fully addressed.

Another possible suggestion for future research concerns the measurement of human capital. Human capital should not just be a proxy by tertiary student enrolments. A separate measurement technique should be developed to account for the human capital formed through on-the-job training as well.

Based on the approach used in this study, we recommend that future research considers measuring the performance of productivity in the various sectors of the economy. The purpose of this is to assess the contribution of productivity performance in each sector to the aggregate productivity. By measuring the sectoral productivity performance, we can identify the performance of the various sectors of the economy and advise policy makers accordingly. This could help improve upon the aggregate productivity growth in Australia.

This research is unable to include research and development expenditure as a separate exogenous factor in the production function for the productivity analysis for Australia due to unavailability of reliable research and development data. It is very important to assess the impact of research and development on the productivity performance in Australia. Accordingly, we recommend that based on the approach use in this study, future studies of the productivity puzzle in Australia consider research and development as a separate factor of production to be included in the model for productivity analysis.

This study should stimulate future research and assist policy makers and the government of Australia. This study provides policy makers with additional insights into what percentage of the forecast error variance of GDP and productivity are explained by the innovations of each production factor. The study also provides policy makers with information that a one standard error shock to each production factor is persistent and permanent in GDP and TFP. The findings that human capital, FDI and ICT all Granger cause GDP and productivity in both the short and long-run periods are very important to policy makers in Australia as earlier productivity research excludes these production factors from productivity analysis.

Of interest to policy makers and government, it is further recommended that human capital, FDI and ICT be included as separate factors of production for long-run projections of Australia's economic growth. Finally, it is recommended that in policy formulation, planning and budgeting in Australia, attention should be given to fixed capital, human and ICT capitals.

7.6 Concluding Remark

Despite the limitations of this study, it is able to achieve its major objective in measuring the performance of productivity in Australia for the period 1950-2005. This study is the first to use the Granger causality test and the impulse response analysis to identify human capital, FDI and ICT as significant determinants of long-run output and productivity growth in Australia. The main contribution of this research is to offer a framework for empirical and theoretical analysis of the role of production factors namely fixed capital, labour, human capital, FDI and ICT in productivity growth in Australia's economy.

The results of this study provide a significant contribution to researchers, policy makers and government. For researchers, this study provides evidence that the previous studies on the Australia's productivity puzzle have made a significant omission by not considering human capital, FDI and ICT as additional exogenous variables and including them in the production function for productivity analysis. Finally, this study raises awareness that fixed capital and labour are not the only important determinants of productivity in Australia, but other factors such as human capital, FDI, ICT, among others are also equally important.

For policy makers and government, the results of this study may serve as a guide for future planning, budgeting and policy formulation.

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APPENDICES

Appendix A

Suppose that the factors of production are measured in efficiency units, and then the production function can be written in the form:

$$Y=F(\hat{K}, \hat{L}, t), \tag{A.1}$$

where the respective levels of capital and labour sources are defined by:

$$\hat{K} = E_K(t)K_t, \quad \text{and} \quad \hat{L} = E_L(t)L_t. \tag{A.2}$$

Thus, $E_K(t)$ is a summary measure of the common factors affecting the efficiency of all units of capital irrespective of their vintages. By similar reason, $E_L(t)$ is a summary measure of the common factors affecting the efficiency of all units of labour irrespective of their vintages.

Assuming that factors are paid prices equal to their respective marginal products and that the shares of the product to capital and labour, S_K and S_L respectively, exhaust the total product, total factor payments is defined as:

$$S_K=Y_K K, \quad \text{and} \quad S_L = Y_L L \tag{A.3}$$

That is $S_K = pK$, $S_L = wL$ and the relative factor shares are defined to be:

$$S_K=\frac{S_K}{Y} = \frac{rK}{PY}, \quad S_L = \frac{S_L}{Y} = \frac{wL}{PY} \tag{A.4}$$

It follows immediately that the relative factor share is equal to the elasticity of output with respect to that particular factor. Thus,

$$S_K=\frac{Y_K K}{Y} = \frac{\partial \ln Y}{\partial \ln K} = \sum Y_K, \quad \text{and} \quad S_L = \frac{Y_L L}{Y} = \frac{\partial \ln Y}{\partial \ln L} = \sum Y_L. \tag{A.5}$$

With constant return to scale assumption,

$$S_K + S_L = \sum Y_K + \sum Y_L = 1. \tag{A. 6}$$

Appendix 1

Table A1: Basic Data

Years	Y	K	L	H	FDI	ICT
1950	59076	10856	2607.2	189.5	11925.3	151
1951	78376	15550	2690.6	186.7	12167.9	169
1952	84569	19584	2673	200.4	12952.4	187
1953	95832	19529	2700.5	207.1	13492.6	214
1954	104661	21574	2770.3	209.3	15064.3	217
1955	111466	23838	2861.9	220.2	15735.5	243
1956	120660	25947	2915.9	232.3	17487.2	249
1957	131312	26873	2925.9	242.1	18485.9	266
1958	134366	28863	2950.7	262.4	19238.9	287
1959	144310	30522	3000.9	272.5	23495.5	299
1960	169376	36070	3107.6	293.2	26662.6	337
1961	174004	37985	4225.1	338.9	29895.5	384
1962	176467	38067	4437.4	362.9	17596.6	431
1963	187473	40358	4533.1	391.2	29700.3	479
1964	200983	43782	4644.5	416.3	30501.1	531
1965	213429	46946	4763	444.1	38222.4	589
1966	218528	50647	4856.5	466.3	31617.7	654
1967	232592	52653	4934.4	472.3	24947.3	722
1968	244641	56046	5063.7	452.6	37811.2	790
1969	261695	59750	5197.4	542.2	40426.5	859
1970	280509	62164	5385.8	581.1	48592.7	926
1971	291607	64140	5525.1	587.9	54219.6	992
1972	303054	65331	5572.6	603.6	47516.8	1059
1973	311820	66655	5701.1	611.9	27171.8	1124
1974	325250	69178	5867.7	671.1	26191.1	1187
1975	329063	64309	5940.1	701.5	23524.7	1249
1976	338176	65907	6088.1	734.6	18166.2	1309
1977	349808	68020	6198	796.9	30306.2	1364
1978	353348	70119	6394	841.2	45836.3	1417
1979	368032	75841	6439.9	882.2	48074.9	1480
1980	379734	77374	6651.4	915.7	49267.2	1555
1981	392630	86582	6741.5	969.1	58297	1634
1982	405073	92887	6854.7	994.1	76518	1737
1983	395481	83428	6859.7	1085.1	72964.2	1842
1984	413998	86247	7132.9	1168.1	76112.7	1942
1985	436147	94358	7238.6	1216.6	83712.5	2061
1986	455432	99512	7481.4	1276.7	84940.3	2218
1987	465798	98824	7679.5	1330.9	119383.1	2409

