The Public R&D and Productivity Growth in Australian Broadacre Agriculture:

A Cointegration and Causality Approach

Farid Khan and Ruhul Salim

Author contact details

Farid Khan, Curtin University, faridecoru@yahoo.co.uk
Ruhul Salim, Curtin University, Ruhul.Salim@cbs.curtin.edu.au

Contributed presentation at the 59th AARES Annual Conference,
Rotorua, New Zealand, February 10-13, 2015

The Public R&D and Productivity Growth in Australian Broadacre Agriculture: A Cointegration and Causality Approach

Abstract: *This study investigates the nexus between research and development expenditure and productivity growth in Australian broadacre agriculture using country-level time-series data for the period 1953 to 2009. Using standard time-series econometrics data are analysed to examine the dynamic relationships between research and development expenditure (R&D) and total factor productivity (TFP) growth. Findings here provide econometric evidence of a co-integrating relationship between R&D and productivity growth, and a unidirectional causality emergent from R&D to TFP growth. Moreover, employing variance decomposition and impulse response function the dynamic properties of the model are explored beyond the sample periods. Findings suggest that R&D can be readily linked to the variation in productivity growth beyond the sample periods. Further, forecasting result suggests a significant out-of-sample relationship exists between the public R&D and productivity in broadacre agriculture. We used a novel method MIRR which is conceptually superior than the conventional IRR to obtain a credible estimate of returns on public research investment. We found MIRR of 10.06% per year for the reinvestment rate of 3% per year. Therefore, results establishing long run relationship between productivity and R&D in Australian agriculture shed light on the future policies in R&D investments in Australia.*

Keywords: Public Research & Development (R&D), Productivity, Australian Broadacre Agriculture, Cointegration, Internal Rates of Return.

JEL Classification: C32, Q16

1. Introduction

Research investments in agriculture are the central to the improvements in agricultural productivity growth, which is a crucial means for achieving economic prosperity and development in an economy (Pardey et al., 2006; Mullen, 2010). A number of studies have been examined the effects of research and development (hereafter, R&D) on total factor productivity (hereafter, TFP) in the agricultural sector. Many of them provide empirical evidence that R&D, both domestic and foreign, is one of the main sources of productivity growth (Hall and Scobie, 2006; Griliches, 1979, 1988; Coe and Helpman, 1995). In recent decades, the concern has been that productivity in agriculture is falling particularly in developed economies.

The declines in the agricultural productivity have renewed interest in the productivity analysis, particularly in the estimation and explanation of the effects of R&D in agriculture. Few studies examining the possible causes of the recent declines in the agricultural productivity growth find the falling public R&D investment in agriculture over past decades as one of the possible causes (Mullen, 2010; Alston and Pardey, 2001; Bervejillo et al., 2012). For example, Piesse and Thirtle (2010) mention a slowdown and retargeting of public R&D as one of the key factors that is primarily causing a slowdown in TFP growth in the United Kingdom. Similar evidence of slowing productivity is also found in the US agriculture (Ball et al, 2013) in recent periods. Studies also provide empirical evidence of long run relationship between research expenditure and agricultural productivity growth in the developed countries such as UK agriculture (Thirtle et al., 2008; Schimmelfenning and Thirtle, 1994) and US agriculture (Wang et al., 2013; Alston et al. 2011).

The falling productivity growth is also evident in Australian agriculture. Recent studies found a slowdown in productivity growth in Australian agriculture over the recent decade compared to earlier periods (Nossal and Sheng, 2010; Sheng, Gray and Mullen, 2011; Khan, Salim and Bloch, 2014). Keating and Carberry (2010) stated that one recent challenge for Australian agriculture is that it has been facing slow agricultural productivity growth in recent periods. They suggest that this decline in productivity growth can be attributed to the lagged impact of the public investment in agricultural research, which is stagnated since 1970s. Some previous studies estimated the rate of return to R&D expenditure in Australian broadacre agriculture and indicated that public investment in agricultural R&D is contributing to TFP growth. In the early 1990s, Mullen and various co-authors conducted a series of econometric research with agricultural R&D and productivity in Australia. Using a unique data set, they found R&D is a major source of productivity in Australian agriculture. Extending their previous data set, Mullen (2007) revisited their previous study and found no evidence that rates of return were declining over the years 1953-2003.

Though previous studies on Australian broadacre agriculture have estimated the growth of TFP over recent decades, the empirical evidence with regard to what determines the slowing TFP growth is apparently very little. Besides, most of their studies have emphasised returns to agricultural research and thus could not confirm the existence of a stable long-term co-integrating relationship between research and productivity growth. To date, there have been very few studies undertaken in Australia that examine the long-run relationship between R&D and productivity growth in Australian broadacre agriculture. To the best of our knowledge, we only find Salim and Islam (2010) explored long-run relationship between R&D and agricultural productivity in broadacre agriculture in Australia. They applied standard time series techniques to investigate the long-term and causal relationship between R&D and TFP but their results are limited for Western Australian broadacre agriculture and do not based on a large time-series data.

This study, therefore, aims to fill this empirical gap examining the relationship between public R&D spending and productivity growth in Australian broadacre agriculture. To achieve this objective this study applies cointegration and Granger causality in order to investigate the relationship between R&D and TFP and the direction of causality running between them. Moreover, it applies variance decomposition, impulse response function and a forecasting exercise to explore the dynamic properties of the relationship beyond the sample periods.

The rest of the study proceeds as follows. The next section gives a short overview of public R&D and agricultural productivity in Australia. Section 3 presents econometric methodology of cointegration and causality tests. A model is specified on what factors affect total factor productivity in section 4. A discussion on data source is followed by in section 5. Section 6 presents empirical estimates and analysis of results. The penultimate section estimates the benefits of research. Finally, Section 8 concludes the study.

2. The Public R&D and Broadacre Agricultural Productivity in Australia

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

The public sector plays a dominant role in R&D investment in Australian agriculture, which accounts generally more than 90 per cent of total agricultural R&D. This statistic strongly contrasts to other OECD countries where the share of private R&D is more than half of the total investment in agricultural R&D (Sheng et al., 2011). Thus, the level of public investment in agricultural R&D and its impact on agricultural productivity have been an important candidate in terms of public policy issue in Australia. However, the concern is that it has been falling in recent periods apparently since 1994. Before 1994, broadacre has experienced about 2.2 per cent of growth in productivity a year, but it has faced a slowdown in productivity growth thereafter. Since 1994, it has declined to 0.4 per cent a year. However, some recent studies indicate that the sluggishness in public R&D since the mid-1970s may have contributed to the slowdown in agricultural productivity growth in recent periods (Sheng et al., 2011; Mullen, 2010).

3. Econometric Methodology: Cointegration and Causality

3.1. Testing for the Order of Integration of the Variables

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

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

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

$$\Delta Y_t = \beta_1 + \beta_2 + \delta Y_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta Y_{t-i} + u_t \qquad (2)$$

Phillips and Perron have developed a more comprehensive test of unit root non-stationarity. Their tests are similar to ADF tests, but they address the issue of autocorrelation by incorporating an automatic correction to the Dickey-Fuller t-test statistic, which allows for unspecified autocorrelation in the disturbance process. Most of the cases the tests give conclusions similar to the ADF tests.

