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Has growth in productivity in Australian broadacre agriculture slowed?

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Abstract

Agricultural productivity growth has been strong relative to other sectors in the Australian economy, and relative to the agricultural sectors of other developed countries. However, as commonly observed among other developed economies, growth in productivity in the broadacre sector of Australian agriculture seems to have slowed in the past decade. This paper uses the adjusted cumulative sum square (CUSQ) index to examine the trend stability of total factor productivity in Australian broadacre agriculture over the period 1952-53 to 2006-07. The results show that a significant slowdown occurred around the mid-1990s. Further analysis shows that the slowdown in productivity growth is driven by a long-term decline in public R&D investment in addition to poor seasonal conditions in the past decade.

Key words
Total factor productivity, structural change analysis, CUSUM index

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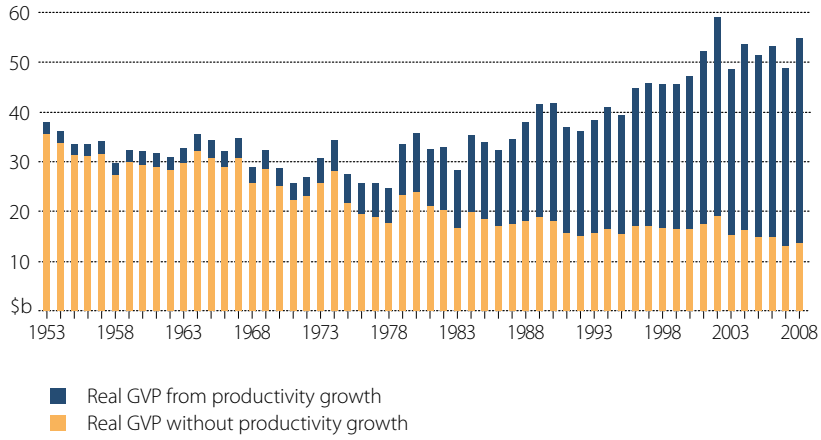
1 Introduction

Productivity growth in Australian agriculture has been an important source of wealth in Australia. The real value of agricultural production in Australia has been more than $40 billion a year since the late 1990s (figure a).[1] If productivity has grown at the rate of 2 per cent a year (Mullen 2010), about two-thirds of the value of production in recent years can be attributed to productivity growth since 1952-53. Agricultural productivity growth in Australia has also been strong relative to other sectors of the economy and relative to the agricultural sectors of other OECD countries (Mullen and Crean 2007).

a Contribution of productivity growth to the real gross value of agricultural production in Australia: 1952-53 to 2007-08 [a]



a The data relate to financial years, but the convention of referring to the 2002-03 year, for example, as 2003 has been adopted.
Source: Adapted from Mullen and Crean (2007)

However, recent data suggest that, similar to other developed countries such as the United States, Germany and the Netherlands, productivity growth in Australian agriculture may have slowed. In particular, the long-term annual growth rate of productivity in the broadacre cropping and livestock industries has declined from 2.1 per cent between 1978 and 1999, to 1.5 per cent between 1978 and 2007 (ABARE 2008). Note that these data relate to financial years, so 1978, for example, refers to 1977-78. This is also the case for the data referred to below.

A series of droughts extending back to the mid-1990s have reduced Australian agricultural production, in particular contributing to the trough of farmers' output in 1994, 2003 and 2007. However, how these droughts may affect the long-term growth of agricultural productivity is still unknown because of a lack of thorough empirical studies. Also, public investment in agricultural research in Australia, which is the predominant source of funding for agricultural R&D in Australia, has shown little growth for the past 30 years. Whether the recent slowing down of agricultural productivity is caused by poor seasonal conditions or the lack of R&D investment is an important question.

1 The value of agriculture production is calculated in 2008 Australian dollars throughout the paper.

This paper uses the adjusted cumulative sum square (CUSQ) index to examine the trend stability of total factor productivity (TFP) in Australian broadacre agriculture over the period 1953 to 2007. The objectives of this paper are:

- to review productivity growth within the broadacre agriculture industry (which comprises the cropping and livestock industries) in Australia and its determinants, using gross output-based TFP measures from ABARE farm survey data
- to assess whether productivity growth in Australian broadacre agriculture has slowed in recent decades and, if such a slowdown has occurred, when it started
- to determine whether real agricultural R&D investment and severe droughts have affected the trend stability of productivity growth in Australian broadacre agriculture.

