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The public R&D and productivity growth in Australia's broadacre agriculture: is there a link?

Farid Khan, Ruhul Salim, Harry Bloch and Nazrul Islam[†]

This paper investigates the dynamic relationships between research and development (R&D) expenditure and productivity growth in Australian broadacre agriculture using aggregate time series data for the period 1953 to 2009. The results show a cointegrating relationship between R&D and productivity growth and a unidirectional causality from R&D to TFP (total factor productivity) growth in Australian broadacre agriculture. Using the dynamic properties of the model, data from beyond the sample period are analysed by employing the variance decomposition and the impulse response function. The findings reveal that R&D can be readily linked to the variation in productivity growth beyond the sample period. Furthermore, the forecasting results indicate that a significant out-of-sample relationship exists between public R&D and productivity in broadacre agriculture.

Key words: Australian Broadacre Agriculture, cointegration, productivity, public research & development.

1. Introduction

There is a broad consensus among economists and researchers that rising agricultural productivity has been the crucial factor in achieving economic prosperity and in meeting the growing global food demand over the past decades (Pardey *et al*. 2013; Alston and Pardey 2014). One of the leading factors that fuels productivity improvements in agriculture is investment in agricultural research and development (hereafter, R&D), which produces new knowledge and achieves technological breakthroughs (Coe and Helpman 1995).

In recent decades, there has been concern that productivity in agriculture is declining throughout most of the developed world (Ball *et al*. 2013). Evidence of a slowdown in productivity growth is revealed over the last decade

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[†] Farid Khan is at Department of Economics, Rajshahi University, Rajshahi, Bangladesh. Ruhul Salim (e-mail: Ruhul.Salim@cbs.curtin.edu.au) and Harry Bloch are at School of Economics & Finance, Curtin University, Perth, WA, Australia. Nazrul Islam is at EMS Research, Agriculture and Resource Economics, Canningvale, WA, Australia.

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compared with earlier periods in Australian agriculture (Sheng *et al.* 2011; Khan *et al.* 2015). Studies also have found that falling public R&D investment in agriculture over the past decades is one of the possible causes of the recent declines in agricultural productivity growth (Schimmelpfennig and Thirtle 1994; Alston *et al.* 2011). The recent decline in productivity has thus renewed interest in productivity analysis.

In the long run, agricultural productivity is largely driven by new knowledge or technology and/or efficiency improvements. However, there are concerns that the declines in productivity growth can be attributed to the lagged impact of the real public investment in agricultural research, which has stagnated since 1970s. Mullen (2007) found R&D to be a major source of productivity growth in Australian agriculture. Similarly, Salim and Islam (2010) also found that R&D matters for long-run productivity growth. A recent study by Sheng *et al.* (2015a) on Australian broadacre agriculture suggests that increasing size is not effective to improve productivity unless the technological capabilities of farms are improved, which is where R&D is an essential element to promote innovation adoption.

Apart from R&D, there are other factors that drive productivity through efficiency improvements. Changes in domestic policy settings and human capital are important determinants of agricultural productivity in Australia (Gray *et al.* 2014). Sheng *et al.* (2015b) show that policy reforms through resource reallocation among farms contribute to the industry-level productivity growth in Australian broadacre agriculture. In addition, studies suggest that economy-wide reforms facilitate transformation and structural adjustment in agriculture and provide a more favourable enabling environment to productivity growth (Gray *et al.* 2014). Changes in institutions and regulatory arrangements create conditions conducive to productivity growth. Among efficiency drivers, farmers' education and training are also important determinants of productivity growth through increasing their capacity to innovate (Mullen 2007; Xayavong *et al.* 2015). Another factor that influences broadacre agricultural productivity in Australia is seasonal conditions which are beyond the control of farmers and government. Islam *et al.* (2014) found across varying rainfall environments that efficiency gains play an increasingly important role in influencing productivity as growing season rainfall increases.

While the previous studies identify the factors that influence farm productivity, so far no study has yet been performed to identify the long-run dynamic relationship between farm productivity and R&D in Australian broadacre agriculture with a dynamic econometric model specification. This paper addresses this gap in the literature. It examines the relationship between public R&D spending and productivity growth in Australian broadacre agriculture with a data series spanning more than 50 years. This paper applies cointegration and Granger causality to investigate the relationship between R&D and TFP and the direction of causality running between them. Apart from estimating short-term and long-term effects of public R&D investments, this paper also focuses on the dynamic effects of R&D by applying variance decomposition, impulse response functions and a forecasting modelling. It explores the properties of the relationship between R&D and productivity growth in a more dynamic fashion and beyond the sample period.

The remainder of this paper proceeds as follows. The next section provides a brief overview of public R&D and agricultural productivity in Australia. A discussion of data sources and variable selection is given in Section 3. Section 4 discusses the time series econometrics and empirical results. Section 5 concludes the paper.

