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Abstract

This paper empirically investigates and identifies the main contributing factors to output and productivity growth in Australia for the period 1950-2005. Cointegration and a vector error-correction model are used along with Granger causality tests, impulse response functions and forecast error variance decomposition analyses to achieve these objectives. Accumulation of human capital and investments in information and communications technology (ICT) are identified as significant in the cointegration analysis of production in Australia and should be included in the long-run production relationship along with fixed capital and labour employed. The vector-error correction model estimates further provide evidence that human capital and ICT are important drivers of output growth in Australia, so their omission from standard productivity measures leads to inaccurate measures and may mislead policy formulation, planning and budgeting decisions.

Key Words: Australia, economic growth, productivity, cointegration, Granger causality, impulse response functions, forecast error variance decomposition, human capital and ICT

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I. Introduction

In the second half of the 19th Century Australia led the world in labour productivity and per capita GDP (Broadberry and Irwin, 2007). However, this high level of labour productivity was not sustained for long and the rate of productivity growth in Australia was comparatively low over most of the 20th century. Parham (2003) notes that Australia's gross domestic product (GDP) per capita was about 81 % of the then productivity leader, the USA in 1950 and it ranked 4th among a group of 22 developed or high-income countries. The post-war period from 1950-1990 saw some European countries including Japan and South Korea, start the catch up towards the USA and some even overtook the productivity leader. However, Australia's growth in average income (GDP per capita) was below the OECD average over this period. According to Parham, by 1990 this relative poor productivity growth meant Australia's ranking on level of GDP per capita moved from 4th to 15th among a group of 22 developed or high-income countries.

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. 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 15th to 7th in 2001. The consensus of the studies on Australia's productivity performance is that the microeconomic policy reforms that were introduced in the economy from the mid-1980s 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 technology, particularly information and communication technology (ICT), has been very strong in the 1990s in Australia.¹

Most studies of Australian productivity performance depend on the conventional growth accounting approach to provide total or multifactor productivity estimates. ABS (2003-2004) for instance provides multifactor productivity estimates for the aggregate Australian

¹ See Parham, 2004 for a survey of studies of Australian productivity growth.

economy extend back to the mid-1960s. However, the ABS considers capital and labour as the only inputs to production in calculating productivity growth for Australia. Also, the conventional growth accounting approach implicitly imposes assumptions of perfect competition and constant returns to scale.

The objective of the current paper is to measure and identify the determinants of output and of productivity growth in Australia. Rather than rely on growth accounting methods, this study utilises a times-series econometric approach. Johansen (1988) cointegration techniques are used to determine the long-run relationship between output and inputs to production, including human capital and ICT among the set of inputs. A vector error-correction model (VECM) is then used to carry out Granger causality tests, impulse response functions and forecast error variance decomposition analyses. The VECM provides a framework for examining the evolution of output, inputs and productivity in response to shocks.

The rest of the study is organised as follows. The next section discusses the data used for the empirical analysis and the methodology used to achieve the objectives of this study. Section III presents and discusses the results of the empirical analysis. Section IV summarises the main findings.

II. Data, Productivity Measurement and Methodology

Data

Five variables are selected as likely to be the key influences on output and productivity growth in Australia: gross domestic product (Y), fixed capital (K), labour employed (L), human capital (H) and information and communication technology (ICT). Annual data for 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 1950, representing the 1949-50 financial year.

Each of the variables in the analysis is measured as a flow. This is standard for GDP and labour employed, but here the capital variables, fixed capital, human capital and ICT, are also measured as flows. Thus, the fixed capital variable is gross fixed capital expenditure, measuring investment in capital plant and equipment. Likewise, investment in information and communication technology is measured by gross expenditure on computers and internet

service, electrical machinery and communication equipment. Finally, the proxy measure used for human capital is current enrolment in tertiary institutions.²

Expenditures on ICT are part of fixed capital expenditure. In this sense their inclusion as a separate variable may be viewed as double counting. However, the impact of investment on output can differ across investment types, particularly at the aggregate level when there are externalities associated with the investment. The ‘new economy’ literature argues that there are positive network externalities associated with investment in communication technology. DCITA (2005) reviews arguments for expecting ICT expenditure to have an impact on output beyond that associated with investment in other fixed capital. Connolly and Fox (2006) find evidence of an impact of ICT on multi-factor productivity growth in many sectors of the Australian economy, but suggest the evidence of excess returns is limited.