1988	491326	106203	7957.6	1372.5	115616.9	2631
1989	511134	117104	8086.2	1373.4	127185.3	2890
1990	531245	117957	8345.7	1451.9	132742.5	3248
1991	528174	105916	8491.5	1520.4	139588.5	3669
1992	528769	100756	8518.4	1602.1	144224.8	4092
1993	548650	106866	8574.4	1697.1	143175.5	4569
1994	571406	113315	8886.3	1701.9	148427.5	5104
1995	596953	126233	9065.5	1873.1	151051.4	5682
1996	621543	129258	9173.1	1975.3	163422.9	6273
1997	645999	139232	9260.6	2107.9	177794.1	6933
1998	674932	152779	9399	2181.7	189049.7	7766
1999	709866	159636	9577.9	2300.9	202763.5	8756
2000	738123	172771	9495	2403.4	223065.4	10025
2001	752434	156317	9676	2405.5	232936.8	11626
2002	780817	171424	9831.5	2579.5	237378.7	13337
2003	806161	195653	10018.5	2647.8	259359.9	15359
2004	838251	211722	10145.5	2540.2	272351	18041
2005	857765	222354	10390.3	2598.5	264099.5	21338

Notes: Gross Domestic Product =Y, Fixed Capital=K, Labour Force=L, Human Capital =H, Foreign Direct Investment=FDI, Information and Communication Technology=ICT. GDP, Fixed Capital, FDI and ICT (2004=Base Year) $AU million, Labour Force = Number of total population capable of work and human capital=Students enrolment number (Thousands of people).

Appendix 2

Table A2: Perron Structural Break Test for Unit Root

					Model	A										Critical
Series	T	TB	K	$\hat{\mu}$	$t(\hat{\mu})$	$\hat{\theta}$	$t(\hat{\theta})$	$\hat{\beta}$	$t(\hat{\beta})$	$\hat{\partial}$	$t(\hat{\partial})$	$\hat{\alpha}$	$t(\hat{\alpha})$	$\hat{\gamma}$	$t(\hat{\gamma})$	Values
LY	45	1976	1	3.032	3.473	-0.06	-3.494	0.01	3.51	0.035	1.66	0.752	-3.406			-2.7
LK	49	1973	1	2.943	3.47	-0.09	-2.505	0.012	3.55	0.06	1.16	0.715	-3.38			-2.74
LL	45	1998	1	6.681	21.737	-0.05	-7.238	0.017	17	0.03	2.64	0.182	-21.104			-2.74
LH	45	2002	1	2.816	3.491	-0.12	-4.043	0.025	3.02	0.09	2.27	0.478	-3.219			-2.74
LFDI	47	1961	1	3.093	4.471	-0.2	-3.679	0.041	4.28	0.07	0.86	0.585	-4.318			-2.74
LICT	47	2002	1	0.218	2.383	0.019	2.037	0.004	2.36	-0.03	-2.77	0.953	-2.258			-2.7
					Model	B										
LY	46	1968	1	7.325	4.487	0.41	4.034	0.04	4.44	-0.05	-1.97	0.343	-4.487	-0.02	-3.92	-3.08
LK	48	1999	1	3.603	3.851	-2.04	-2.212	0.01	3.1	0.14	1.88	0.657	-3.737	0.04	2.3	-3.08
LL	45	1992	1	7.189	24.053	0.34	7.843	0.02	17.9	-0.02	-1.95	0.115	-23.22	-0.01	-8.46	-3
LH	45	2001	1	3.028	3.4	2.23	1.661	0.03	2.97	-0.01	-0.14	0.435	-3.153	-0.04	-1.73	-3
LFDI	48	1962	1	2.649	3.982	-0.26	-1.045	0.022	0.9	-0.05	-0.67	0.659	-3.883	0.01	0.54	-3.08
LICT	46	1994	1	0.775	5.825	-0.47	-5.593	0.012	5.79	0.01	2.02	0.841	-5.77	0.01	5.69	-3.08
					Model	C										
														DTB*	t(DTB*)	
LY	56	1966	0	11.13	515.93			0.074	44.9			0.188	-4.979	-0.04	-20.6	-2.39
LK	56	1963	1	9.481	219.5			0.088	22.6			0.599	-3.77	-0.05	-12	-2.39
LL	56	1969	1	7.729	342.6			0.043	28.3			-0.62	-5.421	-0.02	-11.8	-2.34
LH	56	1976	0	5.101	289.9			0.058	61.4			-0.168	-3.745	-0.01	-7.66	-2.34
LFDI	56	1966	1	7.769	94.8			0.07	11.2			0.691	-3.634	0.03	3.71	-2.39
LICT	56	1996	1	5.08	177.3			0.075	75.1			0.873	-3.471	0.07	9.58	-2.39

Notes: Perron's unit root test for variables (LY, LK, LL, LH, LFDI and LICT), treating the break point TB= as endogenous occurrence. Testing the null hypothesis of a unit root choosing the optimal lag length for the Perron regression by adding lags until the ljung-box test rejects residual correlation at level 0.050.

Appendix 3

Table A3: Test Statistics and Choice Criteria for Selecting the Order of the VAR Model (Two and Three-Factor Models)

Based on 52 observations from 1954 to 2005. Order of VAR = 4					
List of deterministic and/or exogenous variables: C					
List of variables included in the unrestricted VAR: LY LK LL					
Order	LL	AIC	SBC	LR test	Adjusted LR test
4	339.96	300.96	262.91	------	------
3	333.92	303.92	274.65	CHSQ(9)=12.080[.209]	9.0599[.432]
2	328.61	307.61	287.12	CHSQ(18)=22.699[.202]	17.0242[.521]
1	317.71	305.71	294.00	CHSQ(27)=44.500[.018]	33.3749[.185]
0	101.14	98.14	95.22	CHSQ(36)=477.62[.000]	358.22[.000]
List of variables included in the unrestricted VAR: LY LK LL LH					
Order	LL	AIC	SBC	LR test	Adjusted LR test
4	464.023	396.03	329.68	------	------
3	453.62	401.62	350.89	CHSQ(16)=20.808[.186]	14.006[.598]
2	444.40	408.40	373.28	CHSQ(32)=39.252[.177]	26.419[.745]
1	428.84	408.84	389.33	CHSQ(48)=70.363[.019]	47.360[.499]
0	157.00	153.00	149.10	CHSQ(64)=614.039[.000]	413.296[.000]
List of variables included in the unrestricted VAR: LY LK LL LFDI					
Order	LL	AIC	SBC	LR test	Adjusted LR test
4	397.62	329.62	263.28	------	------
3	389.04	337.04	286.31	CHSQ(16)= 17.172[.375]	11.558[.774]
2	378.11	342.11	306.98	CHSQ(32)= 39.035[.183]	26.273[.751]
1	365.27	345.27	325.76	CHSQ(48)= 64.704[.054]	43.551[.656]
0	70.10	66.10	62.20	CHSQ(64)= 655.05[.000]	440.90[.000]
List of variables included in the unrestricted VAR: LY LK LL LICT					
Order	LL	AIC	SBC	LR test	Adjusted LR test
4	527.68	459.68	393.34	------	------
3	504.59	452.59	401.86	CHSQ(16)= 46.171[.000]	31.077[.013]
2	473.57	437.57	402.45	CHSQ(32)=108.218[.000]	72.839[.000]
1	450.52	430.52	411.01	CHSQ(48)=154.312[.000]	103.864[.000]
0	108.53	104.53	100.63	CHSQ(64)=838.290[.000]	564.234[.000]