2. Public R&D and broadacre agricultural productivity in Australia

Australian agriculture is primarily based on extensive cropping and livestock farming activity, which is generally termed 'broadacre' agriculture. Broadacre agriculture is a significant contributor to the country's agricultural and economic growth. It generates more than 54 per cent of the country's gross value of agricultural production (Gray *et al.* 2014). Moreover, Australia exports approximately 60 per cent of its agricultural production, accounting for 10.9 per cent of the total export earnings in 2010–2011 (ABS, 2012).

The public sector plays a dominant role in R&D investment in Australian agriculture, generally accounting for around 75 per cent of total agricultural R&D (Productivity Commission, 2011). This statistics strongly contrasts with those of other OECD countries, where the share of private R&D is typically more than half the total investment in agricultural R&D (Sheng *et al.* 2011).

Figure 1 shows the patterns of public R&D expenditure in broadacre agriculture between 1953 and 2009 at constant 2009 prices. Over this period, Australian real public R&D investment in agriculture has grown from 102.3 million AUD in 1953 to almost 415.9 million AUD in 2009. There was an upward trend in the total public expenditure in agricultural R&D up until the mid-1970s. Since then, expenditure has essentially been static, with a spike in investment in 2001 followed by falling investments. Studies indicate that this sluggishness in public R&D since the mid-1970s may have contributed to the

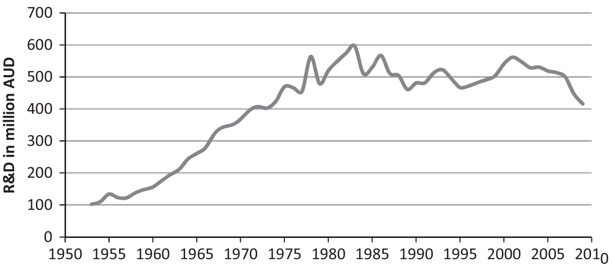

Figure 1 Public R&D expenditure in Australian broadacre agriculture. Source: Calculated with data from Mullen (2007, 2010) and ABARES.

slowdown in agricultural productivity growth in recent periods. Before 1994, broadacre farming experienced approximately 2.2 per cent growth in productivity per year, but since then it has been declining by 0.4 per cent a year (Sheng *et al.* 2011).

In Australia, agricultural research has been largely supported by public investments through different sectoral funding and public research agencies. The research and development corporations (RDCs) are the main funding bodies of the government for rural R&D in Australia. Covering a broad spectrum of Australia's agricultural, fishing and forestry industries, RDCs invest in R&D and innovation to strengthen the competitiveness and profitability of these industries by improving the productivity and quality of products.

3. Methods

This paper uses national time series data for the period 1953 to 2009. Empirical linkages are examined among four variables, namely total factor productivity, domestic public investments in R&D, foreign public investment in R&D and farmers' level of education[1] . The broadacre TFP index (*TFP*) is measured by the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) and is estimated as the ratio of a Fisher quantity index of total output to a Fisher quantity index of total input. A complete description of how ABARES constructs the TFP index for the broadacre industries can be found in Gray *et al.* (2011).

The domestic public investment in R&D (*RD*) in broadacre agriculture series builds on data calculated by Mullen (2010) and data from the Australian Bureau of Statistics (ABS) biannual Australian Research and Experimental Development Survey. Mullen assembles the R&D data from various public sources, including the Australian Bureau of Statistics (ABS) and a previous dataset from Mullen *et al.* (1996). In the absence of broadacre-specific R&D data, the R&D in broadacre alone is derived from the R&D investment in agriculture by assuming that broadacre agriculture's share is equal to its share of the total value of production in agriculture.

This paper uses R&D expenditure in US agriculture, collected from the US Department of Agriculture (USDA), as a proxy for the foreign R&D expenditure (*FRD*). The US plays a significant role in global agricultural R&D in relation to its investment and in terms of research spillovers (Alston 2002). It is often assumed that the transfer of knowledge and technology between countries depends on a trade channel, which facilitates access to the outputs of foreign R&D, thereby enhancing productivity. Therefore, we construct and use an import-share-weighted US R&D variable for the model

[1] Weather is another important potential variable that may explain productivity variation in Australian broadacre agriculture, but that has not been included in this study.

by following Coe and Helpman (1995). These data are weighted by the per cent of agricultural imports to the agricultural gross value of farm production (GVP) in Australia. The agricultural GVP is obtained from ABARES, and imports of agricultural crops and livestock products are obtained from FAO statistics. This series is extrapolated backwards for the period 1953 to 1960 using actual data from 1961 to 2009.