Human capital is included in this study as a separate influence on production, with a measure of human capital used similar to that employed by Romer (1989), World Bank (1994) and Madden and Savage (1998). In particular, human capital formation is assumed to be proportional to enrolment in tertiary institutions based on the idea that the contribution of intellectual capital to economic growth is proportional to the length of time spent in formal education to accumulate skill or training. This excludes human capital augmentation 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.

Annual data on GDP, fixed capital, labour employed, human capital and ICT are collected from the Australian Bureau of Statistics and Education Statistics of Australia data bases. 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 labour employed are taken from the Yearbooks Australia 1952-2006. The data for human

² The vector autoregressive (VAR) model used in estimating the long-run production relationship in this study incorporates up to three years lag on each of the included variables. Utilising capital stock measures, which are formed as weighted averages of current and lagged levels of investment expenditure, with the heaviest weights on recent observations, would be largely redundant and might introduce spurious relationships in the time series for capital. Particularly worrisome is the uncertainty regarding the proper depreciation treatment of different types of capital. If an incorrect depreciation rate is applied, the resulting capital stock series is subject to spurious autocorrelation.

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. The data on each of the five variables are reported graphically in Figure A1.

Productivity Measurement

Measurement of productivity is based on the economic theory of production. Solow (1957) shows how a measure of total factor productivity (TFP) can 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:

$$Y_t = F(K_t, L_t, t), \quad \text{or} \quad Y_t = A_t F(K_t, L_t) \quad (1)$$

where: Y , K , L and t are output, capital, labour and time, respectively.

From equation (1) the expression for total factor productivity (A_t) is:

$$A_t = \frac{Y_t}{F(K_t, L_t)} \quad (2)$$

A_t measures 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.

A standard approach to measuring TFP is to employ growth accounting 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. In this case, the rate of TFP growth is measured by:

$$TFP_t = \left(\frac{\Delta Y_t}{Y_{t-1}} \right) - S_K \left(\frac{\Delta K_t}{K_{t-1}} \right) - S_L \left(\frac{\Delta L_t}{L_{t-1}} \right) \quad (3)$$

where: $\Delta n \equiv n_t - n_{t-1}$, for $n = Y, K, L$. 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 elasticities of GDP with respect to the

respective factor. Having calculated the annual growth of TFP_t on the basis of (3), an index of TFP_t is then estimated by normalising to unity in the first year. The calculated growth rates of TFP_t are then used to construct the index for subsequent years. What makes this procedure controversial is that TFP is treated as a residual category.

Expression (3) is the so-called 'Solow-residual' and is widely used as the dependent variable in statistical analysis with factors of the sort suggested by Felipe (1999) as explanatory variables. However, this approach incorporates assumptions used in calculating TFP as maintained hypotheses. If the maintained hypotheses fail to hold, the dependent variable in the TFP regression is subject to errors and this can easily lead to bias in the estimated relationship.³

Methodology

As an alternative to the growth accounting approach, this study exploits time-series econometrics to analyse the movement of output and productivity in both the long run and the short run. Madden and Savage (1998) and Dowrick (2001) provide a start in this direction by applying time-series econometrics to the analysis of labour productivity in Australia. Dowrick finds evidence of a cointegrating relationship between labour productivity and capital intensity with an implied estimate of the long-run elasticity of output with respect to capital of 0.274. Madden and Savage also find evidence of a cointegrating relationship, with a implied estimates of the long-run elasticity for output of 0.453 with respect to capital and with respect to information and communications technology (measured by number of telephones) of 0.183.