Appendix 4

Table A4: Test Statistics and Choice Criteria for Selecting the Order of the VAR Model (Four and Five-Factor Models)

Based on 50 observations from 1956 to 2005. Order of VAR = 6
List of deterministic and/or exogenous variables: C

List of variables included in the unrestricted VAR: LY LK LL LH LFDI

Order	LL	AIC	SBC	LR test	Adjusted LR test
6	551.48	396.48	248.30	------	------
5	530.34	400.34	276.06	CHSQ(25)= 42.272[.017]	16.0633[.913]
4	506.63	401.63	301.25	CHSQ(50)=89.701[.000]	34.0863[.958]
3	487.89	407.89	331.41	CHSQ(75)=127.167[.000]	48.3233[.993]
2	474.35	419.35	366.77	CHSQ(100)=154.252[.000]	58.6158[1.00]
1	460.15	430.15	401.47	CHSQ(125)=182.662[.001]	69.4115[1.00]
0	158.85	153.85	149.07	CHSQ(150)=785.262[.000]	298.3995[.000]

List of variables included in the unrestricted VAR: LY LK LL LH LICT

Order	LL	AIC	SBC	LR test	Adjusted LR test
6	712.77	557.77	409.59	------	------
5	672.23	542.23	417.95	CHSQ(25)= 81.073[.000]	30.8078[.195]
4	646.44	541.44	441.06	CHSQ(50)=132.661[.000]	50.4113[.457]
3	615.09	535.09	458.61	CHSQ(75)=195.358[.000]	74.2359[.503]
2	584.39	529.39	476.81	CHSQ(100)=256.75[.000]	97.5633[.550]
1	541.30	511.30	482.62	CHSQ(125)=342.94[.000]	130.3182[.354]
0	171.44	166.44	161.66	CHSQ(150)=1082.7[.000]	411.4105[.000]

List of variables included in the unrestricted VAR: LY LK LL LFDI LICT

Order	LL	AIC	SBC	LR test	Adjusted LR test
6	654.91	499.91	351.72	------	------
5	620.69	490.69	366.41	CHSQ(25)= 68.428[.000]	26.003[.407]
4	589.88	484.88	384.50	CHSQ(50)=130.060[.000]	49.423[.496]
3	563.50	483.50	407.02	CHSQ(75)=182.816[.000]	69.470[.658]
2	531.66	476.66	424.08	CHSQ(100)=246.50[.000]	93.670[.659]
1	488.76	458.76	430.08	CHSQ(125)=332.29[.000]	126.269[.451]
0	86.79	81.79	77.01	CHSQ(150)=1136.2[.000]	431.765[.000]

List of variables included in the unrestricted VAR: LY LK LL LH LFDI LICT

Order	LL	AIC	SBC	LR test	Adjusted LR test
6	843.82	621.82	409.59	------	------
5	769.15	583.15	405.33	CHSQ(36)=149.343[.000]	38.829[.343]
4	724.79	574.79	431.39	CHSQ(72)=238.055[.000]	61.894[.796]
3	681.84	567.84	458.85	CHSQ(108)=323.97[.000]	84.233[.956]
2	645.17	567.17	492.60	CHSQ(144)=397.31[.000]	103.301[.996]
1	599.60	557.60	517.45	CHSQ(180)=488.44[.000]	126.994[1.00]
0	173.46	167.46	161.73	CHSQ(216)=1340.7[.000]	348.587[.000]

Appendix 5

Table A5: ML estimates subject to exactly identifying restriction(s)

(Two-Factor Model LY, LK and LL)

Converged after 2 iterations			
Cointegration with restricted intercepts and no trends in the VAR			
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1.			
List of variables included in the cointegrating vector:			
LY	LK	LL	Intercept
List of imposed restriction(s) on cointegrating vectors: A1=1			
	Vector 1		
LY	1.0000 (NONE)		
LK	-.44689 (.25928)		
LL	-.52537 (.35175)		
Intercept	-3.4668 (1.8172)		
LL subject to exactly identifying restrictions= 330.2599			

Notes: Estimates of Restricted Cointegrating Relations (SE's in Brackets)

Appendix 6

Table A6: ECM for Variable LY Estimated by OLS based on Cointegrating VAR (3)
(Two-Factor Model LY, LK and LL)

Dependent variable is dLY -53 observations used for estimation from 1953 to 2005				
Regressor	Coefficient	Standard Error	T-Ratio	[Prob]
dLY1	-.0015508	.16160	-.009597	[.992]
dLK1	.063956	.074710	.85605	[.396]
dLL1	-.17759	.089213	-1.9906	[.052]
dLY2	-.061373	.14809	-.41442	[.680]
dLK2	.023152	.069874	.33135	[.742]
dLL2	-.042303	.094953	-.44551	[.658]
ecm1(-1)	-.14676	.031468	-4.6636	[.000]

List of additional temporary variables created:
dLY = LY-LY(-1)
dLY1 = LY(-1)-LY(-2)
dLK1 = LK(-1)-LK(-2)
dLL1 = LL(-1)-LL(-2)
dLY2 = LY(-2)-LY(-3)
dLK2 = LK(-2)-LK(-3)
dLL2 = LL(-2)-LL(-3)
ecm1 = 1.0000*LY -.44689*LK -.52537*LL -3.4668

R-Squared	.36955	R-Bar-Squared	.28732
S.E. of Regression	.024891	F-stat. F(6, 46)	4.4939[.001]
Mean of Dependent Variable	.043713	S.D. of Dependent Variable	.029485
Residual Sum of Squares	.028501	Equation Log-likelihood	124.2915
Akaike Info. Criterion	117.2915	Schwarz Bayesian Criterion	110.3955
DW-statistic	1.9178	System Log-likelihood	330.2599

Diagnostic Tests

Test Statistics	LM Version	F Version
A:Serial Correlation	CHSQ(1)= 2.9535[.086]	F(1, 45)= 2.6557[.110]
B:Functional Form	CHSQ(1)= .56225[.453]	F(1, 45)= .48250[.491]
C:Normality	CHSQ(2)= 78.3553[.000]	Not applicable
D:Heteroscedasticity	CHSQ(1)= .31916[.572]	F(1, 51)= .30898[.581]