Methodologically, this paper contributes to the previous literature by adopting the developments in structural analysis following Perron (2006) and Zhou and Perron (2008). Using the adjusted CUSQ index, some problems in dating structural breaks in agriculture productivity and analysing the determinants can be overcome. These problems can arise from some statistical difficulties such as endogeneity, heteroscedasticity and non-stationarity. Also, the paper contributes to public knowledge about trends in Australian agricultural productivity over time.

The remainder of the paper is organised as follows. Sections 2 and 3 review productivity growth in Australian broadacre agriculture in the past four decades. In section 4, the adjusted cumulative sum square (CUSQ) index, which is widely used for testing the stability of a statistical process, is discussed. Based on this method, three scenarios are specified for identifying the structural change of Australian broadacre productivity and its determinants since 1953. Section 5 contains a discussion of the estimation results and section 6 presents some conclusions.

2 Productivity growth in Australian broadacre agriculture

The Australian Bureau of Agricultural and Resource Economics (ABARE) has conducted farm surveys since 1953 for broadacre agriculture, including grazing and cropping industries, and since 1989 for the dairy industry[2]. Data from these surveys have been used to monitor trends in productivity using gross output measures[3]. Most farms in Australia jointly produce a range of crop and livestock commodities. Thus, ABARE also follows productivity within segments of broadacre agriculture such as crop, beef and sheep specialists (but only from stratified samples from the overall farm survey). In 2008, the total value of crop production was $21.4 billion, which included $9 billion of grains and oilseeds. Over the same period, the total value of livestock production was $19.8 billion, of which dairying contributed $4.6 billion; wool, $2.6 billion; and livestock slaughtering (including extensive and intensive stock), $12.1 billion (ABARE 2008).

2 The Australian Bureau of Statistics and the Productivity Commission report a value-added TFP series for the agriculture, fisheries and forestry sector. This series is compared with ABARE's gross output series for broadacre agriculture in Mullen (2010a).

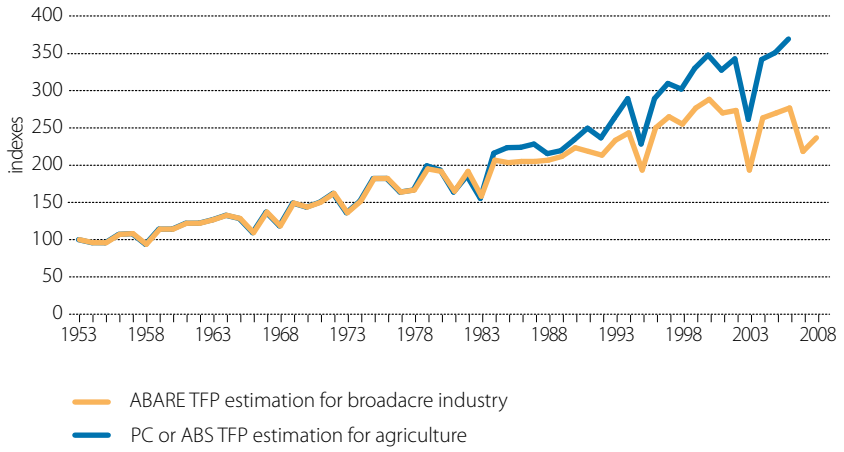
3 Measures of TFP in a sector differ depending on whether a gross output or a value-added approach is used. TFP estimates based on ABARE survey data use a gross output of production approach, while estimates based on Australian Bureau of Statistics (ABS) sectoral data (reported here) use a value-added approach. Zheng (2005) demonstrates that when using the same dataset, the gross output based TFP growth rate is less than the one based on value added by a factor equal to the ratio of the industry value added to its current gross output value. However, this relationship is unlikely to hold exactly between the ABS and ABARE productivity estimates because the data were drawn from different sources.

Mullen and Cox (1996) assembled a TFP series from 1953 to 1994 using ABARE farm survey data. Since then, the series has been extended in a piecemeal fashion, again using ABARE data in several papers, most recently Mullen (2007). Recently, ABARE assembled a consistent productivity dataset back to 1978, which has been used to extend Mullen's original series from 1978. Revisions to the sampling frame and the definition of some inputs and outputs used in the new dataset have shown that broadacre productivity growth is likely to have been overstated in studies until recently[4]. For example, broadacre TFP grew at the rate of 2.7 per cent from 1978 to 2004 using the dataset from Mullen (2007), whereas the new dataset used here suggests that the rate of growth over the same period was 1.7 per cent. Hence, in evaluating differences in the rate of agricultural productivity growth across time periods, it is important to be mindful of differences in measurement approach and use a consistent dataset.