Output rather than labour productivity (output per worker) is the key variable of interest in the present study. Use of output in place of labour productivity makes the restrictive assumption of constant returns to scale unnecessary. Modern "endogenous" growth theory, such as in Romer (1989), incorporates the insight that there are positive externalities for the aggregate economy, particularly associated with knowledge creation, which mean that the neoclassical assumption of diminishing returns to scale for capital expenditures need not hold for the aggregate economy. More broadly, the existence of such externalities opens the

³ These issues are discussed, but not resolved, in the contribution by Connolly and Fox (2006), which uses time-series data on multi-factor productivity in Australia to examine drivers of productivity growth including ICT and human capital. However, their study does not apply vector-error correction to separate the long-run relationship from the short-run dynamics.

possibility of increasing returns to scale for the aggregate production function, which would be expected to incorporate any external effects among sectors of the domestic economy.

In addition to allowing for increasing returns to scale, the production relationship in (1) is extended to consider other potential influences on output in the long run.⁴ In particular, human capital and investment in ICT are included for reasons discussed above. Inclusion of these knowledge-related inputs to production enhances the prospects of capturing externalities and thereby observing increasing returns to scale in production.

To achieve meaningful results from any sort of empirical analysis on long-run relationships between variables it is very important to test for the time-series properties of the data in question. Unit root tests that identify whether the variables are stationary or non-stationary have become the first step of any empirical analysis involving time-series data. There are a number of tests developed in the time-series econometrics for testing for the presence of unit roots. The two most popular tests, namely: the Augmented Dickey-Fuller (ADF) and the Phillips-Peron (PP) tests for testing the presence of unit roots in variables are employed in this study.

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. The Johansen procedure provides a unified framework for estimating and testing of cointegrating relations in the context of vector autoregressive (VAR) models. In the VAR system all variables are treated as endogenous. Based on a vector-error correction model (VECM) derived from the VAR model, Granger causality tests and the impulse response analysis are carried out. Granger (1988) argues that a prerequisite for two variables to establish a long-run equilibrium relationship is the existence of a dynamic causal relationship between them.

Impulse response analysis offers a technique for examining the VAR system dynamics that are reflected in the relative strength of the Granger causality. Impulse response functions trace out the impact on 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

⁴ A similar approach is taken by Agbenyegah et al. (2003) in their study of growth and productivity in New Zealand.

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. 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 $z = 1, 2, \dots, z$. The advantage of using variance decomposition lies in its ability to provide information about the relative importance of random innovations. In particular, it is able to provide information on the percentage of variation in the forecast error of a variable explained by its own innovations and the proportion explained by innovations in other variables in the system through the dynamic structure of the VAR. Sims (1980) notes that if a variable is truly exogenous with respect to the other variables in the system, own innovations will explain all of the variables' forecast error variance.

III. Results and Interpretation

Time-series properties

Unit root tests to GDP, fixed capital expenditure, labour employed, human capital accumulation and ICT expenditures by applying both the ADF and the PP tests are reported in Table 1. In general, the ADF and PP unit root tests results suggest that the time series LY is an integrated process of order 0; while LK, LL, LH, and LICT are integrated processes of order 1. As GDP is the main variable of interest in this analysis, it is included as a candidate variable in the cointegration relationship. An inclusion of a variable integrated in an order of $I(0)$ may be unnecessary to obtaining cointegration, but it provides a proper basis for establishing the long-run relationship between GDP and the other variables.

The next stage of the analysis determines whether these variables are cointegrated following Johansen and Juselius (1990) approach. Table 2 reports the results of the Johansen cointegration test for the null hypothesis of no cointegrating vectors under the trace statistic for the vector LY, LK, LL, LH and LICT. Each test is based on a vector autoregression with a lag length of three years based on model selection criteria. 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 value for the one percent critical value of

(76.07), indicating that there is at least one cointegrating vector. The null hypothesis of $r \leq 1$ 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.