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

To estimate the effects of R&D, three alternative R&D variables are constructed following the previous time series studies (Mullen and Cox 1995; Thirtle *et al*. 2008; Sheng *et al*. 2010). First, a single lagged value of R&D expenditure is used. Like Thirtle *et al*. (2008), this paper finds a 12 year R&D lag (RD_{t-12}) as the strongest influence on TFP. The strongest R&D lag is determined by using the Ramsey RESET specification test, and different model selection criteria are reported in the online appendix, Table S1[2] . Second, we construct a simple R&D knowledge stock variable ($\mathrm{RDS}^{\mathrm{PIM}}$) following the perpetual inventory method (PIM), which is commonly used to construct stocks for physical capital flows in the literature.

Finally, another R&D knowledge stock ($\mathrm{FRD}^{\mathrm{gamma}}$) is constructed using the gamma distribution function. In the literature, there are different lag structures and lag lengths used to approximate the lag effects of R&D with a gamma distribution, but there is hardly any consensus among the researchers regarding lag selection. For example, in US agriculture a recent study by Huffman and Evenson (2006) uses a 35 year lag profile. Also in Australian broadacre agriculture, Binenbaum *et al*. (2008) assumed that the knowledge stock is built up following a 35 year trapezoidal research profile. Studies in UK and Australian agriculture largely use 16 to 35 years for the lag. For example, Cox *et al*. (1997) used 30 year lag specifications of the research impacts on productivity in Australian broadacre agriculture.

[2] The ordinary least squares regression is fitted to determine strongest R&D lag by using the following log-linear relationship: $\mathrm{LnTFP}_t = \beta_0 + \beta_1 \mathrm{LnRD}_{t-i} + \beta_2 \mathrm{LnFRD}_t + \beta_3 \mathrm{LnEDU}_t + \varepsilon_t$.

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 for the gamma distribution function, which is consistent with previous studies in Australian broadacre agriculture, e.g. Cox *et al*. (1997). The number of observations on R&D and the degrees of freedom available for identifying relationships are also a consideration for this lag selection. In addition, the preliminary investigation mentioned previously finds 12 (or 15) years as the strongest lag, implying a maximum lag of 24 to 30 years for the gamma distribution. Following Alston *et al*. (2011), the parameters of the gamma lag distribution are assigned values of $\lambda = 0.70$ and $\delta = 0.90$.

In the next section, we apply a set of standard unit root tests, including the Augmented Dickey Fuller, the Dickey–Fuller generalised least squares (DF-GLS), the Phillips–Perron and the KPSS (Kwiatkowski, Phillips, Schmidt, and Shin) tests, to examine time series properties of all series. Then, we apply a cointegration test proposed by Johansen and Juselius (1990) to investigate the cointegrating relationship between R&D and productivity growth. In addition, the Granger causality test is used to shed light on the direction of possible causality between R&D and TFP growth along with the Toda–Yamamoto Granger noncausality test for the robustness check. A few robustness checks are also performed to test the consistency of the empirical results, including after allowing for unknown structural breaks.

4. Time series econometrics and empirical results

4.1 Unit root tests

To provide valid empirical evidence on long-run dynamic relationships among variables, we investigate the time series properties of the variables using widely used unit root tests: the Augmented Dickey–Fuller (ADF) test, the GLS detrended Dickey–Fuller test (DF-GLS), the Phillips–Perron tests and the KPSS test. The ADF test adjusts a higher-order autoregressive process by adding lagged difference terms of the dependent variable in the parametric test regression. DF-GLS is a simple modification of the ADF test proposed by Elliott *et al*. (1996), where the time series is transformed via a generalised least squares (GLS) regression before performing the test, and this is considered to be better in terms of the statistical power of the test (Apergis 2014). Both the Phillips–Perron and the KPSS tests apply nonparametric methods for controlling serial correlation in testing for a unit root. The KPSS test differs from the other unit root tests, such as the ADF, DF-GLS and PP, in that it assumes stationarity of the series under the null hypothesis. Test results for the time series data covering the period 1953–2009 are presented in the online appendix. These results confirm that all variables are nonstationary in their levels, but they are stationary in their first differences, i.e. they are each integrated of order one, *I(1)*[3] ,[4] .

4.2 Cointegration and the VEC model

4.2.1 Cointegration test: Johansen approach based on VAR

Economic theory and the existing empirical studies regarding the short-run and the long-run dynamic relationships between TFP and R&D provide limited guidance in modelling the relationship between research expenditures and total factor productivity. To identify the relationships, we adopt a modelling strategy based upon the information provided by the time series data. We apply an unrestricted VAR (vector autoregression) model that allows the data to speak to the possible links and directions among these variables. The VAR-based Johansen cointegration test uses maximum likelihood estimation methodology to test for the cointegration rank *r,* which represents the number of independent cointegrating vectors.