The TFP index for Australian broadacre agriculture almost tripled from 100 in 1953 to 288 in 2000. It then declined to 193 in 2003, reflecting drought in that year, before reaching 277 in 2006 then falling to 218 in the drought year of 2007 (figure b). The index is highly variable, falling in 20 of the 55 sampled years, reflecting adverse seasonal conditions as well as some other unobserved factors (figure c). Such variability makes it difficult to discern trends in the more stable underlying rate of technical change. The average annual rate of growth over the entire period was 2 per cent, which was 0.5 per cent lower than the long-term rate previously reported by Mullen (2007).

Productivity growth in broadacre agriculture since 1978 came from output growth of 0.8 per cent a year and declining input use at the rate of -0.6 per cent a year (Nossal et al. 2009). Labour use declined (-1.7 per cent) more than the use of capital (-1.2 per cent) and land (-0.7 per cent), while the use of purchased inputs increased (2.4 per cent) which resulted in higher rates of growth in the partial factor productivity of labour (2.5 per cent) and capital (2.1 per cent).

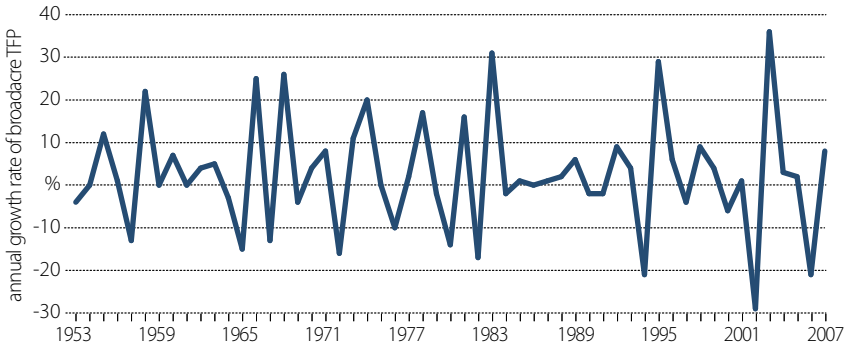
b TFP trends as estimated by ABARE for broadacre agriculture and by the Productivity Commission for agriculture, fisheries and forestry



Source: Adapted from Mullen and Crean (2007)

4 A detailed explanation of the differences can be found in Mullen (2010).

C Year-to-year fluctuation of estimated broadacre TFP: 1953 to 2007



Source: Adapted from Mullen and Crean (2007)

As noted above, the ABARE broadacre dataset can be stratified to provide estimates of productivity growth for many of the most important industry sectors. According to the current stratification used by ABARE, the broadacre industry includes four sub-industries including cropping, mixed crop–livestock, beef and sheep[5].

Since 1978, cropping (2.2 per cent) specialists have achieved much higher rates of TFP growth than beef (1.5 per cent) and sheep (0.3 per cent) specialists (table 1). Generally, output has grown while input use has been static or declining. However, for cropping specialists there was a large increase in the use of purchased inputs (4 per cent) and reduced use of labour (-0.2 per cent) and capital (-0.4 per cent) and strong growth in partial productivity of labour and capital (Nossal et al. 2009). A switch toward reduced tillage cropping also associated with more diverse cropping rotations and opportunistic cropping to exploit available soil moisture (as opposed to fixed rotations and fallows) partly explains the changes in input use and the strong rate of productivity growth.

1 Growth in TFP for broadacre industries and by state, 1978 to 2007 (%)

By industry	TFP growth	Output growth	Input growth
Total broadacre	1.5	0.8	-0.6
Cropping	2.1	3.1	1
Mixed crop-livestock	1.5	0.1	-1.5
Beef	1.5	1.7	0.1
Sheep	0.3	-1.4	-1.8
By state			
NSW	1.2	0.3	-0.9
VIC	1.4	0.6	-0.8
QLD	0.8	0.6	-0.2
SA	2	1.5	-0.5
WA	2.4	1.8	-0.6
TAS	0.8	-2.1	-2.9
NT(beef)	1.7	1.6	-0.1

Source: Nossal et al. (2009) for the industry data. The state data comes from the same database but was not published in Nossal et al. (2009).