3.2. Testing for Cointegration

The Johansen technique based on VAR Model

This VAR-based cointegration test proposed by Johansen (1995) uses the Maximum Likelihood estimation methodology to test for the cointegration rank *r,* which represents the number of independent cointegrating vectors. It is more generally applicable than the traditional Engle–Granger two-step methodology to explore a single cointegrating relationship. The VAR approach models every endogenous variable within the system. The following mathematical form gives the VAR of order *p* in standard form:

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + \varepsilon_t \qquad (3)$$

where y_t is a *k* vector of endogenous variables that are integrated of order one, *I(1),* and A_1 ... A_p are (*k x k*) matrices of coefficients to be estimated, and ε_t is a vector of disturbances that are serially uncorrelated with all the right-hand side variables. The issue of simultaneity does not arise in this specification as all endogenous variables of (3) are only predetermined lagged variables. Hence, each equation in the system can be estimated using *OLS* technique, which gives consistent and asymptotically efficient estimates.

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

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t \qquad (4)$$

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

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

The number of cointegrating vectors can be obtained based on significance of the number of characteristic roots λ of the coefficient matrix Π, as the rank of a matrix is equal to the number of its characteristics roots. Johansen proposes two types of likelihood ratio test: the trace test and maximum eigenvalue test for the number of characteristic roots using the following two statistics:

$$\lambda_{trace} = -T \sum_{i=r+1}^{k} \ln(1-\hat{\lambda}_i) \qquad (5)$$

$$\lambda_{\max} = -T \ln(1-\hat{\lambda}_{r+1}) \qquad (6)$$

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

3.3. Vector Error Correction Model

The evidence of cointegration only suggests an existence of a long-term, or equilibrium relationship[1] between time series variables under consideration. It does not consider the short-term dynamics of the model explicitly. However, the presence of cointegration among variables does not necessarily rule out short-term disequilibrium among them. The Granger representation theorem states that a cointegrated system of variables can be expressed as an error correction model (ECM) (Engle and Granger, 1987). The ECM reconciles the short-run behaviour of variables with its long-run behaviour using the error term of the cointegrating equation, which is also termed as 'equilibrium error'.

As a simple example, for the two-variable case with only one lagged difference the ECM can be written as:

$$\Delta y_{1t} = \alpha_1 (y_{2t-1} - \beta_1 y_{1t-1}) + \beta_{11} \Delta y_{1t-1} + \beta_{12} \Delta y_{2t-1} + \varepsilon_{1t} \quad (7)$$

$$\Delta y_{2t} = \alpha_2 (y_{2t-1} - \beta_1 y_{1t-1}) + \beta_{21} \Delta y_{1t-1} + \beta_{22} \Delta y_{2t-1} + \varepsilon_{2t} \quad (8)$$

where Δ denotes the difference operator, y_1 and y_2 are the two variables of integrated of order one, and ε_t is a random error term which is independently and identically distributed. The inclusion of lags of the dependent variable as the explanatory variable to the regression is necessary as the dependent variable itself may be correlated with its lags. Note that the error correction term $(y_{2t-1} - \beta_1 y_{1t-1})$ is one-period lagged value of error u_{t-1} from the cointegrating equation, which equals zero in a long-run equilibrium relationship. However, if it is non-zero, variables adjust in the short run to correct the equilibrium error to make the model equilibrium. In the short-run, the error correction term is non-zero and each variable adjusts to restoring the equilibrium. The coefficients α_1 and α_2 are the adjustment parameters, which represent the speed of adjustment in error correction mechanism. The ECM has both long-run property, which is built in error correction term, u_{t-1} and short-term property, which is captured by the error correction coefficient α .

3.4. Granger Causality

[1] Long-term relationship measures at the level form of the variables while short-run dynamics measure at the first-differences of the variables.

Granger causality is used to shed light on the direction of possible causality between pairs of variables. According to the Granger representation theorem, there will be Granger causality in at least from one direction if two variables integrated of order one, *I(1),* are cointegrated. In a simple model with two variables, y_1 and y_2, Granger causality tests whether past values of y_1 help in predicting y_2 given the effects of past values of y_2 on y_2 are accounted for. If they do, then y_1 is presumed to "Granger causes" y_2. Granger causality can be examined using following VAR framework of order-*p*:

$$y_{1t} = \beta_{10} + \beta_{11} y_{1t-1} + \ldots + \beta_{1p} y_{1t-p} + \alpha_{11} y_{2t-1} + \ldots + \alpha_{1p} y_{2t-p} + \varepsilon_{1t} \qquad (9)$$

$$y_{2t} = \beta_{20} + \beta_{21} y_{2t-1} + \ldots + \beta_{2p} y_{2t-p} + \alpha_{21} y_{1t-1} + \ldots + \alpha_{2p} y_{1t-p} + \varepsilon_{2t} \qquad (10)$$

The equation (9) models y_1 as a linear function of its own lagged values, plus lagged values of y_2. If lagged values of y_2 have non-zero effects on y_1, then y_2 Granger causes y_1 conditional on the effects of its own lagged accounted for. In this simple VAR, Granger causality testing sets the null hypothesis that y_2 does not Granger causes y_1.

$$H_0 : \alpha_{11} = \ldots = \alpha_{1p} = 0.$$

This joint hypothesis can be tested using a standard Wald F or χ^2 test, since each individual set of parameters restricted is drawn from only one equation. Similarly, in equation (10) the null hypothesis that y_1 does not Granger causes y_2 can be expressed as

$$H_0 : \alpha_{21} = \ldots = \alpha_{2p} = 0.$$

If y_1 cases y_2, lags of y_1 should be significant in the equation for y_2. If it does so and no vice versa, they indicate that there exists unidirectional causality from y_1 to y_2. On the other hand, if y_1 cases y_2, lags of y_1 should be significant in the equation for y_2. If it does so and not vice versa, they indicate that there exists unidirectional causality from y_1 to y_2.

4. Model Specification

On modelling the relationship between total factor productivity and research expenditures, this paper employs a production function approach of the following form:

$$TFP_t = A_t R \& D_{t-i}^{\beta_1} FR \& D_t^{\beta_2} ENROL_t^{\beta_3} \qquad (11)$$

where t is a time index; *R&D* is lagged domestic public R&D expenditures (or R&D stocks) in broadacre agriculture; *FR&D* is foreign public R&D, which is proxied by US R&D in agriculture; *ENROL* is a measure of farmer education, which is proxied by school enrolment; and *TFP* is total factor productivity. *A* is the part of TFP not caused by the included variables and β s are the respective weights to the factors mentioned. The functional form is specified as log-linear - the four variables are all in logarithmic term. Given limited guidance in the economic theory regarding the short-run and the long-run dynamic relationships between TFP and R&D, we adopt a modelling strategy based upon the information provided by the time-series data. Hence, we use an unrestricted VAR model that allows data to speak to the possible links and directions among the variables of interest.