To use the Johansen test, a vector error correction model (VECM) of the following form can be specified:

$$\Delta y_t = \prod y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t \tag{1}$$

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

The Johansen test examines the coefficient matrix Π, particularly 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. However, if $1 \leq r < k$, there is a single cointegrating vector or multiple cointegrating vectors in the system.

Johansen proposes two types of likelihood ratio tests: the trace test and maximum eigenvalue test, for the number of characteristic roots using the following two statistics:

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

[4] We also employ the Zivot–Andrews unit root tests which suggest that all series are integrated of order one after allowing breaks by following Salim and Bloch (2009). Detailed results are available upon request.

$$\lambda_{trace} = -T \sum_{i=r+1}^{k} \ln\left(1 - \widehat{\lambda}_i\right) \quad (2)$$

$$\lambda_{max} = -T \ln\left(1 - \widehat{\lambda}_{r+1}\right) \quad (3)$$

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

We use the multivariate maximum likelihood approach of Johansen and Juselius, which allows the estimation of multiple cointegrating relationships. The results for the trace test and the eigenvalue test (Table 1) reject the null hypothesis of no cointegrating vector, but they cannot reject the hypothesis of, at most, one cointegrating equation. Both the trace test and the max-eigenvalue test indicate one cointegrating equation at the 5 per cent significance level.[5,6]

4.2.2 Vector error correction model: Johansen and Juselius method

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

Table 1 Cointegration tests: Johansen and Juselius approach

Series tested: *LnTFP LnRD LnFRD LnEDU*				
Hypothesised	Eigenvalue	Statistic	5%	
No. of CE(s)			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	0.089	7.407	15.49471	0.5308
At most 3	0.042	2.348	3.84146	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	0.089	5.059	14.26460	0.7343
At most 3	0.042	2.348	3.84146	0.1255

*MacKinnon–Haug–Michelis *P*-values. †Rejection of the hypothesis at the 0.05 level.

[5] Cointegration tests are conducted using the original R&D variable not lagged or stock values.

[6] For sensitivity, we performed Gregory and Hansen cointegration test which suggests that allowing for an unknown structural break does not affect results. Detailed results are available on request.

$$\Delta \mathrm{TFP}_t = \beta_1 + \sum_{i=1}^{m} \beta_{11i} \Delta \mathrm{TFP}_{t-i} + \sum_{i=1}^{n} \beta_{12i} \Delta RD_{t-i} + \sum_{i=1}^{n} \beta_{13i} \Delta \mathrm{FRD}_{t-i} + \sum_{i=1}^{r} \beta_{14i} \Delta \mathrm{EDU}_{t-i} + \alpha_1 \mathrm{ECT}_{t-1} + \varepsilon_{1t} \tag{4}$$

$$\Delta \mathrm{RD}_t = \beta_2 + \sum_{i=1}^{m} \beta_{21i} \Delta \mathrm{TFP}_{t-i} + \sum_{i=1}^{n} \beta_{22i} \Delta \mathrm{RD}_{t-i} + \sum_{i=1}^{n} \beta_{23i} \Delta \mathrm{FRD}_{t-i} + \sum_{i=1}^{r} \beta_{24i} \Delta \mathrm{EDU}_{t-i} + \alpha_2 \mathrm{ECT}_{t-1} + \varepsilon_{2t} \tag{5}$$

$$\Delta \mathrm{FRD}_t = \beta_3 + \sum_{i=1}^{m} \beta_{31i} \Delta \mathrm{TFP}_{t-i} + \sum_{i=1}^{n} \beta_{32i} \Delta \mathrm{RD}_{t-i} + \sum_{i=1}^{n} \beta_{33i} \Delta \mathrm{FRD}_{t-i} + \sum_{i=1}^{r} \beta_{34i} \Delta \mathrm{EDU}_{t-i} + \alpha_3 \mathrm{ECT}_{t-1} + \varepsilon_{3t} \tag{6}$$

$$\Delta \mathrm{EDU}_t = \beta_4 + \sum_{i=1}^{m} \beta_{41i} \Delta \mathrm{TFP}_{t-i} + \sum_{i=1}^{n} \beta_{42i} \Delta \mathrm{RD}_{t-i} + \sum_{i=1}^{n} \beta_{43i} \Delta \mathrm{FRD}_{t-i} + \sum_{i=1}^{r} \beta_{44i} \Delta \mathrm{EDU}_{t-i} + \alpha_4 \mathrm{ECT}_{t-1} + \varepsilon_{4t} \tag{7}$$

where Δ denotes the difference operator; TFP, RD, FRD and EDU are the endogenous variables that are integrated of order one; and ε_t are random errors that are each independently and identically distributed. The inclusion of lags of the dependent variable as explanatory variables in the regression is necessary, as the dependent variable itself may be correlated with its lags. The error correction term ECT is the one-period lagged value of the error term from the cointegrating equation, which equals zero in the long-run equilibrium relationship. The coefficients α_1, α_2, α_3, and α_4 are the adjustment parameters, and they represent the speed of adjustment in the error correction mechanism.