Table 1: 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
LICT	2.1174	0.61351	1	2.63175	1.58139	1
1st Difference Series						
LK	-7.2535	-7.2578	1	-7.5102	-7.3642	3
LL	-4.8589	-5.1135	1	-6.3523	-6.4631	3
LH	-4.9526	-5.2994	1	-7.2623	-7.6592	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	
Critical Values 1st Difference						
1%	-3.5572	-4.1383		-3.5547	-4.1348	
5%	-2.9167	-3.4952		-2.9157	-3.4919	

Notes: Critical values from Mackinnon (1991). The optimal lag length is determined by Schwartz Information Criterion.

Table 2: Cointegration Test for the LY, LK, LL, LH and LICT

Vector	Null Hypothesis	Alternative Hypothesis	Eigen-value	Trace Statistic	Critical Value	
					5%	1%
LY, LK, LL, LH & LICT	$R = 0^{**}$	$r = 1$	0.588	89.22	68.52	76.07
LY, LK, LL, LH & LICT	$r \leq 1$	$r = 2$	0.344	43.13	47.21	54.46

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

Long-run relationship

The estimated long-run elasticity for each variable from the cointegrating relationship based on a vector autoregressive (VAR) model with up to 3 lags is presented in Table 3. Each variable has an estimated elasticity of the anticipated positive sign and is less than one as is consistent with diminishing returns to that variable as a factor of production. Further, each variable is found to be significantly related to GDP.⁵ The sum of the estimated elasticities is 1.07, which is greater than one and suggests the existence of increasing returns to scale. A log-likelihood ratio test statistic for the over-identifying restriction that returns to scale are constant (sum of elasticities equal one) is 12.9, which is above the 99% critical value of the χ^2 distribution with one degree of freedom, rejecting the constant return to scale hypothesis.

Table 3: Estimated Long-Run Coefficients

Regression Equation: Equation $LY_t = A_t + \alpha LK_t + \beta LL_t + \psi LH_t + \gamma LICT_t$			
Variable	Coefficient	Standard Error	t-ratio (probability)
LK	0.277	0.068	4.05 (0.000)
LL	0.547	0.084	6.51 (0.000)
LH	0.107	0.062	1.71 (0.038)
LICT	0.145	0.039	3.72 (0.000)
Intercept (A_t)	3.119		

Causality and short-run dynamics

A vector error-correction model (VECM) is used to examine causality and short-run dynamics in the long-run relationship. The results of the Granger causality test for the VECM are shown in Table 4. The F-statistics reported in Table 4 indicate that labour, human capital, and ICT Granger cause GDP, 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

⁵ Diagnostic tests for the significance of human capital and ICT generate log-likelihood ratio statistics for testing the over-identifying restrictions that the true coefficient is zero of 18.2 and 12.5, respectively, which are both above the 99% critical value of the χ^2 distribution with one degree of freedom.

cause GDP.⁶ 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. Thus, the Granger causality test results suggest that causality between GDP and each of the following production factors labour, human capital and ICT is bi-directional, while causality between GDP and fixed capital in the short run is also uni-directional and it runs from GDP to fixed capital.

Table 4: Granger Causality Tests for LY, LK, LL, LH, LFDI and LICT

Null Hypothesis:	F-Statistic	Prob.
LK does not Granger Cause LY	0.75112	0.3901
LY does not Granger Cause LK	5.85253	0.0191
LL does not Granger Cause LY	5.886	0.0188
LY does not Granger Cause LL	10.9453	0.0017
LH does not Granger Cause LY	37.2984	0.0000
LY does not Granger Cause LH	7.51958	0.0084
LICT does not Granger Cause LY	23.0711	0.0002
LY does not Granger Cause LICT	19.4883	0.0004