To control the spillover effects of foreign research this study uses R&D expenditure in US agriculture as a proxy for the foreign R&D expenditure. US play a significant role in global agricultural R&D in relation to its investment and in terms of research spillovers (Alston, 2002; Sheng et al., 2011). Besides, Australia maintains a considerable economic and trade relation with US. Moreover, assuming the effects of foreign research and development usually depend on how the country is exposed to foreign trade, we construct and use an import-share-weighted US R&D variable to the model following Coe and Helpman (1995) rather than simply using US R&D as a crude proxy for foreign R&D. Because, it is often assumed that the transfer of knowledge and technology between countries depend on trade channel, which facilitates access to the outputs of foreign R&D, thereby enhance productivity (Ang and Madsen, 2013).

Another control variable is farmers' education, which is proxied by school enrolment (*ENROL*) i.e. the proportion of primary school-age students in the total population enrolled in primary schools in rural areas. Inclusion of human capital is natural in the TFP regressions because education makes people better to organize work, communicate, and help to be innovative, all of which contribute to a higher productivity level.

5. Data

This study uses the country-level time-series data for the period 1953 to 2009. The broadacre TFP index is measured by the Australian Bureau of Agricultural and Resource Economics

Society (ABARES), which is estimated as the ratio of a Fisher quantity index of total output to a Fisher quantity index of total input. Empirically, TFP growth is measured as a part of farm output growth, which is not contributed by growth of the factor inputs to the control of farmers (Solow, 1957). TFP thus includes the effects of advances of knowledge or technological progress along with other factors affecting it (Jorgenson and Griliches, 1967). A complete description of how ABARES constructs TFP index for the broadacre industries can be found in Gray et al. (2011).

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

Total R&D expenditure on agricultural production in US to proxy for foreign R&D expenditure is collected from US Department of Agriculture (USDA). This data is weighted by trade openness, the percentage of the agricultural imports to the agricultural gross value of farm production (GVP) in Australia. Agricultural GVP is obtained from ABARES and imports of agricultural crops and livestock products are obtained from FAO statistics. However, trade openness data is extrapolated backwards for the period 1953 to 1960 using actual data from 1961 to 2009. Similarly, school enrolment is also extrapolated backwards for the period 1953 to 1970 using the actual data. This study uses the World Development Indicators database to obtain data on the proportion of primary school-age students in the total population enrolled in primary school in Australia to proxy for the level of education of broadacre farmers.

6. Empirical Results and Discussion

6.1. Unit root test

We investigate the time-series properties of the variables using two widely used unit root tests, the Augmented Dickey-Fuller (ADF) and the Philips-Peron tests. Table 3.1 reports the test statistics for the time-series data covering the period 1953-2007 in their natural form. The results show that all variables TFP, public agricultural R&D expenditures, farmer education and foreign R&D expenditures are non-stationary in their levels, but they are stationary in the first differences, or integrated of order one, *I(1)*. We also find similar integration order for all variables by Phillips-Perron tests statistics.

Table 3.1 Unit Root Tests: ADF and Phillips-Perron

Variables	ADF Test		Phillips-Perron Test		Order of Integration
	P-value	Intercept, Trend and Intercept	P-value	Intercept, Trend and Intercept	
TFP	0.75	Intercept	0.67	Intercept	
ΔTFP	0.00	Both	0.00	Both	I(1)
R&D	0.36	Both	0.99	Both	
ΔR&D	0.00	Both	0.00	Both	I(1)
FR&D	0.42	Intercept	0.08	Both	
ΔFR&D	0.00	Both	0.00	Both	I(1)
ENROL	0.20	Intercept	0.54	Both	
ΔENROL	0.01	Both	0.01	Both	I(1)

Note: In case of *Both* test statistics are reported for *Trend and Intercept*.

Table 3.2 Zivot Andrews Unit Root Tests

Series	Level	Break at	First diff.	Break at	Lag length
TFP	-7.985***	1999	-7.935***	2001	1
R&D	-4.173	1980	-5.497**	1984	1
FR&D	-3.018	1983	-12.082***	1979	1
ENROL	-6.110***	1975	-4.739	1981	1

Critical values: 1%: -5.57 and 5%: -5.08; *** significant at 1% level, ** significant at 5% level. Note: Breaks are considered both in intercept and in trend. All variables are in logarithm form.

However, the standard unit root tests may not be appropriate if the concerned series contain any structural breaks (Bloch et al., 2012; Shahiduzzaman and Alam, 2012). The results of ADF or PP tests might lead to conclude a non-stationary series as stationary because of not allowing breakpoint in the series if any. Considering the possibility of a structural break in the data series this test can be treated as a cross check of the other usual unit root tests. Table 3.2 shows the results from the Zivot-Andrews tests (Zivot and Andrews, 1992) considering structural breaks in the series if any. Similar to the Dickey-Fuller test, the Z-A test also maintains the null hypothesis of a unit root in the process, i.e., non-stationary series. The Z-A test suggests to reject the null of *I(1)* for all variables as the t-statistics are larger than the critical values, which substantiate the unit root results of stationarity in first difference found in two other tests ADF and PP. However, for TFP and Enrol variables, we cannot reject the null of *I(0)* suggesting they are integrated in the levels while we consider the structural break in the series.

6.2. Cointegration and VEC Model

6.2.1. Cointegration test: Johansen Approach based on VAR

To test for cointegration using Johansen approach, we need first to specify how many lags to include in the VAR model with *I(1)* variables. Table 3.3 presents the statistical results for determining optimal lag length. As there is no explicit theory to guide optimal lag lengths, we rely on different statistical techniques commonly applied to the literature in selecting the optimal lag for the VAR model. Results indicate that the sequential modified likelihood ratio (LR) test, the Schwarz information criterion (SC) and the Hannan-Quinn information criterion (HQ) suggest for only one lag in the model, as indicated by "*" in the table. Results reported in Table 3.3 show that according to LR and AIC methods the number of optimal lag is three though two other tests SC and HQ favour two lags.

Table 3.3 Selection of the number of VAR lags

Endogenous variables: LnTFP LnR&D LnFR&D LnEnrol

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

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

Determining the common integration properties of all the variables in the model as well as selecting the number of optimal lag, we can proceed to test the presence of cointegrating vector. However, as all the variables are stationary in the first difference i.e. I(1), there may present a cointegrating relationship in the model. We use multivariate maximum likelihood approach of Johansen and Juselius (1990) which allows estimation of multiple cointegrating relationships. The results for trace test and eigenvalue test are presented in Table 3.4. The results suggest rejecting the null hypothesis of no cointegrating vectors but cannot reject the hypothesis of at most one cointegrating equation according to the tests statistics. Both Trace test and Max-eigenvalue test indicate one cointegrating equation at 5% significance level.

Table 3.4 Cointegration Tests: Johansen and Juselius Approach

Series Tested: *LnTFP LnR&D LnFR&D LnEnrol*

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

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

6.2.2. Vector Error Correction Model: Johansen and Juselius Method

Having established cointegration, we can proceed to test the short-run dynamic relationship between variables. Table 3.5 presents the test results for error correction by using Johansen-Juselius vector error correction method for different lag specifications of R&D. In the table, *Panel A* shows result for 12 years of lag value of R&D, following a study by Thirtle et al. (2008) in UK agriculture where they used 12 years lag structure. This type of lag structure has been fitted to other studies as well, including Salim and Islam (2010), Piesse and Thirtle (2010), and Schimmelpfennig and Thirtle (1994). The result of statistically significant and non-zero equilibrium error term provides the evidence of the adjustment of the short-run disequilibrium condition towards the long-run equilibrium for the model.