Table 2 presents the test results for error correction by using the Johansen–Juselius vector error correction method with specifications of R&D. In the table, *Panel A* shows results for 12 years of lag values of R&D and foreign R&D. This type of lag structure has been applied in other studies, including Salim and Islam (2010) and Thirtle *et al*. (2008). The statistically significant and negative coefficient of the equilibrium error term provides evidence of the adjustment of the short-run disequilibrium towards the long-run equilibrium for the model. For the ΔTFP equation, the negative sign indicates that TFP moves towards its equilibrium level in the case of the 12 year lagged R&D. The coefficient of -0.924 suggests a 92.4 per cent adjustment towards the long-run equilibrium in each year.

Table 2 Unrestricted VECM results: dependent variable ΔlnTFP

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

*Rejection of the null hypothesis at the 1%.

Panel B and *Panel C* report results based on R&D stocks constructed by two alternative specifications of R&D lag structure: the perpetual inventory method (PIM) and gamma distribution, respectively. Under the PIM method, R&D stocks are calculated assuming a depreciation rate fixed at 5 per cent. In Panel C, R&D stocks are calculated assuming a gamma distribution with a 30 year research lag length. The results show that in the ΔTFP equation, the coefficient associated with the error correction term reported in *Panel B* is statistically significant and negative, suggesting a move towards long-run equilibrium. In *Panel C*, the error correction term is not statistically significant, suggesting no error correction adjustment towards long-run equilibrium. Besides, the low R-square and F-statistic does not suggest that this specification fits data well.

The coefficients on the first-difference terms reported in Table 2 represent short-run elasticities as all variables are in natural logarithms. The short-run adjustment parameters of the explanatory variables R&D stock and foreign R&D stock under the PIM method are positive and significant, indicating that both domestic and foreign R&D have positive short-run impacts on TFP, while the other short-run parameters are not significant[7] . This result

[7] The ECM results for the other variables indicate that none of the equations contains a statistically significant error correction term. Details are available from the authors on request.

shows that lagged R&D is significant in explaining changes in total factor productivity and implies that increased R&D expenditure leads to productivity growth in Australian broadacre agriculture.

The long-run parameters of the cointegrating equations estimated from the ECM are reported in the following equations. The estimated parameters are exactly identified, and the model fits well[8]. The results of the normalised cointegrating coefficients are presented in the following relationship for different specifications of the R&D variable where '***' and '**' denote that the associated long-run parameters are statistically significant at the 0.01 and 0.05 levels, respectively:

$$\text{LnTFP} = 6.158 + 0.1279\text{LnRD}^{***}_{t-12} + 0.0945\text{LnFRD}_{t-12} - 0.6074\text{LnEDU}^{***}_{t} \tag{8}$$

$$\text{LnTFP} = 12.863 + 0.3146\text{LnRDS}^{PIM***}_{t} - 0.1861\text{LnFRDS}^{PIM}_{t} - 2.343\text{LnEDU}^{**}_{t} \tag{9}$$

$$\text{LnTFP} = 15.583 + 0.2488\text{LnRDS}^{gamma}_{t} - 1.440\text{LnFRDS}^{gamma***}_{t} - 3.778\text{LnEDU}_{t} \tag{10}$$

The normalised cointegrating Equation 8 considers 12 years of R&D lag. Equations 9 and 10 are specified with research stocks (*RDS*) based on the PIM and the gamma distribution, respectively. In the case of both 12 year lagged R&D and research stock based on the PIM specifications, the coefficients for R&D are positive and statistically significant, indicating a long-term marginal effect on TFP. Because a double-logarithmic functional form is used, the coefficient can be interpreted as a long-term elasticity. The long-run elasticities of TFP with respect to the 12 year peak R&D lag and research stock based on the PIM are 0.128 and 0.315, respectively, suggesting substantial impact for the public investments in agricultural R&D in Australia.

Further results in Equation 8 show that foreign R&D is positively related to TFP in the case of 12 year R&D lag, although the coefficient is not statistically significant, and that the long-run coefficient of school enrolment variable (*EDU*) is negative and significant. The ratio of primary school enrolment is a crude proxy for the farmers' level of education. However, the variable is included in this analysis following other studies (e.g. Mullen and Cox 1995 and Sheng *et al.* 2010) without considering the possibility of its

[8] $P > \chi^2 = 0.00$ in the case of the cointegrating equations. Overall model fits statistics report $P > \chi^2 = 0.00$; the coefficients on cointegrating equations are largely statistically significant, as are the adjustment parameters.

lagged effects on productivity due to limitations on data availability. The negative sign, though, is not expected, but similar evidences of wrong sign are found in the standard literature. Perhaps this finding indicates that Australian farmers have poor capacity to facilitate precision agriculture, technology adoption and managing the complexity of the modern farming or to receive the benefits of ICT-based technologies. Other studies show that the adoption rates of information technologies is not as fast as expected in Australian agriculture (Kingwell and Pannell 2005; Kingwell 2011).