Appendix 7

Table A7: ML Estimates Subject to Exactly Identifying Restriction(s) - Three-Factor Models

Cointegration with restricted intercepts and no trends in the VAR 53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1. List of imposed restriction(s) on cointegrating vectors: A1=1	
List of variables included in the cointegrating vector: LY LK LL LH Intercept	
LY	1.0000 (NONE)
LK	-.34774(0.13219)
LL	-.15287(0.16306)
LH	-.34662(0.097694)
Intercept	-5.3367(1.1756)
LL subject to exactly identifying restrictions= 442.4564	
List of variables included in the cointegrating vector: LY LK LL LFDI Intercept	
LY	1.0000 (NONE)
LK	-.017086(0.50969)
LL	-.52205(0.35562)
LFDI	-.26344(.19184)
Intercept	-5.5317(3.0593)
LL subject to exactly identifying restrictions= 357.1400	
List of variables included in the cointegrating vector: LY LK LL LICT Intercept	
LY	1.0000 (NONE)
LK	-.13348(.10369)
LL	-.62312(0.088593)
LICT	-.20276(0.030367)
Intercept	-4.4599(0.56796)
LL subject to exactly identifying restrictions= 489.5725	

Notes: Estimates of Restricted Cointegrating Relations (SE's in Brackets)

Appendix 8

Table A8: ECM for Variable LY Estimated by OLS based on Cointegrating VAR (3) (Three-Factor Model LY, LK, LL and LH)

Dependent variable is dLY- 53 observations used for estimation from 1953 to 2005

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
dLY1	-.043767	.14536	-.30110[.765]
dLK1	.050096	.069212	.72382[.473]
dLL1	-.10608	.091428	-1.1603[.252]
dLH1	-.0073066	.090972	-.080318[.936]
dLY2	-.17435	.14259	-1.2227[.228]
dLK2	-.0096950	.064060	-.15134[.880]
dLL2	-.071660	.089840	-.79764[.429]
dLH2	.052779	.093302	.56568[.574]
ecm1(-1)	-.33252	.063712	-5.2191[.000]

List of additional temporary variables created:

dLY = LY-LY(-1)
dLY1 = LY(-1)-LY(-2)
dLK1 = LK(-1)-LK(-2)
dLL1 = LL(-1)-LL(-2)
dLH1 = LH(-1)-LH(-2)
dLY2 = LY(-2)-LY(-3)
dLK2 = LK(-2)-LK(-3)
dLL2 = LL(-2)-LL(-3)
dLH2 = LH(-2)-LH(-3)
ecm1= 1.0000*LY -.34774*LK -.15287*LL -.34662*LH -5.3367

R-Squared	.49383	R-Bar-Squared	.40180
S.E. of Regression	.022805	F-stat. F(8, 44)	5.3660[.000]
Mean of Dependent Variable	.043713	S.D. of Dependent Variable	.029485
Residual Sum of Squares	.022882	Equation Log-likelihood	130.1101
Akaike Info. Criterion	121.1101	Schwarz Bayesian Criterion	112.2438
DW-statistic	1.9365	System Log-likelihood	442.4564

Diagnostic Tests

Test Statistics	LM Version	F Version
A:Serial Correlation	CHSQ(1)= .33236[.564]	F(1,43)= .27135[.605]
B:Functional Form	CHSQ(1)= .015588[.901]	F(1,43)= .012651[.911]
C:Normality	CHSQ(2)= 113.9447[.000]	Not applicable
D:Heteroscedasticity	CHSQ(1)= .53324[.465]	F(1,51)= .51833[.475]

Appendix 9

Table A9: ECM for Variable LY Estimated by OLS based on Cointegrating VAR (3) (Three-Factor Model LY, LK, LL and LFDI)

Dependent variable is dLY - 53 observations used for estimation from 1953 to 2005

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
dLY1	-.17020	.16267	-1.0463[.301]
dLK1	.11773	.072772	1.6178[.113]
dLL1	-.16703	.083800	-1.9933[.052]
dLFDI1	-.021090	.018497	-1.1402[.260]
dLY2	-.19630	.14676	-1.3376[.188]
dLK2	.047676	.066386	.71816[.476]
dLL2	-.066004	.091853	-.71858[.476]
dLFDI2	-.010274	.016935	-.60668[.547]

List of additional temporary variables created:

dLY = LY-LY(-1)
dLY1 = LY(-1)-LY(-2)
dLK1 = LK(-1)-LK(-2)
dLL1 = LL(-1)-LL(-2)
dLFDI1 = LFDI(-1)-LFDI(-2)
dLY2 = LY(-2)-LY(-3)
dLK2 = LK(-2)-LK(-3)
dLL2 = LL(-2)-LL(-3)
dLFDI2 = LFDI(-2)-LFDI(-3)

R-Squared	.46976	R-Bar-Squared	.37336
S.E. of Regression	.023340	F-stat. F(8,44)	4.8727[.000]
Mean of Dependent Variable	.043713	S.D. of Dependent Variable	.0295
Residual Sum of Squares	.023970	Equation Log-likelihood	128.88
Akaike Info. Criterion	119.8789	Schwarz Bayesian Criterion	111.013
DW-statistic	1.9059	System Log-likelihood	357.140

Diagnostic Tests

Test Statistics	LM Version	F Version
A:Serial Correlation	CHSQ(1)= 1.1477[.284]	F(1, 43)=.95173[.335]
B:Functional Form	CHSQ(1)= .85668[.355]	F(1, 43)=.70646[.405]
C:Normality	CHSQ(2)= 55.4449[.000]	Not applicable
D:Heteroscedasticity	CHSQ(1)=1.3060[.253]	F(1,51)= 1.2885[.262]

Appendix 10

Table A10: ECM for Variable LY Estimated by OLS based on Cointegrating VAR (3)
(Three-Factor Model LY, LK, LL and LICT)

Dependent variable is dLY-53 observations used for estimation from 1953 to 2005			
Regressor	Coefficient	Standard Error	T-Ratio[Prob]
dLY1	.29253	.13475	2.1709[.035]
dLK1	.012353	.072648	.17004[.866]
dLL1	-.077093	.093104	-.82803[.412]
dLICT1	-.20297	.12809	-1.5845[.120]
dLY2	-.062860	.14840	-.42358[.674]
dLK2	-.0050246	.072951	-.068876[.945]
dLL2	.0076568	.089873	.085195[.932]
dLICT2	.099886	.15244	.65524[.516]
ecm1(-1)	-.28731	.084086	-3.4169[.001]