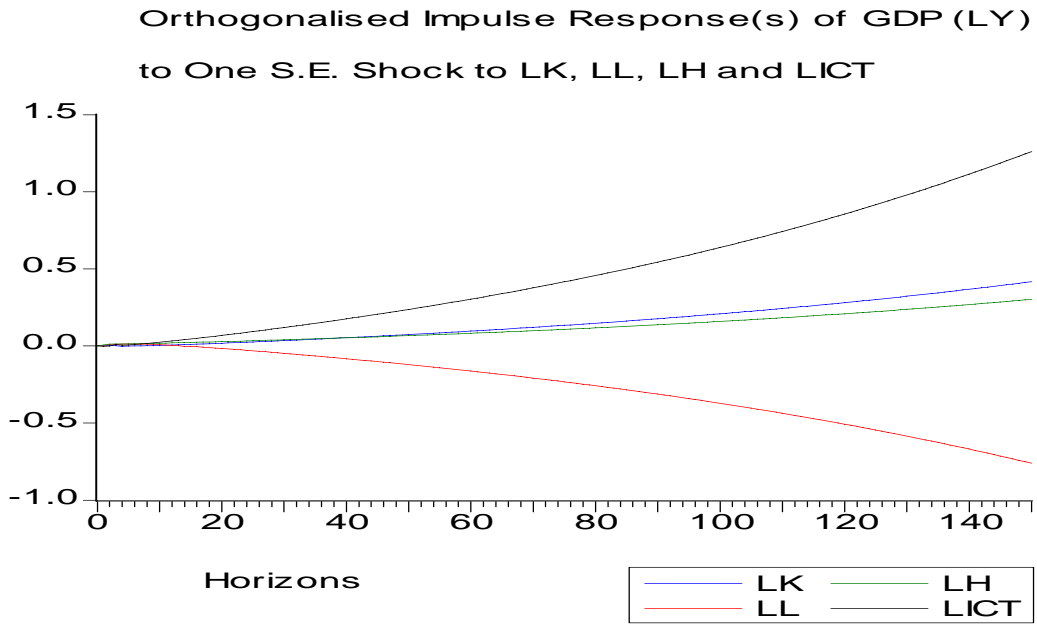
Notes: Lag order =1

The results of the Granger causality test suggest that human capital 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 impulse response functions and forecast error variance decomposition which are discussed next provide such information.

⁶ Our use of current expenditures on fixed capital in place of an accumulated stock variable means that the potential for measurement error due to an incorrect choice of depreciation rate is avoided. However, estimating the impact of fixed capital on GDP is still problematic when the aggregate relationship is unstable due to fluctuations in capacity utilisation, positive spillover effects (as in Romer's (1989) model of long-run growth) and negative spillover effects (as in Schumpeter's (1942) model of creative destruction).

The VECM is used to generate impulse response functions for shocks to each of the variables in the system. Figures 1 shows the orthogonalised impulse response functions for GDP (LY), labour (LL), fixed capital (LK), human capital (LH) and information and communications technology (LICT). As can be seen from the figures, GDP responds positively to shocks to fixed capital, human capital, and ICT. The effects are persistent and increase as the number of forecast horizons is increased, especially for ICT. The results further show that the response of GDP to a shock to labour is negative and persistent, even though there is a strong positive relationship between labour and GDP in the long-run coefficients shown in Table 3.

Figure1: 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



A final step in the analysis of short dynamics is variance decomposition for the forecast error. GDP (LY) is the primary variable of interest and its variance decomposition is shown in Figure 2 and Table 5. 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%. For the remainder of the variance in GDP 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.