Like the error correction term, the long-run coefficient of R&D in Equation 10 is not statistically significant in the case of both domestic and foreign R&D stocks based on the gamma distribution. Limited data availability might be one possible reason for this weak result. An alternative model is tested considering R&D stock based on the gamma distribution for domestic R&D only, and results suggest a long-run cointegrating relationship between TFP and domestic R&D like the result using the R&D stock based on PIM[9]. A series of diagnostic tests are performed to check the specifications of the model and to ensure the validity of the estimated coefficients and inferences. The results obtained from the likelihood ratio (LR) test also confirm the cointegrating relationships between TFP and R&D (both 12 year lagged R&D and research stock based on the PIM)[10] . The stability tests of the VECM estimates suggest that the number of cointegrating equations have been correctly specified. Further, an LM test for autocorrelation suggests that there is no autocorrelation in the residuals at either lag order one or two. Results are not reported here to conserve space.

Overall, we find strong econometric evidence of the existence of a long-run equilibrium relationship between the TFP and the public R&D in Australian broadacre agriculture. This result supports the logic of the research and development corporation (RDC) system, where a levy is collected from farmers to invest into R&D that leads to increased GVP via higher agricultural TFP growth. This evidence of a cointegrating relationship between R&D expenditure and productivity growth implies that productivity growth in Australian broadacre agriculture is to be driven by technological advancements. Public policies directed at scientific research and development likely to lift longer-term productivity growth in Australian agriculture.

4.3 Granger causality tests

To explore the direction of the causality among the variables in the cointegrated vector, we apply the Granger causality test. The presence of one cointegrating vector implies that there should be Granger causality in at least one direction. Granger causality can be examined using the following VAR framework of order p:

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[9] $\mathrm{LnTFP} = 16.2565 + 0.3144\mathrm{LnRDS}_t^{gamma***} + 0.109\mathrm{LnFRD}_t - 2.933\mathrm{LnEDU}_t^{**}$
[10] Detailed results are available from the authors upon request.

$$\begin{aligned}\mathrm{TFP}_t =& \beta_1 + \sum_{i=1}^{p} \beta_{11i}\mathrm{TFP}_{t-i} + \sum_{i=1}^{p} \beta_{12i}\mathrm{RD}_{t-i} + \sum_{i=1}^{p} \beta_{13i}\mathrm{FRD}_{t-i} \\ &+ \sum_{i=1}^{p} \beta_{14i}\mathrm{EDU}_{t-i} + \varepsilon_{1t}\end{aligned} \tag{11}$$

$$\begin{aligned}\mathrm{RD}_t =& \beta_2 + \sum_{i=1}^{p} \beta_{21i}\mathrm{TFP}_{t-i} + \sum_{i=1}^{p} \beta_{22i}\mathrm{RD}_{t-i} + \sum_{i=1}^{p} \beta_{23i}\mathrm{FRD}_{t-i} \\ &+ \sum_{i=1}^{p} \beta_{24i}\mathrm{EDU}_{t-i} + \varepsilon_{2t}\end{aligned} \tag{12}$$

$$\begin{aligned}\mathrm{FRD}_t =& \beta_3 + \sum_{i=1}^{p} \beta_{31i}\mathrm{TFP}_{t-i} + \sum_{i=1}^{p} \beta_{32i}\mathrm{RD}_{t-i} + \sum_{i=1}^{p} \beta_{33i}\mathrm{FRD}_{t-i} \\ &+ \sum_{i=1}^{p} \beta_{34i}\mathrm{EDU}_{t-i} + \varepsilon_{3t}\end{aligned} \tag{13}$$

$$\begin{aligned}\mathrm{EDU}_t =& \beta_4 + \sum_{i=1}^{p} \beta_{41i}\mathrm{TFP}_{t-i} + \sum_{i=1}^{p} \beta_{42i}\mathrm{RD}_{t-i} + \sum_{i=1}^{p} \beta_{43i}\mathrm{FRD}_{t-i} \\ &+ \sum_{i=1}^{p} \beta_{44i}\mathrm{EDU}_{t-i} + \varepsilon_{4t}\end{aligned} \tag{14}$$

Equation 11 models *TFP* as a linear function of its own lagged values plus the lagged values of all other variables treated as excluded. If the lagged values of all excluded variables have nonzero effects on *TFP*, then these variables Granger cause *TFP* in a manner conditional on the effects of its own lagged values. Granger causality testing sets as the null hypothesis that *RD* does not Granger cause *TFP*: H_0:β_{121} = ... = β_{12p} = 0 This joint hypothesis can be tested using a standard Wald F or χ^2 test because each individual set of restricted parameters is drawn from only one equation. Similarly, in Equation 12, the null hypothesis that *TFP* does not Granger cause *RD* can be expressed as H_0:β_{211} = ... = β_{21p} = 0.