List of additional temporary variables created:
dLY = LY-LY(-1)
dLY1 = LY(-1)-LY(-2)
dLK1 = LK(-1)-LK(-2)
dLL1 = LL(-1)-LL(-2)
dLICT1 = LICT(-1)-LICT(-2)
dLY2 = LY(-2)-LY(-3)
dLK2 = LK(-2)-LK(-3)
dLL2 = LL(-2)-LL(-3)
dLICT2 = LICT(-2)-LICT(-3)
ecm1 = 1.0000*LY -.13348*LK -.62312*LL -.20276*LICT -4.4599

R-Squared	.39629	R-Bar-Squared	.2865
S.E. of Regression	.024905	F-stat. F(8, 44)	3.6103[.003]
Mean of Dependent Variable	.043713	S.D. of Dependent Variable	.0295
Residual Sum of Squares	.027292	Equation Log-likelihood	125.440
Akaike Info. Criterion	116.4399	Schwarz Bayesian Criterion	107.574
DW-statistic	1.8622	System Log-likelihood	489.573

Diagnostic Tests

Test Statistics	LM Version	F Version
A:Serial Correlation	CHSQ(1)=1.0871[.297]	F(1,43)= .90047[.348]
B:Functional Form	CHSQ(1)= 4.6679[.031]	F(1,43)= 4.1529[.048]
C:Normality	CHSQ(2)= 232.4530[.000]	Not applicable
D:Heteroscedasticity	CHSQ(1)= .026297[.871]	F(1, 51)= .025317[.874]

Appendix 11

Table A11: Diagnostic Test for Constant Return to Scale - Three-Factor Model (LY, LK, LL and LH)

ML estimates subject to over identifying restriction(s)	
Estimates of Restricted Cointegrating Relations (SE's in Brackets)	
Converged after 21 iterations	
Cointegration with restricted intercepts and no trends in the VAR	
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1.	
List of variables included in the cointegrating vector:	
LY LK LL LH Intercept	
List of imposed restriction(s) on cointegrating vectors:	
A1=1; A2+A3+A4=1	
	Vector 1
LY	1.0000 (NONE)
LK	2.2303 (2.2323)
LL	.94659 (1.6436)
LH	-2.1769 (.86291)
Intercept	-33.4341 (7.7866)
LR Test of Restrictions	CHSQ (1)= 6.0155[.014]
DF=Total no of restrictions (2) - no of just-identifying restrictions (1)	
LL subject to exactly identifying restrictions= 442.4564	
LL subject to over-identifying restrictions= 439.4487	

Appendix 12

Table A12: Diagnostic Test for Constant Return to Scale–Three-Factor Model (LY, LK, LL and LFDI)

ML estimates subject to over identifying restriction(s)	
Estimates of Restricted Cointegrating Relations (SE's in Brackets)	
Converged after 21 iterations	
Cointegration with restricted intercepts and no trends in the VAR	
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1.	
List of variables included in the cointegrating vector:	
LY LK LL LFDI Intercept	
List of imposed restriction(s) on cointegrating vectors:	
A1=1; A2+A3+A4=1	
	Vector 1
LY	1.0000 (NONE)
LK	.51547 (1.5524)
LL	.82502 (1.4183)
LFDI	-.34048 (.18562)
Intercept	-24.6680 (4.4744)
LR Test of Restrictions	CHSQ(1)= .81145[.368]
DF=Total no of restrictions(2) - no of just-identifying restrictions(1)	
LL subject to exactly identifying restrictions= 376.0534	
LL subject to over-identifying restrictions= 375.6477	

Appendix 13

Table A13: Diagnostic Test for Constant Return to Scale–Three Factor Model (LY, LK, LL and LICT)

ML estimates subject to over identifying restriction(s)	
Estimates of Restricted Cointegrating Relations (SE's in Brackets)	
Converged after 27 iterations	
Cointegration with restricted intercepts and no trends in the VAR	
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1.	
List of variables included in the cointegrating vector:	
LY LK LL LICT Intercept	
List of imposed restriction(s) on cointegrating vectors:	
A1=1; A2+A3+A4=1	
	Vector 1
LY	1.0000 (NONE)
LK	6.0341 (3.6454)
LL	-3.6891 (3.2288)
LICT	-1.3450 (.62190)
Intercept	-39.5056 (9.9717)
LR Test of Restrictions	CHSQ (1) = 11.6178[.001]
DF=Total no of restrictions (2) - no of just-identifying restrictions (1)	
LL subject to exactly identifying restrictions= 491.7553	
LL subject to over-identifying restrictions= 485.9464	

Appendix 14

Table A14: ML Estimates Subject to Exactly Identifying Restriction(s)
(Four-Factor Model LY, LK, LL LH and LFDI)

Cointegration with restricted intercepts and no trends in the VAR 53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1. List of imposed restriction(s) on cointegrating vectors: A1=1	
List of variables included in the cointegrating vector: LY LK LL LH LFDI Intercept	
	Vector 1
LY	1.0000 (NONE)
LK	-.32754 (.17249)
LL	-.15985(.18585)
LH	-.32907(.12664)
LFDI	-.022429 (.071738)
Intercept	-5.3798 (1.2679)
LL subject to exactly identifying restrictions= 467.8641	

Notes: Estimates of Restricted Cointegrating Relations (SE's in Brackets)
Converged after 2 Iterations

Appendix 15

Table A15: ECM for Variable LY Estimated by OLS based on Cointegrating VAR (3)
(Four-Factor Model LY, LK, LL, LH and LFDI)

Dependent variable is dLY- 53 observations used for estimation from 1953 to 2005			
Regressor	Coefficient	Standard Error	T-Ratio[Prob]
dLY1	-.068826	.15001	-.45881[.649]
dLK1	.065867	.071853	.91670[.365]
dLL1	-.11669	.092553	-1.2608[.214]
dLH1	.015320	.093652	.16358[.871]
dLFDI1	-.010870	.018354	-.59226[.557]
dLY2	-.18549	.14577	-1.2725[.210]
dLK2	-.0018213	.065775	-.027690[.978]
dLL2	-.090173	.098784	-.91283[.367]
dLH2	.073642	.096867	.76024[.451]
dLFDI2	-.0040562	.017045	-.23797[.813]
ecm1(-1)	-.31795	.061538	-5.1666[.000]

List of additional temporary variables created:
dLY = LY-LY(-1)
dLY1 = LY(-1)-LY(-2)
dLK1 = LK(-1)-LK(-2)
dLL1 = LL(-1)-LL(-2)
dLH1 = LH(-1)-LH(-2)
dLFDI1 = LFDI(-1)-LFDI(-2)
dLY2 = LY(-2)-LY(-3)
dLK2 = LK(-2)-LK(-3)
dLL2 = LL(-2)-LL(-3)
dLH2 = LH(-2)-LH(-3)
dLFDI2 = LFDI(-2)-LFDI(-3)
ecm1 = 1.0000*LY-0.3275*LK-0.1599*LL-0.3291*LH-0.02243*LFDI-5.3798