Figure 2: Orthogonalised Forecast Error Variance Decomposition

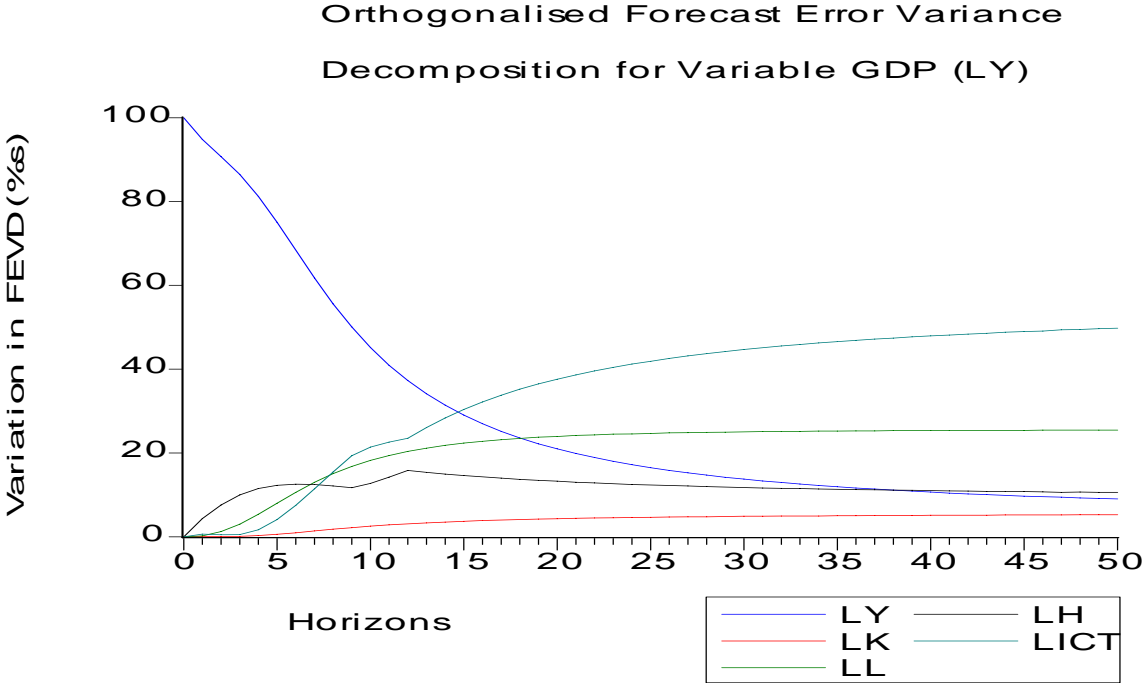


Table 5: Orthogonalised Forecast Error Variance Decomposition for Variable GDP (LY), LK, LL, LH and LICT.

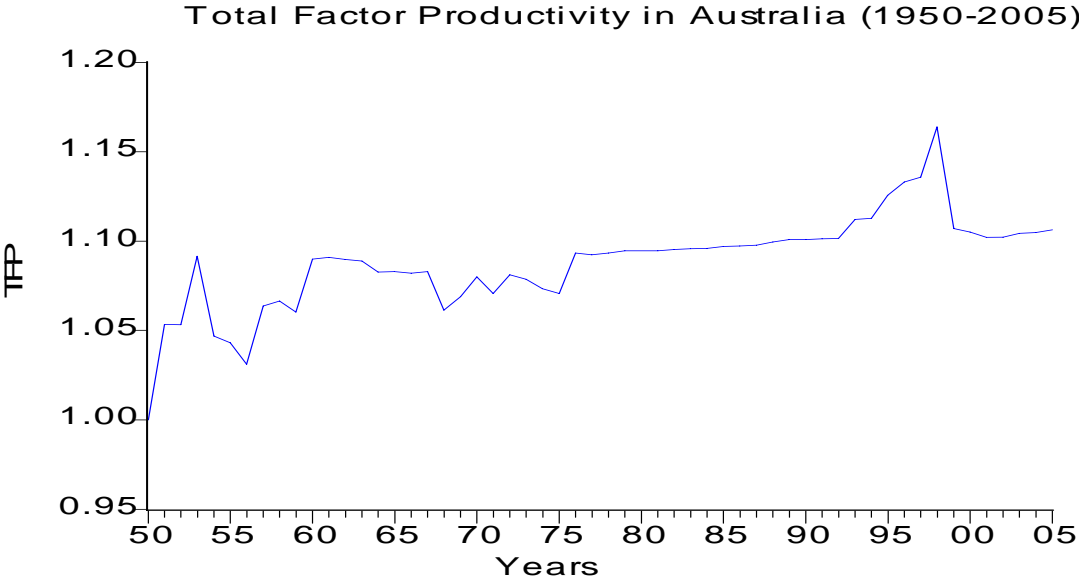
H	LY	LK	LL	LH	LICT
0	100	0	0	0	0
1	94.82	0.01	0.21	4.34	0.62
5	75.03	0.58	7.98	12.3	4.11
10	45.16	2.52	18.22	12.72	21.38
15	29	3.69	22.34	14.6	30.37
20	20.94	4.29	23.95	13.23	37.59
25	16.47	4.64	24.67	12.34	41.88
30	13.73	4.86	25.03	11.74	44.64
35	11.92	5	25.22	11.32	46.54
40	10.64	5.1	25.33	11.01	47.92
45	9.7	5.18	25.4	10.77	48.95
50	8.99	5.24	25.44	10.58	49.75