In addition, *Panel B* and *Panel C* report results based on R&D stocks constructing by two alternative specifications of R&D lag structure: perpetual inventory method (PIM) and gamma distribution, respectively. Under the PIM method, R&D stocks are calculated assuming a depreciation rate fixed at 5%. In panel C, R&D stocks are calculated assuming a gamma distribution with 30-year research lag length. Given the data limitation and considering the relatively applied nature of public agricultural R&D in Australia, we allow 30-year lagged specifications of the research impacts on productivity, which is consistent with previous studies in Australian broadacre agriculture e.g., Cox et al., (1997). Following Alston et al. (2011) the parameters of the gamma lag distribution are assigned with values of λ= 0.70 and δ= 0.90. Results show that in ΔTFP equation the equilibrium error term is statistically significant and non-zero reflecting adjustment of the short-run disequilibrium condition towards the long-run equilibrium. The negative value to the adjustment coefficient, which gives the required sign, suggests that ΔTFP will be negative about restore the equilibrium for the system. This implies that agricultural TFP growth responds to shocks from the R&D spending.

Table 3.5 Error-correction model

Panel A. **12-year Lag** R&D

alpha	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ΔTFP_t						
_ce1 L1.	-.9045544	.203866	-4.44	0.000	-1.304125	-.5049843
$\Delta R\&D_{t-12}$						
_ce1 L1.	.134605	.1946363	0.69	0.489	-.2468751	.5160851
$\Delta FR\&D_t$						
_ce1 L1.	-.12445	.4385757	-0.28	0.777	-.9840427	.7351426
$\Delta ENROL_t$						
_ce1 L1.	-.0032984	.0193497	-0.17	0.865	-.0412231	.0346264

Panel B. With R&D Stocks (PIM)

alpha	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ΔTFP_t						
_ce1 L1.	-1.02207	.1928832	-5.30	0.000	-1.4001	-.644026
$\Delta R\&DS^{PIM}$						
_ce1 L1.	.0219243	.0264405	0.83	0.407	-.02989	.0737468
$\Delta FR\&D_t$						
_ce1 L1.	-.0176685	.3991445	-0.04	0.965	-.79997	.7646404
$\Delta ENROL_t$						

_ce1 L1.	-.0139582	.0169274	-0.82	0.410	-.04714	.0192189

Panel C. With R&D Stocks (Gamma distribution)

alpha	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ΔTFP_t						
_ce1 L1.	-.57612	.16401	-3.51	0.000	-.89757	-.25467
$\Delta R\&DS^{gamma}$						
_ce1 L1.	.05386	.01226	4.39	0.000	.02983	.07790
$\Delta FR\&D_t$						
_ce1 L1.	.09381	.28146	0.33	0.739	-.45783	.64545
$\Delta ENROL_t$						
_ce1 L1.	-.00985	.01211	-0.82	0.416	-.03359	.01388

The detail results of the cointegrating equations are reported in appendix Table A.3.1 with Johansen's normalization restriction is imposed on TFP to be unity. The estimated parameters of the cointegrating vector are exactly identified, and the model fits well. Overall, the outputs indicate the existence of an equilibrium relationship between the TFP and R&D. The results of normalized cointegrating coefficients are presented in the following cointegrating relationship for different specifications:

$$LnTFP = 7.23 + 0.156 LnR\&D_{t-12}^{***} + 0.028 LnFR\&D_t - 0.84 LnENROL_t^{***} \quad (12)$$

$$LnTFP = 11.25 + 0.187 LnR\&DS_t^{PIM\,***} + 0.019 LnFR\&D_t - 1.91 LnENROL_t^{**} \quad (13)$$

$$LnTFP = 16.7245 + 0.306 LnR\&DS_t^{gamma\,***} + 0.105 LnFR\&D_t - 3.022 LnENROL_t^{**} \quad (14)$$

The normalized cointegrating equation (12) considers 12 years of R&D lag. Equations (13) and (14) specified with research stocks based on PIM and gamma distribution, respectively. In all specifications, the beta coefficients for R&D are positive and statistically significant across different R&D lag length structure. This beta coefficient indicating positive relationship between lagged R&D and TFP can be considered as long-term marginal effects on TFP. As we used double logarithmic functional form, the beta coefficients can be interpreted as long-term elasticity. In addition, foreign R&D is positively related to TFP, though the coefficients are not significant. However, though it is likely that the enrolment coefficient is positively related to TFP in the long run, but in the model, the result shows a negative relationship between them.

We use the LR test for linear restrictions to see whether the beta coefficients are significant in the cointegrating relationship. Table 3.6 reports the chi-squared test statistics for zero restrictions (coefficient restricted to zero) tests to see whether each of the variables can be excluded from the cointegrating space. Results suggest that R&D (both 12-year lagged R&D and research stock based on gamma distribution) contributes significantly to the cointegrating relationship. This outcome does valid our model that R&D has a long-run impact on the TFP. The result also shows that TFP and Enrol variables enter the cointegrating relationship significantly since each restriction is rejected at the 5% level. In addition, foreign R&D cannot be excluded from the model at 10% significant level.

Table 3.6 LR test for exclusion of variables from cointegrating space (zero restriction)

	12 Years R&D Lag		R&D Stocks Gamma distribution	
	chi2	p-value	Chi2	p-value
$LnTFP_t$	13.828	0.000	21.19	0.000
LnR&D	4.087	0.043	19.85	0.000
$LnFR\&D_t$	3.029	0.082	2.665	0.103
$LnENROL_t$	6.781	0.009	5.346	0.021

z statistics in the parentheses

6.2.3. Specification testing

We conduct a series of diagnostic tests to check specification of the model, which is crucial for the validity of the estimates and inferences of the model. Table 3.7.a reports result for checking the stability condition of VECM estimates. The results suggest that we have correctly specified the number of cointegrating equations as we find $K - r$ (K endogenous variables and r cointegrating equations) unit moduli in the stability tests and the remaining moduli are strictly less than one. In addition, we also perform LM test for autocorrelation in the residuals. Result reported in Table 3.7.b suggests that we cannot reject the null hypothesis that there is no autocorrelation in the residuals at either lag order one or two. Thus, test indicates no evidence of autocorrelation in the model.

Table 3.7.a Eigenvalue stability condition

Eigenvalue	Modulus
1	1
1	1
1	1
0.7354733	0.735473
-0.4575463	0.457546

0.3426255 + 0.1186199i	0.362578
0.3426255 - 0.1186199i	0.362578
-0.1185675	0.118567

The VECM specification imposes 3 unit moduli.

Table 3.7.b Lagrange-multiplier Test

lag	chi2	df	Prob > chi2
1	17.55	16	0.35034
2	20.21	16	0.21081

H0: no autocorrelation at lag order

6.3. Granger Causality Tests

To explore the direction of the causality among the variables in the cointegrated vector, we applied Granger causality test. The presence of one cointegrating vector implies that there should be Granger causality in one direction. Table 3.8.a presents the Granger causality Wald test based on vector autoregressions to establish the direction of causality of the cointegrated vector. The *chi2* statistics in the first row tests if R&D, foreign R&D and enrolment are Granger-prior to TFP, the dependent variable in this case. The probabilities in the next row show that R&D is Granger-prior to TFP, and this is also true for all explanatory variables together, which is an expected outcome. We run similar test for each of the remainder dependent variables such as R&D, foreign R&D, and enrolment to find if they are Granger-caused by any variables. The results suggest no evidence of any feedbacks in the opposite direction, which establish the presence of one granger causality running from R&D to TFP.