R-Squared	.50031	R-Bar-Squared	.38133
S.E. of Regression	.023192	F-stat. F(10, 42)	4.2051[.000]
Mean of Dependent Variable	.043713	S.D. of Dependent Variable	.0295
Residual Sum of Squares	.022590	Equation Log-likelihood	130.451
Akaike Info. Criterion	119.4511	Schwarz Bayesian Criterion	108.615
DW-statistic	1.9634	System Log-likelihood	467.864

Diagnostic Tests

Test Statistics	LM Version	F Version
A:Serial Correlation	CHSQ(1)=0.077101[.781]	F(1, 41)= .0597[.808]
B:Functional Form	CHSQ(1)=0.0057738[.939]	F(1, 41)= .0045[.947]
C:Normality	CHSQ(2)= 99.9265[.000]	Not applicable
D:Heteroscedasticity	CHSQ(1)=0.55697[.455]	F(1, 51)= .5416[.465]

Appendix 16

Table A16: Testing for Cointegration between LY, LK, LL, LH and LICT

Sample: 1950 2005 - Included observations: 52					
Test assumption: Linear deterministic trend in the data					
Series: LY LK LL LH LICT- Lags interval: 3 to 3					
Eigen-value	Like-lihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)	
0.5878	89.2266	68.52	76.07	None **	
0.3442	43.1426	47.21	54.46	At most 1 *	
0.2294	21.2075	29.68	35.65	At most 2	
0.1295	7.6598	15.41	20.04	At most 3	
0.0086	0.4468	3.76	6.65	At most 4	
*(**) denotes rejection of the hypothesis at 5%(1%) significance level					
L.R. test indicates 2 cointegrating equation(s) at 5% significance level					
Unnormalized Cointegrating Coefficients:					
LY	LK	LL	LH	LICT	
-3.4261	0.9472	1.8735	0.3652	0.4957	
-1.3825	1.8893	-1.4478	0.4506	-0.0983	
-1.9253	-0.5585	0.3726	0.7454	0.5556	
3.3832	-1.6888	-1.6073	-0.43	0.05609	
0.4869	-0.2715	0.6105	-1.7789	0.8525	
Normalized Cointegrating Coefficients: 1 Cointegrating Equation(s)					
LY	LK	LL	LH	LICT	C
1.0000	-0.2765	-0.5468	-0.1066	-0.1447	-3.1187
	(0.0682)	(0.0840)	(0.0622)	(0.0389)	
Log Likelihood		554.722			

Appendix 17

Table A17: Testing for Cointegration between LY, LK, LL, LFDI and LICT

Sample: 1950 2005 - Included observations: 52					
Test assumption: Linear deterministic trend in the data					
Series: LY LK LL LFDI LICT- Lags interval 3 to 3					
Eigen- value	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)	
0.5542	93.556	68.52	76.07	None **	
0.4217	51.546	47.21	54.46	At most 1 *	
0.2231	23.067	29.68	35.65	At most 2	
0.1468	9.937	15.41	20.04	At most 3	
0.03182	1.681	3.76	6.65	At most 4	
*(**) denotes rejection of the hypothesis at 5%(1%) significance level					
L.R. test indicates 2 cointegrating equation(s) at 5% significance level					
Unnormalized Cointegrating Coefficients:					
LY	LK	LL	LFDI	LICT	
-3.214	0.6831	2.1635	0.1428	0.5625	
-1.103	1.0289	-0.6998	0.3197	0.0027	
-0.732	-1.4613	0.9509	0.1076	0.6404	
-2.304	1.1171	1.7449	0.0792	-0.1134	
2.066	-1.4714	0.1446	0.4051	-0.577	
Normalized Cointegrating Coefficients: 1 Cointegrating Equation(s)					
LY	LK	LL	LFDI	LICT	C
1.0000	-0.2126	-0.6733	-0.0444	-0.1750	-2.7424
	(0.0840)	(0.0838)	(0.0221)	(0.0303)	
Log Likelihood		462.0322			

Appendix 18

Table A18: Testing for Cointegration between LY, LK, LL, LH, LFDI and LICT

Sample: 1950 2005 - Included observations: 52						
Test assumption: Linear deterministic trend in the data						
Series: LY LK LL LH LFDI LICT- Lags interval 3 to 3						
Eigen-value	Like-lihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)		
.6668	136.48	94.15	103.18	None **		
0.5413	81.53	68.52	76.07	At most 1 *		
0.3716	42.56	47.21	54.46	At most 2		
.2113	19.33	29.68	35.65	At most 3		
0.1014	7.46	15.41	20.04	At most 4		
0.0415	2.12	3.76	6.65	At most 5		
*(**) denotes rejection of the hypothesis at 5%(1%) significance level						
L.R. test indicates 2 cointegrating equation(s) at 5% significance level						
Unnormalized Cointegrating Coefficients:						
LY	LK	LL	LH	LFDI	LICT	
-2.8224	0.5614	1.3084	0.2358	0.2115	0.4588	
-2.2628	0.5976	1.2075	0.8704	-0.2772	0.0039	
-2.9275	0.9129	0.4991	0.618	0.1592	0.124	
-1.6494	2.2186	0.7920	-0.2527	-0.0199	-0.3071	
1.3174	-1.8135	1.6860	-0.6454	0.2642	-0.0054	
-1.7052	0.1406	0.8689	-0.4253	-0.2648	0.9402	
Normalized Cointegrating Coefficients: 1 Cointegrating Equation(s)						
LY	LK	LL	LH	LFDI	LICT	C
1.0000	-0.1989	-0.4636	-0.0836	-0.0749	-0.1626	-3.896
	(0.0879)	(0.0871)	(0.0414)	(0.0253)	(0.0367)	
Log Likelihood		517.25				

Appendix 19

Table A19: Diagnostic Test for Constant Return to Scale-Four-Factor Model (LY, LK, LL, LH and LFDI)

ML estimates subject to over identifying restriction(s)	
Estimates of Restricted Cointegrating Relations (SE's in Brackets)	
Converged after 19 iterations	
Cointegration with restricted intercepts and no trends in the VAR	
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1.	
List of variables included in the cointegrating vector:	
LK LL LH LFDI Intercept	
List of imposed restriction(s) on cointegrating vectors:	
A1=1; A2+A3+A4+A5=1	
	Vector 1
LY	1.0000 (NONE)
LK	3.5891 (3.9522)
LL	-.97386 (3.8458)
LH	.015414 (2.4591)
LFDI	-1.6307 (1.7710)
Intercept	-29.6770 (8.9380)
LR Test of Restrictions	CHSQ(1)= 3.1801[.075]
DF=Total no of restrictions(2) - no of just-identifying restrictions(1)	
LL subject to exactly identifying restrictions= 467.8641	
LL subject to over-identifying restrictions= 466.2740	

Appendix 20

Table A20: Diagnostic Test for Constant Return to Scale–Four-Factor Model (LY, LK, LL, LH and LICT)