Productivity in Australia

Conventional measures of total factor productivity (TFP) growth from growth accounting consider only fixed capital and labour as inputs to GDP. The results in Table 3 based on an estimated cointegrating relationship suggest that human capital and expenditure on information and communications technology (ICT) also contribute to GDP in Australia. Further, the conventional TFP measures are based on restrictive assumptions of constant returns to scale and perfect competition. The test for constant returns to scale using the elasticity estimates in Table 3 leads to rejection of the null hypothesis of constant returns.

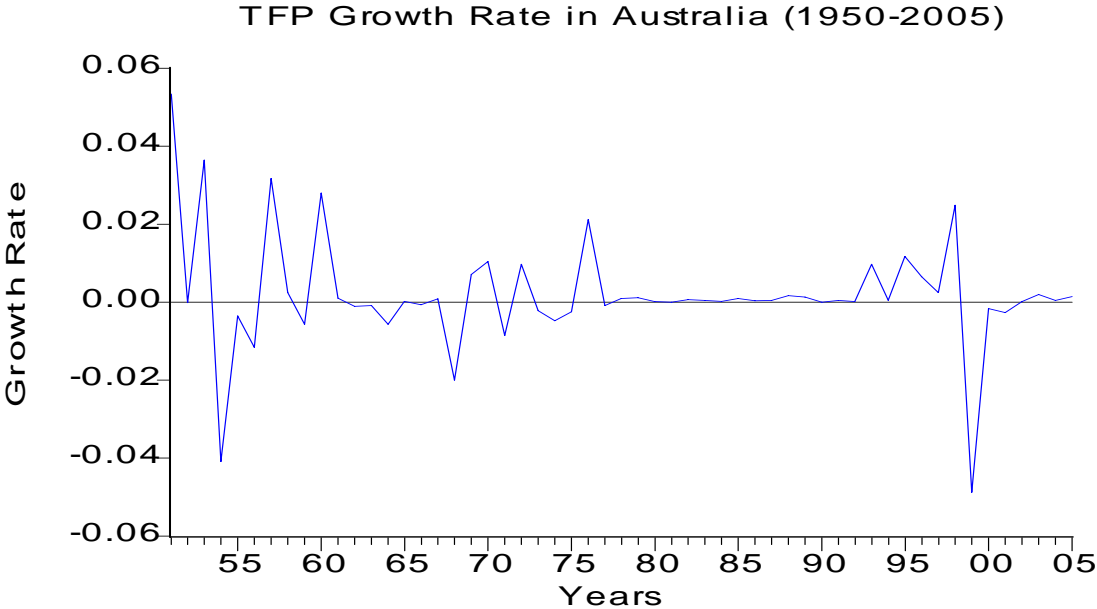
Applying the concept of TFP as the unexplained residual in a production function suggests an alternative measure of TFP. This measure is based on the formula in (2) above, but with human capital and ICT as additional inputs. Also instead of using shares from the national income accounts as weights in the calculation, the weights are the long-run elasticity estimates from Table 3. The resulting TFP estimates are shown in Figure 3, with TFP rising somewhat erratically to a level in 2005 that is some 10.6% higher than in 1950. TFP growth rates are shown in Figure 4, with the highest TFP growth rate achieved over the period 1950-2005 is 5.34% (1951) and the lowest TFP growth rate is -4.88% is achieved in 1999. The annual average growth rate of TFP estimates obtained for the period 1950-2005 is 0.193%.