Table 3.8.a Granger causality Wald tests – Vector autoregressions

	Dependent Variable	Excluded Variables: TFP	R&D	FR&D	ENROL	All
chi2	TFP		14.620	5.421	6.935	32.785
Prob > chi2			0.001*	0.067	0.031*	0.000*
chi2	R&D	0.057		0.154	0.167	0.554
Prob > chi2		0.972		0.926	0.920	0.997
chi2	FR&D	0.323	0.180		2.739	5.634
Prob > chi2		0.851	0.914		0.254	0.465
chi2	ENROL	1.569	0.160	1.189		6.502
Prob > chi2		0.456	0.923	0.552		0.369

* denotes rejection of the hypothesis at the 0.05 level

Table 3.8.b Toda-Yamamoto Granger non-causality tests

Dependent Variable	Excluded Variables				
	TFP	R&D	FR&D	ENROL	All
TFP		16.970***	5.079**	0.961	35.161***
R&D	0.583		0.121	0.019	0.945
FR&D	1.153	8.190***		3.591*	11.878**
ENROL	0.924	0.965	3.722*		7.727

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

This study also follows the Toda-Yamamoto (TY) procedure to test for Granger causality for sensitivity check, i.e. to make sure that the causality testing is done properly. Toda and Yamamoto (1995) indicate that economic series likely to be either integrated of the different orders or non-integrated or both. Hence, the usual Wald test statistic does not follow its usual asymptotic distribution, which could lead to a flawed inference. Toda and Yamamoto (1995), therefore, developed an alternative augmented Granger causality test, which is useful when series are even not integrated in the same order. Table 3.8.b reports the results of the TY augmented Granger Non Causality test. The test's results support the view that R&D Granger-causes the TFP and evidence of no feedback in the opposite direction. From the table, we find in the case of the dependent variable TFP, the result suggests rejecting the null hypothesis of Granger non-causality implies the presence of Granger causality running from R&D to TFP. On the contrary, when R&D considers as a dependent variable result does not suggest rejecting the null, the presence of no Granger causality of TFP to R&D. This implies Toda-Yamamoto procedure also suggests that the R&D Granger cause TFP.

6.4. Variance Decomposition and Impulse-Response Function

The variance decomposition and impulse response function provide more information of the dynamic properties to the model and allow predicting the relative importance of the variables beyond the sample period (Salim and Islam, 2010). Variance decomposition measures the proportion of variation in the dependent variable that is induced by their own shocks or shocks emanating from other variables. Table 3.9 presents the variable decomposition estimates for TFP for 30 years of the time horizon. The result shows in the case of TFP, about 90% of the forecast error variances at the fifth-year horizon are accounted for by its own shock, and the R&D, foreign R&D, and Enrolment contribute the remaining 10% of shocks. The R&D explains about 7.5% and 14.2% in 10^{th} and 20^{th} year, respectively, which remain almost persistent over the future period. The results indicate the future variability to TFP largely originate from its own shocks, which is thus appeared to be exogenous. In 30 years, 71.1% of future variation in TFP is due to its own innovations and R&D explains about 18.1%. On the other hand, other variables such as foreign R&D and enrolment do not considerably explain in the long run.

Table 3.9 Variance Decomposition of LNTFP

Period	S.E.	LnTFP	LnR&D	LnFR&D	LnENROL
1	20.236	100	0	0	0
5	23.926	90.359	2.725	0.339	6.574
10	26.630	82.274	7.450	0.713	9.561
15	29.434	77.606	11.32	1.635	9.433
20	32.044	74.647	14.21	2.357	8.777
25	34.392	72.618	16.405	2.790	8.181
30	36.517	71.116	18.123	3.039	7.720

Cholesky Ordering: LnTFP LnR&D LnFR&D LnENROL

This study, further, uses Cholesky one standard deviation impulse response function as part of the robustness checks of the cointegration findings beyond the sample period. The impulse response functions provide the response of the dependent variables to the shocks to each of the variables in the VEC model. Figure 3.2 shows the impulse response functions based upon the VAR estimates. As the main interest of this study is to examine the responses of TFP, we only present the effects of shock in all variables to the variable TFP. The impulse response functions for the rest of the variables are presented in the appendix Figure A.3.1. Figure shows that the response of productivity growth to a one standard deviation innovation in research and development is positive and persistent. The graph suggests, in response to a shock in R&D, future TFP initially increases, and then it remains positive and nearly permanent for the future periods at 3%. Figure also shows a negative and transitory response of productivity to the shocks both in foreign R&D and in enrolment as the effects die out in the future.

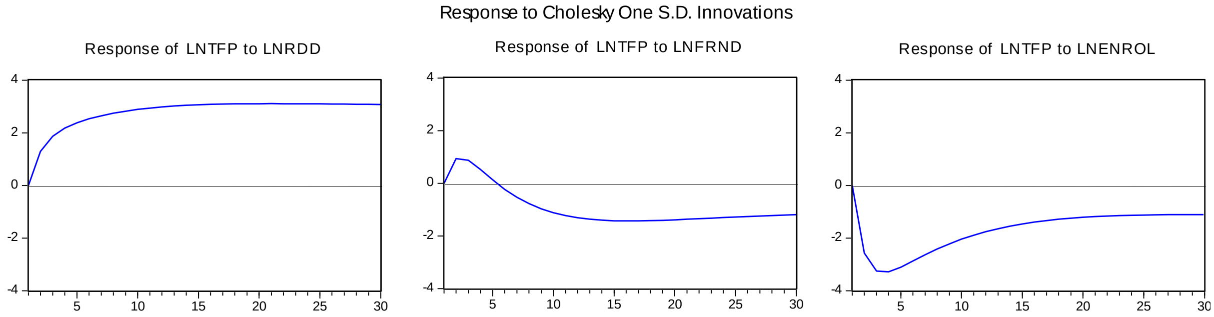

Figure 3.2 Generalized Impulse Response Functions in LNTFP Equation

6.5. Forecasting Exercise

This section presents a forecasting exercise in order to evaluate whether changes in R&D stocks contain information about future changes in the productivity of Australian broadacre agriculture. We produce forecasts from the estimated VEC model where both lagged values of TFP and R&D stocks are used for forecasting. Model also includes foreign R&D and enrolment as two exogenous variables. Figure 3.3 shows estimated forecasts of TFP for the forecast period 2010 to 2020 along with confidence error bands. Based on the estimated VEC model the graph shows that productivity declines over the forecasts period. We use dynamic forecasting approach for this out of sample forecasting. This approach uses the forecasted value of the lagged dependent variable. As a result, the confidence error bands widen towards to the end of the forecast sample because the forecasts errors tend to compound over time.