5 More detail about beef and slaughter lamb producers defined using slightly different rules can be found in Nossal et al. (2008).

3 Is productivity growth in agriculture slowing?

There is some concern that productivity growth in Australian agriculture may have slowed as has occurred in the agricultural sectors of other developed economies. In Australia, a decade of poor seasonal conditions caused the estimated total factor productivity of broadacre farms to be quite volatile, and has made it difficult to discern from simple descriptive statistics whether productivity growth has slowed and, if so, the causes of the slowdown. A particular concern is that any slowing in growth may arise from a slower rate of technical change associated with (at best) stagnant public investment (in real terms) in agricultural research (Mullen 2007).

ABARE estimates for broadacre agriculture suggest that productivity growth has slowed in the 10 years to 2007. During this period, the TFP index peaked at 288 in 2000 and was second highest in 2006 at 276 (figure b). Trends in productivity growth have not been even across industries within broadacre agriculture (table 2). For cropping specialists, the estimated TFP grew at the rate of 5.8 per cent from 1980 to 1994 but declined at the rate of -2.1 per cent a year for the 10 years to 2007. For this period, TFP for all broadacre agriculture fell at the rate of -1.4 per cent a year. There is less evidence of a slowing in TFP growth for beef and sheep specialists, and Nossal et al. (2009) speculated that productivity growth among sheep specialists, usually ranked the lowest of the industry groups, might finally be catching up.

2 Growth rate of TFP for broadacre agriculture, 1978 to 2007 (%)

	All broadacre	Cropping	Mixed crop -livestock	Sheep	Beef
1980 to 1989	2.2	4.8	2.9	0.4	–0.9
1985 to 1994	1.8	4.7	3.2	–1.7	3.1
1989 to 1998	2.0	1.9	1.4	–1.2	1.6
1994 to 2003	0.7	–1.2	0	3.4	1.0
1998 to 2007	–1.4	–2.1	–1.9	0.5	2.8
1978 to 2007	1.5	2.1	1.5	0.3	1.5

Source: Nossal et al. (2009).

Reasons that productivity in broadacre agriculture may be slowing include:

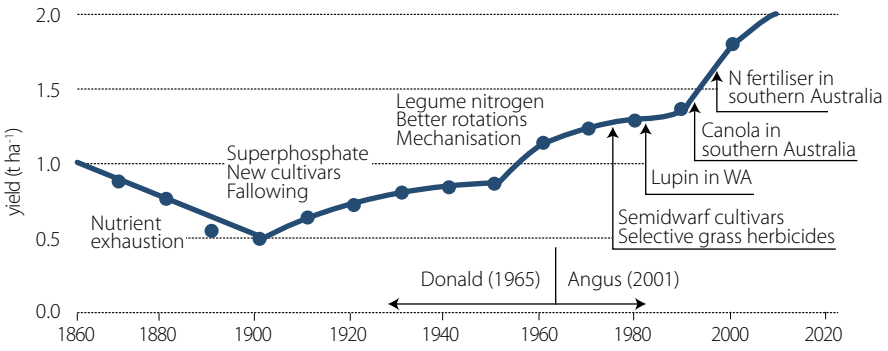
- fewer research opportunities
- unfavourable climate
- reduced investment in R&D.

With respect to the argument that 'all the big gains have been made', research agronomists still seem confident there are practical research opportunities and opportunities for farmers to grow crops more efficiently. For example, Angus (2001) argued that trends in Australian wheat yields showed little signs of slowing down (figure d).

Andrews and Angus (World Wheat Book, in press) noted:

'Despite the new technology, the mean yield is only 2.0 ton(ne) per ha, about half of the water-limited potential… Further research will be needed to increase yield closer to the water-limited potential. The gains are most likely to come from tactics that enable crops to take advantage of the more favorable seasons in the variable climate, and concentration of inputs on the parts of farms with the highest yield potential.'