Figure 3: Index of TFP in Australia (1950-2005) based on coefficients from Table 3



The ABS provides data on an index of multifactor productivity for the aggregate Australian economy for the period since 1965.⁷ The index is based on conventional growth accounting, with the weighted average growth in labour and fixed capital subtracted from aggregate output growth. With an index base of 100 for 2006, the 1965 value is 60.6 and the 2005 value is 99.8. The almost two thirds rise in productivity occurs over a shorter period than the increase of approximately ten percent shown in Figure 3 for the TFP index derived from the estimated long-run production relationship over the period from 1950 to 2005.

Figure 4: TFP Growth Rate in Australia (1950-2005) for LY, LK, LL, LH and LICT.



In part the slower rise in TFP in Figure 3 than in the ABS measure is explained by the fact that the calculation of TFP in Figure uses a sum of the weights on inputs that exceeds one. The elasticity estimates from Table 3 on which these weights are based support the hypothesis of increasing returns to scale, rather than the assumption of constant returns to scale, and sum of weights equal to one, that is implicit in the ABS measure. Further, substantial weight is given to both human capital and ICT as inputs to production, which are each growing faster over the comparison period than are labour and fixed capital inputs. TFP as a residual measure of productivity gains has been diminished compared to the ABS measure by separating out the

⁷ Australian Bureau of Statistics (ABS), Australian System of National Accounts, Catalogue 5204.0, Table 22.

contribution from human capital and ICT, and by removing the productivity bonus associated with increasing returns to scale. It is important to note that by including human capital and ICT in the explanation of output growth, two of the key factors driving technical progress are no longer part of the residual TFP. Thus, technical progress is incorporated into the explanation of output growth, as is appropriate from the perspective of endogenous growth theory.

IV. Conclusions

Time-series econometrics are used in this study to investigate and identify the main contributing influences on growth and productivity in Australia. An advantage to this approach as compared to conventional growth accounting is that it is unnecessary to implicitly impose the restrictive assumptions of perfect competition and constant returns to scale. Also, it is possible to allow for contributions from inputs that are normally excluded from the growth accounting calculation even though they are identified as important drivers of growth in the modern theory of economic growth. In particular, human capital and ICT are included in the estimates presented here. Finally, the introduction of lagged values of the capital variables makes it unnecessary to impose assumed depreciation regimes to accumulate current expenditure into measures of capital stock.

Based on the results of unit root tests on the individual variables, the long-run production relationship is estimated by applying vector autoregression to the following variables: GDP, labour, fixed capital, human capital and expenditure on information and communications technology (ICT). The results suggest that, in addition to fixed capital and labour employed, human capital and ICT are also significantly related to GDP in Australia and should be included in the production relationship. Further, the results reject the hypothesis of constant returns to scale in the production relationship and, instead, provide evidence that there are increasing returns in the aggregate Australian production relationship.

The estimated coefficients of the long-run relationship are used to calculate a measure of TFP for Australia. The calculated index shows an increase of only about ten percent over the period of 1950 to 2005. This compares to a rise of some two thirds in the conventional growth accounting index of multifactor productivity provided by the ABS over the shorter period 1965 to 2005. The difference in productivity measures is attributed to a combination of

increasing returns to scale and the rapid growth in human capital and ICT, which are not explicitly included in the conventional growth accounting. Thus, as predicted by the modern theory of economic growth, use of the time-series econometrics approach to examine growth and productivity leads to a much smaller unexplained residual productivity bonus than does conventional growth accounting.

Results are also presented for tests of causality and for the short-run dynamics of the production relationship. Granger causality tests show that human capital and ICT, in addition to fixed capital and labour, have a significant causal role in explaining the evolution of aggregate GDP. Further, the analysis of impulse response functions demonstrates that shocks to human capital and ICT have persistent impacts on output growth in Australia. Finally, analysis of decomposition of forecast error for GDP indicates that a substantial proportion of deviations from trend growth in GDP are attributable to shocks in accumulation ICT in particular. Overall, the findings suggest that human capital and ICT are each important to the explanation of the observed pattern of GDP growth in Australia in both the short run and the long run.

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Appendices

Figure A1: Graphs of the Series LTFP, LK, LL, LH and LICT