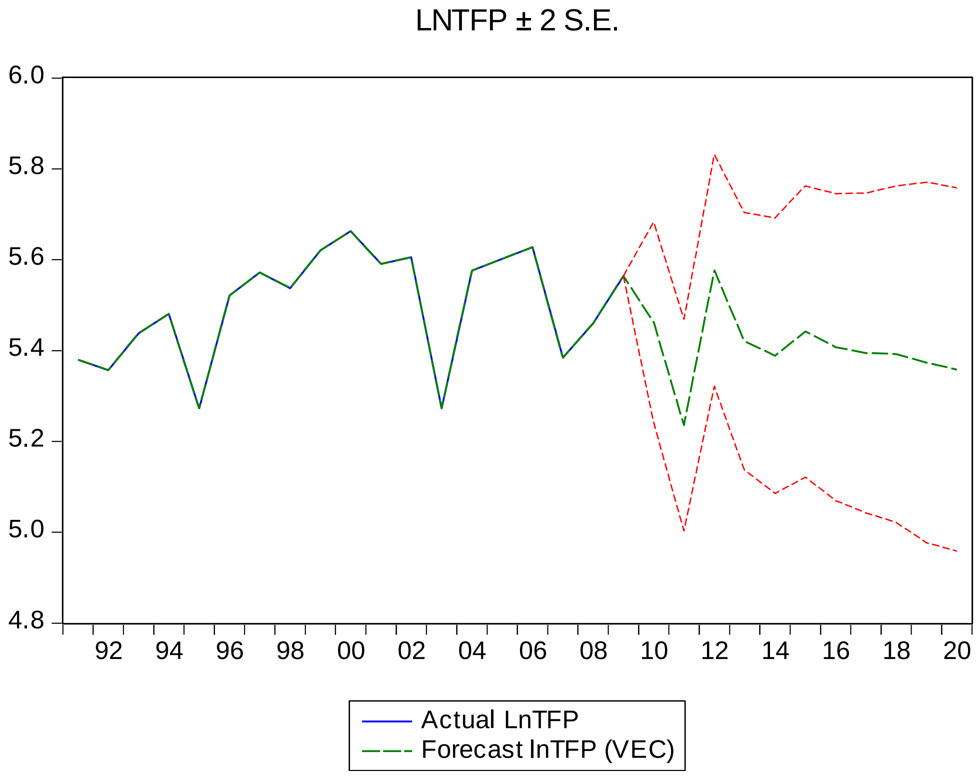

Figure 3.3 Out of Sample Forecasts of TFP for sample 2010-2020

To see out-of-sample performance of the VEC model we estimate forecast evaluation and compares with other models. To obtain out-of-sample forecasting evaluation we reserve part of our sample by not including it in the estimation sample. We estimate VEC and other models for the sample period 1953 to 2002 (reserving seven years of actual data for the evaluation purpose) and perform out of sample forecasting for the period 2003 to 2020. Following, Apergis (2014), we compare the VEC-based TFP forecasts with those of the random walk model (RW) and basic forecasting model (with constant and trends) by using two statistics: root mean squared errors (RMSE) and the Theil coefficients. Table 3.10 reports and compares forecast evaluations across different forecasting models. The results indicate that the VEC model that includes R&D knowledge stocks performs better than other two models giving smaller values of RMSE and Theil coefficient. These results necessarily imply that inclusion of information on R&D knowledge stocks gives better predictive ability of future TFP.

Table 3.10 Out of sample forecasting of TFP for the period 2003 - 2020

	RMSE	Theil Inequality Coefficient

VEC Model	0.237512	0.021073
RW Model	0.259072	0.023074
Basic	0.257132	0.022905

7. Internal Rate of Return

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

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

$$\Delta \ln \overline{KS}_t = \ln\left(\frac{\overline{KS}_t}{KS_t}\right) \tag{15}$$

where KS_t is the actual knowledge stock and $\overline{KS}_t$ is the simulated knowledge stock after including a hypothetical increase of $1,000 in R&D investment in 1954, the year that represents the present value in the analysis at which $t = 0$. For constructing knowledge stock, we assumed gamma lag distribution with the research lag length of 30 years including implicit gestation period.

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

$$PVB = \sum_0^N \left(\hat{\beta}_1 \times \Delta ln\overline{KS}_t \times V_t\right) \times e^{-rt} \tag{16}$$

where V_t denote the real value of agricultural output in period *t*, *r* denote a real interest rate, *N* is the research lag length and $\hat{\beta}_1$ is the elasticity of productivity with respect to a change in the knowledge stock in Eq. (11).

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

$$BCR = \frac{PVB}{PVC} = \frac{\sum_0^N (\hat{\beta}_1 \times \Delta ln\overline{KS}_t \times AV_t) \times e^{-rt}}{\$1,000} \quad (17)$$

In addition to benefit-costs ratio, we compute internal rate of return (IRR) which is the interest rate received for an investment that makes the net present value equal to zero. Next, the future value of benefits after *N* years is defined as:

$$FVB = e^{(r \times N)} PVB \quad (18)$$

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

$$MIRR = \left[\frac{FVB}{PVC}\right]^{\frac{1}{N}} - 1 \quad (19)$$

According to Alston et al. (2011) and Andersen and Song (2013), in evaluating the return to public investments in R&D a MIRR is superior to a conventional IRR for a conceptual reason. Specifically, the conventional IRR implicitly assumes that the flows of benefits that accrue over time can be reinvested in the same initial investment. However, it may not be suited for the public agricultural R&D where the benefits that accrue over time go to producers and consumers of farm products by reducing production costs and food prices. The IRR measure is best suited for an investment situation where the investor reaps all of the returns. We compute the modified internal rate of return as an alternative of conventional internal rate of return, which has an advantage that it allows for alternative reinvestment rates of the stream of benefits.

Table 3.11 Benefit-cost ratios, IRR and MIRR

	30 years research lag length			50 years research lag length		
Reinvestment rate (1)	Benefit-Cost Ratio (2)	IRR (3)	MIRR (4)	Benefit-Cost Ratio (5)	IRR (6)	MIRR (7)
		Percent per Year			Percent per Year	
5%	20.79	26	16.31	17.17	23	11.28

3%	31.43	26	15.59	26.94	23	10.06
1%	47.79	26	14.90	42.80	23	8.87

Our estimates of benefit-costs ratio, conventional internal rate of return and modified internal rate of return are reported in Table 3.11. Results show that measure of benefit-cost ratios range from 17.17 to 47.79 depending on the assumed maximum lag lengths and discount rates. In case of 30 years of research lag length and at an assumed real discount rate of 3% per year the benefit-cost ratio is 31.43. The benefit-cost ratios are consistent with other recent studies. For example, in US agriculture, Alston et al. (2011) found benefit-cost ratios 17.5 and 21.9 for 50-years and 35-years research lag length, respectively. Similarly, Andersen and Song (2013) also found the estimated benefit-cost ratio for the base model with the preferred estimation procedure is 24.38 in the US agriculture.

We also calculate the conventional IRR reported in column (3) and (6) in Table 3.11. Although IRR is not a preferred measure, but is common in the literature. Most of precedent literature estimated IRR as it is useful for purposes of comparison. The estimated IRR for the maximum research lag length of 30 years and 50 years are respectively 26% per year and 23% per year. This result is consistent with some recent studies in US agriculture, where Alston et al. (2011) and Andersen and Song (2013) found the estimated IRR are approximately 22.7% per year and 21% per year, respectively. Similarly, in case of Australia, Mullen (2007) found the real rate of return of the public research of 15% per year in Australian broadacre agriculture. Recently, for all agriculture Sheng et al. (2011) also computed an average estimate of real rate of return of 28.4% in Australian agriculture. However, this rate is reported to be relatively smaller compare to the results from surveys of the numerous studies over the years where the estimate of the rates of return is in the range of approximately 20-80 percent per year as reported in Alston et al. (2009). Also, in a meta-analysis of 292 studies, Alston et al. (2000) reported an overall mean internal rate of return of 64.6%using a sample of 1,128 estimates.