Table 3 presents the Granger causality Wald test based on vector autoregressions to establish the direction of causality of the cointegrated vector. The χ^2 statistics in the first row tests whether *RD* (R&D), *FRD* (foreign R&D) and *EDU* (school enrolment) are Granger prior to TFP, the dependent variable in this case. The probabilities in the next row show that R&D and EDU are Granger prior to TFP, and this is true for all excluded variables together, which is an expected outcome. We run a similar test for each of the remaining dependent variables and find no evidence of any feedbacks in the opposite direction, which establishes the

Table 3 Granger causality Wald tests—vector autoregression

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

Note All variables are in logarithmic form, and R&D variables are in original form not lagged or stock values. *Rejection of the hypothesis at the 0.05 level

presence of unidirectional Granger causality running from R&D and EDU to TFP. More specifically, the results indicate unidirectional causality from R&D to TFP as the lags of R&D are significant for the TFP regression, but the lags of TFP are not significant for the R&D regression. Thus, the results show evidence of a unidirectional causal relationship between R&D and TFP growth with causality running from R&D to TFP growth.

4.4 Variance Decomposition and Impulse Response Function

The variance decomposition and impulse response functions provide more information on the dynamic properties of the model and allow prediction of the relative importance of the variables beyond the sample period. Variance decomposition measures the proportion of variation in the dependent variable that is induced by its own shocks or shocks emanating from other variables. Table 4 presents the variable decomposition estimates for TFP for 30 years of the time horizon.

The result shows that in the case of the TFP, approximately 80 per cent of the forecast error variance at the fifth-year horizon is accounted for by its own shock, and the R&D, foreign R&D and enrolment contribute the remaining 20 per cent of shocks. R&D explains approximately 8.7 per cent and 17.4 per cent in the 10th and 20th years, respectively, remaining nearly persistent over the future period.

We use Cholesky one standard deviation impulse response functions as part of the robustness checks of the cointegration findings beyond the sample period. The impulse response functions provide the response of the dependent variables to the shocks to each of the variables in the VEC model. Figure 2 shows the impulse responses of TFP, as this is the variable of main interest. In response to a shock in R&D, the future TFP initially increases and then remains positive and nearly constant for the future periods. This result indicates that TFP responds positively and persistently in the future period to

Table 4 Variance decomposition of LnTFP

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

Note Cholesky ordering: LnTFP LnRD LnFRD LnEDU. Standard errors based on Monte Carlo simulations (100 repetitions) are reported in the parentheses. Both the domestic R&D and the foreign R&D are used in the original form, not as lagged or stocks form.

an increase in R&D and implies that government investment in research and development in agriculture would result in future productivity growth. In the graph, the broken lines indicate confidence limits around the estimates based on asymptotic standard errors[11] .

4.5 Forecasting modelling

This section presents a forecasting exercise to evaluate whether changes in R&D stocks contain information about future changes in the productivity of Australian broadacre agriculture. Forecasts are produced from the estimated VEC model, where both lagged values of TFP and R&D stocks are used for forecasting. The model also includes foreign R&D and education enrolment as two exogenous variables. Figure 3 shows estimated forecasts of TFP for the forecast period 2010 to 2020 along with confidence error bands (red broken lines). Based on the estimated VEC model, the graph shows that productivity declines over the forecast period. The confidence error bands widen towards the end of the forecast sample because the forecasts errors tend to compound over time.

To obtain the out-of-sample forecasting evaluation, part of the sample is reserved by not including it in the estimation sample. The VEC and other models are estimated for the sample period 1953 to 2002 (reserving seven years of actual data for evaluation purposes), and out-of-sample forecasting is performed for the period 2003 to 2020.

Following Apergis (2014), the VEC-based TFP forecasts is compared with those of the random walk model (RW) and basic forecasting model (with

[11] The impulse response functions for the rest of the variables are available from the authors on request.