ML estimates subject to over identifying restriction(s) Estimates of Restricted Cointegrating Relations (SE's in Brackets) Converged after 24 iterations Cointegration with restricted intercepts and no trends in the VAR	
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1. List of variables included in the cointegrating vector: LY LK LL LH LICT Intercept List of imposed restriction(s) on cointegrating vectors: A1=1; A2+A3+A4+A5=1	
	Vector 1
LY	1.0000 (NONE)
LK	2.8735 (2.3769)
LL	-2.0997 (2.2219)
LH	.032322 (.78703)
LICT	-.80611 (.67469)
Intercept	-21.6837 (6.4511)
LR Test of Restrictions	CHSQ(1)= 12.8690[.000]
DF=Total no of restrictions(2) - no of just-identifying restrictions(1) LL subject to exactly identifying restrictions= 591.1295 LL subject to over-identifying restrictions= 584.6950	

Appendix 21

Table A21: Diagnostic Test for Constant Return to Scale–Four-Factor Model (LY, LK, LL, LFDI and LICT)

ML estimates subject to over identifying restriction(s)	
Estimates of Restricted Cointegrating Relations (SE's in Brackets)	
Converged after 24 iterations	
Cointegration with restricted intercepts and no trends in the VAR	
53 observations from 1953 to 2005. Order of VAR = 3, chosen r =1.	
List of variables included in the cointegrating vector:	
LY LK LL LFDI LICT Intercept	
List of imposed restriction(s) on cointegrating vectors:	
A1=1; A2+A3+A4+A5=1	
	Vector 1
LY	1.0000 (NONE)
LK	8.5710 (7.3408)
LL	-5.5950 (6.0419)
LFDI	.38107 (.54389)
LICT	-2.3571 (1.8784)
Intercept	-47.4908 (21.4401)
LR Test of Restrictions	CHSQ(1)= 9.0658[.003]
DF=Total no of restrictions(2) - no of just-identifying restrictions(1)	
LL subject to exactly identifying restrictions= 529.4611	
LL subject to over-identifying restrictions= 524.9282	

Appendix 22

Table A22: Othorgonalised Forecast Error Variance Decomposition Analysis for GDP (LY) (Three-Factor Models and the Four-Factor Model LY, LK, LL, LH and LFDI)

Table A22a

H	LY	LK	LL	LH
0	100	0	0	0
1	94.01	4.19	0.04	1.76
5	59.72	10.4	7.73	22.14
10	39.62	7.55	18.6	34.28
15	31.27	7.19	23.2	38.35
20	27.08	6.5	26.3	40.11
25	24.63	6.11	28.2	41.02
30	23.06	5.86	29.5	41.56
35	21.97	5.69	30.4	41.9
40	21.18	5.57	31.1	42.14
45	20.59	5.48	31.6	42.31
50	20.14	5.41	32	42.44

Table A22b

H	LY	LK	LL	LFDI
0	100	0	0	0
1	95.3	2.95	1.1	0.62
5	67.8	4.3	1	26.84
10	46.1	7.01	4.3	42.64
15	35	6.81	7	51.16
20	30	6.44	7.8	55.75
25	26.7	6.26	9	58.01
30	24.6	6.18	9.9	59.37
35	23.1	6.13	11	60.27
40	22	6.11	11	60.89
45	21.2	6.1	11	61.34
50	20.5	6.09	12	61.68

Table A22c

H	LY	LK	LL	LICT
0	100	0	0	0
1	98.76	0.3	0.49	0.45
5	87.16	0.61	11	1.24
10	82.62	1.33	7.87	8.18
15	75.78	2.76	3.42	18.04
20	67.11	4.24	1.89	26.75
25	58.96	5.46	2.47	33.11
30	52.22	6.37	3.94	37.47
35	46.91	7.04	5.64	40.42
40	42.76	7.52	7.27	42.45
45	39.5	7.89	8.74	43.88
50	36.9	8.17	10	44.91

Table A22d

H	LY	LK	LL	LH	LFDI
0	100	0	0	0	0
1	93.88	4.03	0.07	1.98	0.04
5	60.34	6.31	6.06	18.46	8.84
10	40.41	6.62	13.3	27.8	11.84
15	32.19	5.42	18.7	30.51	13.15
20	28.07	5.33	21.2	31.54	13.82
25	25.67	5	23.1	32.02	14.2
30	24.12	4.79	24.4	32.27	14.45
35	23.05	4.65	25.3	32.42	14.62
40	22.27	4.55	25.9	32.52	14.74
45	21.68	4.48	26.4	32.58	14.84
50	21.23	4.42	26.8	32.62	14.91

Notes: "H" stands for the number of forecast horizons

Appendix 23

Table A23: Othorgonalised Forecast Error Variance Decomposition Analysis for GDP (LY) (Four-Factor Models LY, LK, LL, LH and LICT; and LY, LK, LL, LFDI and LICT)

Table A23a

H	LY	LK	LL	LH	LICT
0	100	0	0	0	0
1	94.82	0.01	0.21	4.34	0.62
5	75.03	0.58	7.98	12.3	4.11
10	45.16	2.52	18.2	12.72	21.38
15	29	3.69	22.3	14.6	30.37
20	20.94	4.29	24	13.23	37.59
25	16.47	4.64	24.7	12.34	41.88
30	13.73	4.86	25	11.74	44.64
35	11.92	5	25.2	11.32	46.54
40	10.64	5.1	25.3	11.01	47.92
45	9.7	5.18	25.4	10.77	48.95
50	8.99	5.24	25.4	10.58	49.75

Table A23b

H	LY	LK	LL	LFDI	LICT
0	100	0	0	0	0
1	99.13	0.003	0.24	0.21	0.41
5	82.84	3.64	5.27	4.15	4.1
10	43.77	5.59	19.4	12.58	18.62
15	23.05	6.71	25.6	17.58	27.03
20	13.67	7.23	28	18.21	32.89
25	8.97	7.51	29	18.41	36.12
30	6.34	7.67	29.5	18.46	38.09
35	4.73	7.77	29.7	18.45	39.38
40	3.68	7.83	29.8	18.42	40.28
45	2.95	7.88	29.8	18.39	40.94
50	2.43	7.92	29.9	18.35	41.44

Notes: “H “stands for the number of forecast horizons

Appendix 24

Table A24: Othorgonalised Forecast Error Variance Decomposition Analysis for GDP (LY) (Five-Factor Model)

Horizons	LY	LK	LL	LH	LFDI	LICT
0	100	0	0	0	0	0
1	84.2	4.4	2.32	3.06	3.1	2.92
5	69.06	4.96	6.89	4.95	8.96	5.18
10	71.03	4.49	5.41	5.9	8.55	4.62
15	68.1	2.46	3.43	4.45	9.96	11.6
20	61.23	3.11	2.95	5.68	7.46	19.57
25	54.22	3.93	3.27	6.43	6.5	25.65
30	48.4	4.68	3.86	6.64	5.9	30.52
35	43.81	5.29	4.46	6.8	5.72	33.92
40	40.22	5.79	5.01	6.93	5.73	36.32
45	37.39	6.19	5.49	7.03	5.82	38.08
50	35.13	6.52	5.89	7.11	5.95	39.4

Appendix 25

Table A25: Summary of Total Factor Productivity and TFP Growth Rates Yearly Averages, Maximum and Minimum Values for the Periods 1950-2005.