A great number of the previous literature used internal rate of return as a common summary measure of investment performance in the agricultural R&D evaluation despite of its methodological criticisms by economists for more than half a century. We compute the modified internal rates of return (MIRR) which addresses the methodological concern with using the IRR (Hurley et al., 2014). The estimates of MIRR are reported in column (4) and

(7) in Table 3.11 under the assumption of a real reinvestment rate of 1%, 3% and 5% per year. Depending on the maximum research lag length and the assumed reinvestment rate, results indicate that the estimates of MIRR is somewhere in the range of 8.87% per year to 16.31% per year. For 50-years maximum lag length, the estimated MIRR is 10.06% per year when the reinvestment rate is 3% per year. The estimated MIRR in this study is consistent with some recent studies with US agriculture. For example, Alston et al. (2011) computed an average of 9.9% per year across US states. Similarly, Andersen and Song (2013) found that the MIRR is 9.84% per year for the public investment in agricultural R&D in the United States. Our estimates of MIRR of 10.06% per year is also consistent with a recent study by Hurley et al. (2014) which re-examined the reported rates of return from 372 separate studies from 1958 to 2011. They found that the median MIRR varies from 9.7% to 10.4% per year for a range of reinvestment rates of benefits from 0 to 50%.

8. Conclusions

This study investigates the long-run relationship between the public R&D and the TFP in broadacre agriculture in Australia over the period of five decades. A production function approach is used as an analytical model by making total factor productivity a function of research and development expenditure. This model also incorporates the variables that control foreign technology transfer (foreign public R&D) and human capital (farmers' education level). To ensure that cointegration is possible, first we use the Augmented Dickey Fuller and the Phillips Perron unit root tests to determine time-series properties of the variables. Then, using the cointegration and causality analysis, we find econometric evidence of cointegrating relationship between research and development expenditure and productivity growth. Results also show the evidence of a causal relationship between R&D to TFP growth. With respect to the direction of causality, the empirical evidence indicates a unidirectional causality running from R&D to TFP growth. In other words, research and development expenditure Granger causes total factor productivity as current and past values of R&D improve predicts of TFP above the past values of TFP alone. This result is robust according to the Toda-Yamamoto Granger non-causality test.

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

Moreover, this study also computed and compared different measures of economic performances for the public investments in agricultural R&D. The results show that the benefit-cost ratio is 26.94, the internal rate of return is 23% per year, and the modified internal rate of returns is 10.06% per year. The measures of conventional internal rates of return are consistent with some recent studies, e.g., Alston et al. (2011) and Andersen and Song (2013), yet relatively lower than some previous studies. The estimated modified internal rate of returns is approximately 8.87–16.31% per year, depending on the research lag length and reinvestment rate of benefits. This estimated modified return to public R&D is lower than the reported conventional IRR and is methodologically more justified and plausible.

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

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

References

Alston, J. M. (2002). Spillovers. *Australian Journal of Agricultural and Resource Economics, 46*(3), 315-346.

Alston, J. M., Andersen, M. A., James, J. S., & Pardey, P. G. (2011). The economic returns to US public agricultural research. *American Journal of Agricultural Economics*, 93(5), 1257-1277.

Alston, J. M., Marra, M. C., Pardey, P. G., & Wyatt, T. J. (2000). Research returns redux: a meta-analysis of the returns to agricultural R&D. *Australian Journal of Agricultural and Resource Economics, 44*(2), 185-215.

Alston, J. M., & Pardey, P. G. (2001). Attribution and other problems in assessing the returns to agricultural R&D. *Agricultural Economics, 25*(2–3), 141-152.

Alston, J. M., Pardey, P. G., James, J. S., & Anderson, M. A. (2009). The Economics of Agricultural R&D. *Annual Review of Resource Economics, 1*(1), 537-566.

Andersen, M. A., & Song, W. (2013). The Economic impact of public agricultural research and development in the United States. Agricultural Economics, 44(3), 287-295. doi: 10.1111/agec.12011

Ang, J. B., & Madsen, J. B. (2013). International R&D spillovers and productivity trends in the Asian miracle economies. *Economic Inquiry*, 51(2), 1523-1541.

Apergis, N. (2014). Can gold prices forecast the Australian dollar movements? *International Review of Economics & Finance, 29,* 75-82.

Ball, E., Schimmelpfennig, D., & Wang, S. L. (2013). Is U.S. Agricultural Productivity Growth Slowing? *Applied Economic Perspectives and Policy* 35(3): 435-450.

Bervejillo, J. E., Alston, J. M., & Tumber, K. P. (2012). The benefits from public agricultural research in Uruguay. *Australian Journal of Agricultural and Resource Economics*, 56, 1-23.

Bloch, H., Rafiq, S. and Salim, R. (2012). Coal consumption, CO2 emission and economic growth in China: Empirical evidence and policy responses. *Energy Economics* 34(2): 518-528.

Coe, D. T., & Helpman, E. (1995). International R&D spillovers. *European Economic Review, 39*(5), 859-887.

Cox, T., Mullen, J., & Hu, W. (1997). Nonparametric measures of the impact of public research expenditures on Australian broadacre agriculture. *Australian Journal of Agricultural and Resource Economics, 41*(3), 333-60.

Engle, R. F., & Granger, C. W. J. (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica, 55*(2), 251-276.

Gray, E. M., Jackson, T. and Zhao, S. (2011). Agricultural Productivity: Concepts, Measurement and Factors Driving It: A perspective from the ABARES productivity analyses. Rural Industries Research and Development Corporation. RIRDC publication no. 10/161, Canberra.

Griliches, Z. (1979). Issues in Assessing the Contribution of Research and Development to Productivity Growth. *The Bell Journal of Economics, 10*(1), 92-116.

Griliches, Z. (1988). Productivity Puzzles and R & D: Another Nonexplanation. *The Journal of Economic Perspectives, 2*(4), 9-21.

Hall, J., & Scobie, G. M. (2006). The Role of R&D in Productivity Growth: The Case of Agriculture in New Zealand: 1927 to 2001. *New Zealand Treasury Working Paper 06/01*

Hurley, T. M., Rao, X., & Pardey, P. G. (2014). Re-examining the Reported Rates of Return to Food and Agricultural Research and Development. *American Journal of Agricultural Economics*. doi: 10.1093/ajae/aau047

Johansen. S. (1995). Likelihood based Inference on Cointegration in the Vector Autoregressive Model. Oxford University Press

Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration – with application to the demand for money. *Oxford Bulletin of Economics and Statistics*, 52, 169-210.

Jorgenson, D. W., & Griliches, Z. (1967). The Explanation of Productivity Change. *The Review of Economic Studies*, 34(3), 249-283.