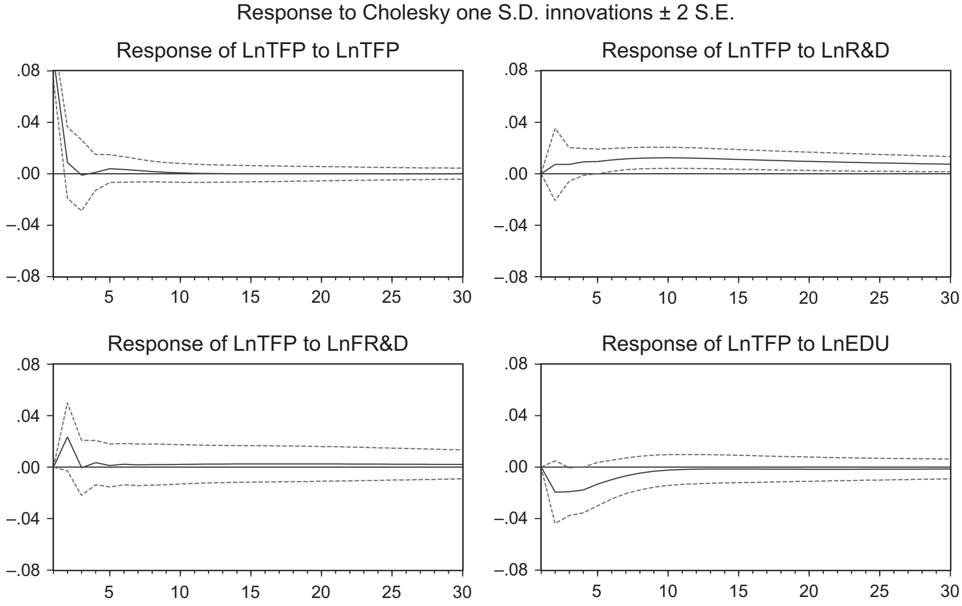

Figure 2 Generalised impulse response functions for the TFP equation. *Note:*Y-axis presents responses of TFP to one S.D. change in impulse variables, and X-axis is the periods.

constant and trends) by using two statistics: root-mean-squared errors (RMSE) and the Theil coefficients. Table 5 reports and compares forecast evaluations across different forecasting models. The results indicate that the VEC model that includes R&D knowledge stocks performs better than the other two models giving smaller RMSE values and Theil coefficients. These imply that the inclusion of information on R&D knowledge stocks gives better predictive ability of future TFP. However, the idea of forecasting productivity growth incorporating R&D and other control variables is a new

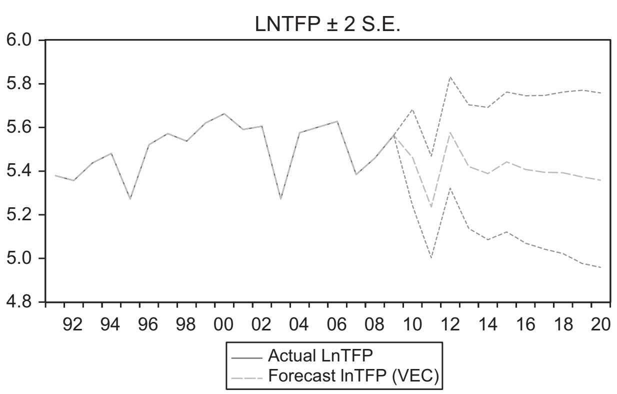

Figure 3 Out-of-sample forecasts of TFP for sample 2010–2020. *Note:*Y-axis presents LnTFP, and X-axis is the time period.

Table 5 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

application in the literature of the time series analysis of agricultural productivity. It provides further evidence of the importance of R&D in productivity growth in agriculture, showing that incorporation of the information on R&D investment improves productivity forecasts significantly.

5. Conclusions

This paper investigates the long-run relationship between public R&D and the TFP in broadacre agriculture in Australia over a period of five decades. To ensure valid empirical evidence on long-run dynamic relationships among variables in question, a set of standard unit root tests is first used, including the augmented Dickey–Fuller, DF-GLS, Phillips–Perron and KPSS tests to determine time series properties of the variables. Then, using the cointegration analysis, econometric evidence is found of a cointegrating relationship between R&D expenditure and productivity growth in Australian broadacre agriculture. Having established cointegration, an error correction model is constructed that shows that lagged R&D is significant in explaining changes in total factor productivity. This result implies that increased R&D expenditure leads to better outcomes for productivity in Australian broadacre agriculture. The results also show evidence of a causal relationship between R&D and TFP growth. With respect to the direction of causality, the empirical evidence indicates a unidirectional causality running from R&D to TFP growth.

In addition, the dynamic properties of the model are explored using variance decomposition and impulse response functions, which show that TFP responds positively and persistently in the future period because the effect of a shock in public R&D does not die out over time. Furthermore, the out-of-sample forecasting exercise that indicates that investment in public R&D in agriculture does matter in forecasting productivity growth is a new application in the agriculture literature. The results show that information on R&D investment improves productivity forecasts significantly.

The insight behind the findings of 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. This implies that productivity growth in Australian broadacre agriculture is to be driven mostly by technological advancements.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Table S1 Selection of the strongest R&D lag.

Table S2 Unit Root Tests: ADF; DF-GLS; Phillips-Perron; and KPSS Tests.