	TFP GROWTH RATES			**TFP - PRODUCTIVITY**			
Factor-Models	Yearly Average 1950-2005	Maximun	Minimum	Yearly Average 1950-2005	Average 1950-2005	Max	Min
LK and LL	0.003727	0.0435	-0.0504	0.010904	1.2834	1.2457	1
LK, LL and LH	0.001889	0.0334	-0.017	0.009316	1.1271	1.1097	1
LK, LL and LFDI	0.004235	0.06	-0.033	0.019747	1.302	1.2731	1
LK, LL and LICT	0.002425	0.0502	-0.0184	0.009775	1.1652	1.1622	1
LK, LL, LH and LFDI	0.001927	0.0346	-0.0095	0.009573	1.1322	1.1186	1
LK, LL, LH and LICT	0.001949	0.0534	-0.0488	0.005489	1.10984	1.1639	1
LK, LL LFDI and LICT	0.002758	0.0514	-0.0296	0.00678	1.1285	1.2085	1
LK, LL, LH, LFDI and LICT	0.001922	0.0512	-0.0274	0.006889	1.1091	1.1464	1

Appendix 26

Table A26: Othorgonalised Forecast Error Variance Decomposition Analysis for TFP (Three-Factor Models and the Four-Factor Model LY, LK, LL, LH and LFDI)

Table A26a

H	TFP	LK	LL	LH
0	100	0	0	0
1	83.67	0.28	16	0.54
5	55.66	9.54	34	0.74
10	50.75	14.5	33	2.17
15	46.3	16	29	9.01
20	40.74	15.2	24	19.74
25	35.36	13.4	21	30.42
30	30.93	11.7	18	39.2
35	27.5	10.2	16	45.95
40	24.88	9.03	15	51.07
45	22.87	8.09	14	54.99
50	21.29	7.35	13	58.04

Table A26b

H	TFP	LK	LL	LFDI
0	100	0	0	0
1	94.59	1	0.29	4.16
5	87.49	2.6	6.71	3.22
10	86.25	4.6	6.11	3.09
15	80.7	6.9	6.65	5.8
20	71.05	8.6	9.29	11.1
25	61.01	9.3	13	16.7
30	53.24	9.3	16.3	21.2
35	48.02	8.9	18.9	24.2
40	44.69	8.4	20.7	26.1
45	42.58	8	22.1	27.4
50	41.21	7.6	23	28.2

Table A26c

H	TFP	LK	LL	LICT
0	100	0	0	0
1	89.26	2.43	2.4	5.93
5	60.83	15.7	4.1	19.41
10	52.38	21.8	5.7	20.17
15	50.04	26.3	5.6	18.04
20	47.9	28.8	5.6	17.72
25	44.35	28.8	5.5	21.3
30	39.46	27.4	5.5	27.66
35	34.19	23.5	5.4	36.9
40	29.45	19.3	5.3	45.95
45	25.67	15.5	6.3	52.62
50	22.83	12.3	6.2	58.67

Table A26d

H	TFP	LK	LL	LH	LFDI
0	100	0	0	0	0
1	89.71	0.2	2.02	4.03	4.01
5	85.3	2.8	2.24	4.92	4.71
10	75.73	8.1	2.73	6.02	7.38
15	65.71	15	3.25	7.17	8.07
20	57.12	21	3.69	9.43	8.95
25	50.27	26	4.04	10.1	9.26
30	44.92	30	4.32	11	9.49
35	40.72	34	4.53	11.4	9.68
40	37.39	36	4.7	11.7	9.83
45	34.71	39	4.84	11.9	9.94
50	32.53	40	4.95	12.1	10

Notes: “H” stands for the number of forecast horizons

Appendix 27

Table A27: Othorgonalised Forecast Error Variance Decomposition Analysis for TFP (Four-Factor Models LY, LK, LL, LH and LICT; and LY, LK, LL, LFDI and LICT)

Table A27a

H	TFP	LK	LL	LH	LICT
0	100	0	0	0	0
1	83.48	1.07	0.01	9.56	5.88
5	74.72	2.56	2.14	13.7	6.9
10	67.45	4.37	4.36	15.1	8.73
15	66.98	4.3	4.68	15	9.01
20	64.35	4.27	5.02	16.8	9.54
25	61.63	4.74	5.83	17.5	10.26
30	60.84	4.72	6.12	17.2	11.08
35	58.99	5.2	6.88	16.9	12.01
40	56.08	5.17	7.11	17.6	14.03
45	55.12	5.15	7.32	17.3	15.13
50	54.11	5.13	7.51	17	16.29

Table A27b

H	TFP	LK	LL	LFDI	LICT
0	100	0	0	0	0
1	83.56	2.53	4.46	6.22	3.23
5	68.69	3.49	11.39	10.3	6.13
10	63.56	3.29	16.52	10.3	6.37
15	58.43	4.32	18.03	10.7	8.52
20	55.36	5.53	17.8	11.2	10.15
25	54.03	5.89	17.02	11.2	11.88
30	50.25	6.37	16.83	12.2	14.31
35	45.85	6.94	15.36	15.4	16.48
40	42.73	7.58	13.74	15.6	20.38
45	36.86	8.25	12.11	16.8	25.94
50	32.31	8.92	10.61	17.2	30.99

Notes: “H” stands for the number of forecast horizons

Appendix 28

Table A28: Othorgonalised Forecast Error Variance Decomposition Analysis for TFP (Five-Factor Model)

Horizons	TFP	LK	LL	LH	LFDI	LICT
0	100	0	0	0	0	0
1	88.26	4.15	1.44	3.99	1.1	5.06
5	53.88	11.39	7.64	7.73	7.3	12.06
10	45.24	16.92	7.34	8.65	9.06	12.8
15	42.51	18.78	7.2	8.65	9.87	12.99
20	41.17	19.68	7.17	8.66	10.31	13.01
25	39.4	20.2	7.19	9.67	10.6	12.95
30	38.91	20.53	7.23	9.68	10.81	12.85
35	38.59	20.75	7.28	9.68	10.98	12.72
40	38.36	20.91	7.34	9.69	11.13	12.57
45	38.2	21.01	7.41	9.7	11.26	12.41
50	38.09	21.09	7.49	9.71	11.39	12.24