Keating, B. A., & Carberry, P. S. (2010). Emerging opportunities and challenges for Australian broadacre agriculture. *Crop and Pasture Science*, *61*(4), 269-278.

Khan, F., Salim, R., and Bloch, H. (2014), Nonparametric estimates of productivity and efficiency change in Australian Broadacre Agriculture. *Australian Journal of Agricultural and Resource Economics*. doi: 10.1111/1467-8489.12076

Mullen, J. D. (2007). Productivity growth and the returns from public investment in R&D in Australian broadacre agriculture. *The Australian Journal of Agricultural and Resource Economics, 51*(4), 359-384.

Mullen, J. D. (2010). Trends in investment in agricultural R&D in Australia and its potential contribution to productivity. *Australasian Agribusiness Review, University of Melbourne, Melbourne School of Land and Environment, vol. 18*

Mullen, J. D., Lee, K., & Wrigley, S. (1996). Agricultural production research expenditure in Australia: 1953-1994. *N. S. W. Agriculture, Agricultural economics bulletin 14, Orange.* (Accessed from http://nla.gov.au/nla.cat-vn1555767)

Nossal, K. & Sheng, Y. (2010). Productivity growth: Trends, drivers and opportunities for broadacre and dairy industries. *Australian commodities*, vol. 10.1, March quarter, 216-230

Pardey, P. G., Alston, J. M., & Piggot, R. R. (2006). "Shifting ground: agricultural R&D worldwide,". *International Food Policy Research Institute (IFPRI)*(Issue briefs 46)

Piesse, J., & Thirtle, C. (2010). Agricultural R&D, technology and productivity. *Philosophical transactions of the Royal Society of London. Series B, Biological sciences*, *365*(1554), 3035-3047.

Salim, R. A., & Islam, N. (2010). Exploring the impact of R&D and climate change on agricultural productivity growth: the case of Western Australia. *Australian Journal of Agricultural and Resource Economics, 54*(4), 561-582.

Schimmelpfennig, D. & Thirtle, C. (1994). Cointegration, And Causality: Exploring The Relationship Between Agricultural And Productivity. *Journal of Agricultural Economics,* 45(2), 220-231.

Shahiduzzaman, M., & Alam, K. (2012). Cointegration and causal relationships between energy consumption and output: Assessing the evidence from Australia. *Energy Economics*, 34(6), 2182-2188.

Sheng, Y., Gray, E. M., & Mullen, J. D. (2011). Public investment in R&D and extension and productivity in Australian broadacre agriculture. In *ABARES conference paper 11.08 presented to the Australian Agricultural and Resource Economics Society,* February, (pp. 9-11).

Solow, Robert M. (1957). Technical Change and the Aggregate Production Function. *Review of Economics and Statistics.* (The MIT Press) 39 (3), 312–320

Thirtle, C., Piesse, J. and Schimmelpfennig, D. (2008). Modeling the length and shape of the R&D lag: an application to UK agricultural productivity. *Agricultural Economics,* 39, 73–85.

Toda, H. Y. and Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics,* 66, 225-250

Wang, S. L., P. W. Heisey, and K. O. Fuglie. (2013). Public R&D, Private R&D, and U.S. Agricultural Productivity Growth: Dynamic and Long-Run Relationships. *American Journal of Agricultural Economics* 95(5), 1287-1293.

Zivot, E. and Andrews, D. (1992). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. Journal of Business and Economic Statistics, 10(3), 251-270

Appendix

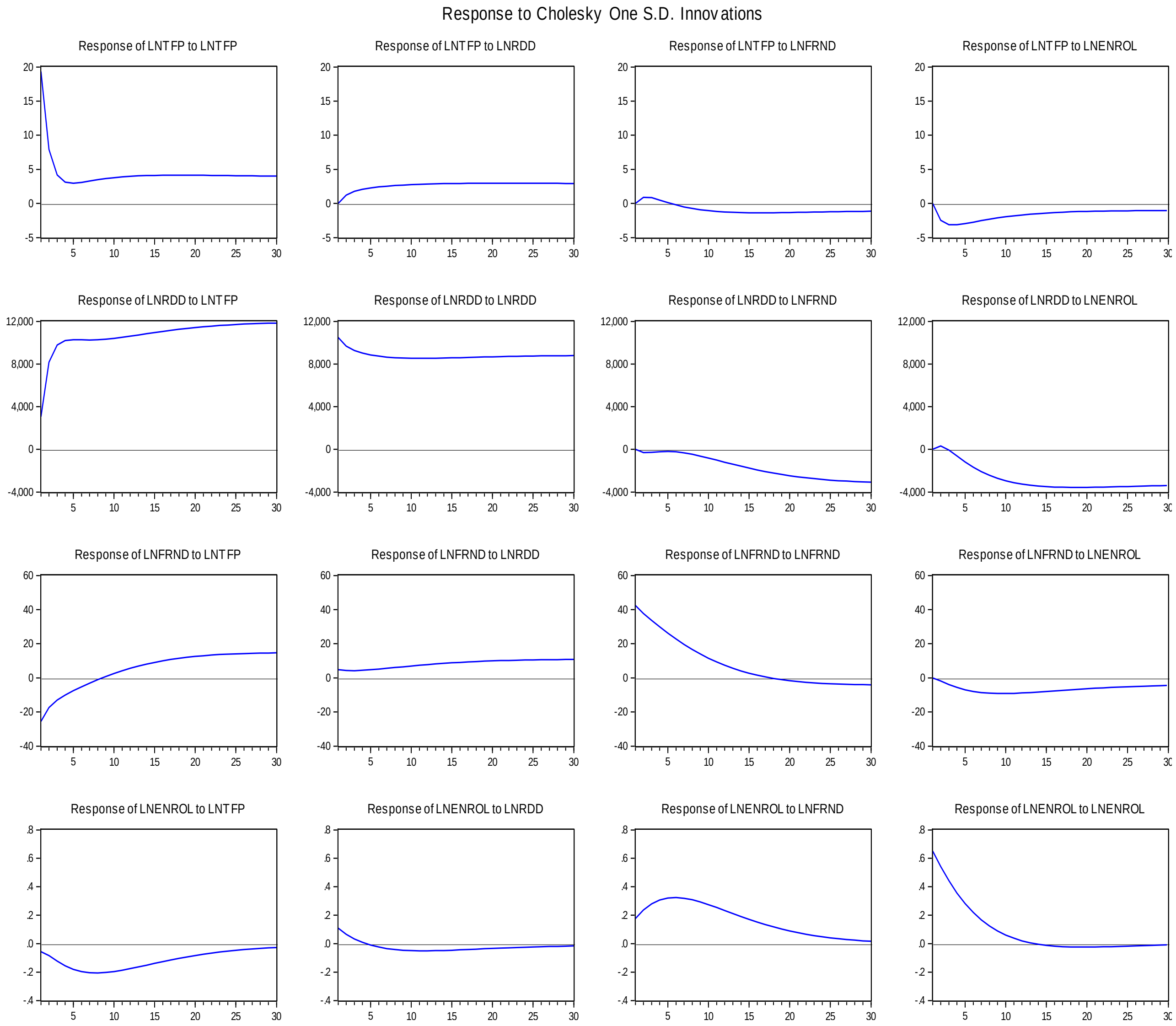

Figure A.1: Impulse Response Function