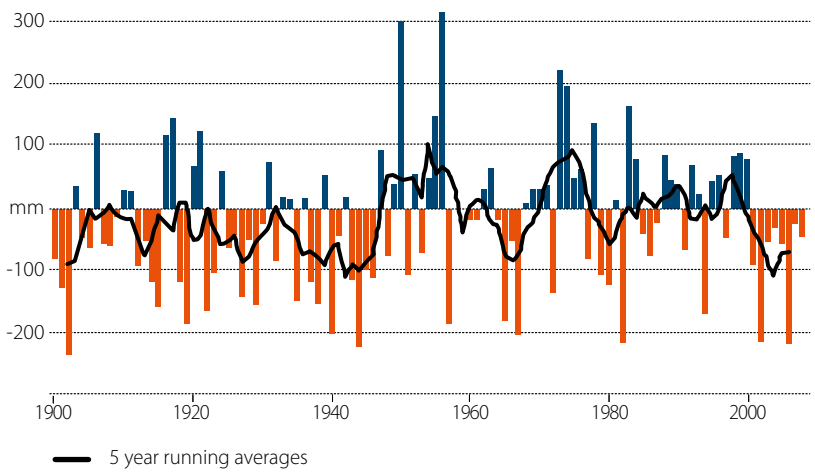
d Trends in average wheat yield in Australia: 1860 to 2000



Source: Donald (1965) modified by Angus (2001).

With respect to climate[6], the annual rainfall anomaly for the Murray-Darling Basin (figure e) published by the Australian Bureau of Meteorology shows the annual deviation in rainfall from average annual rainfall between 1961 and 1990. While the timing of rainfall remains a critical factor in agricultural production, there have now been eight consecutive years of below average rainfall. If farmers are using inputs in expectation of a normal season but a dry season eventuates, then TFP falls. In addition, farmers' expectations about seasons may now be more conservative such that they are operating on a less efficient part of the production function. This is an area for future research.

e Annual rainfall anomaly – Murray-Darling Basin
Based on a 30 year climatology (1961-1990)



Source: Australian Bureau of Meteorology.

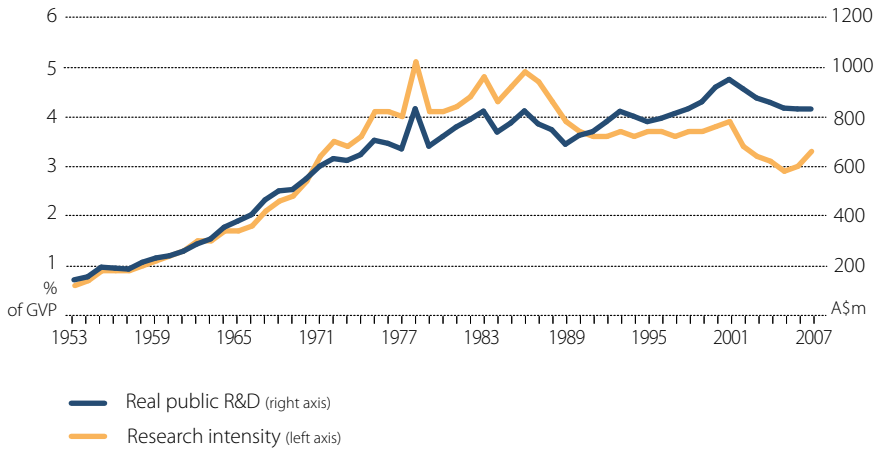
6 The term climate is used to include elements of both climate variability and climate change.

Mullen (2010b) describes how the data on R&D investment have been assembled from Australian Bureau of Statistics (ABS) sources. R&D expenditure is attributed to research providers, rather than funders. As a result, expenditure by state departments of agriculture or universities, for example, includes funds obtained from rural RDCs. Attention is focused on farm production research and investment in R&D. Fisheries and forestry R&D is not included.

Total public expenditure on agricultural R&D in Australia has grown from $140 million in 1953 to almost $830 million in 2007 (in 2008 dollars). Figure f shows expenditure growth was strong to the mid-1970s. There has been little growth in expenditure since that time although there was a spike in investment (nearly $950 million) in 2001. Likewise, agricultural research intensity, which measures the investment in agricultural R&D as a percentage of agricultural GDP, grew strongly in the 1950s and 1960s, but has been drifting down from about 4 to 5 per cent annually of agriculture GDP in the period between 1978 and 1986 to about 3 per cent a year in recent years (compared with 2.6 per cent a year in developed countries). In the analysis below of trends in broadacre TFP, investment in R&D in broadacre agriculture has been derived as a proportion of this total public investment in agricultural R&D.

Although there have been many discussions in previous literature on the relative role of climate and R&D in affecting agriculture productivity, no attempt has been made to empirically assess the relative contribution of the influences of climate (poor seasonal conditions) and investment in R&D. In the following section, the adjusted cumulative sum square (CUSQ) index (one of the structure change analysis approaches) is used to examine the stability of the TFP index for Australian broadacre agriculture between 1953 and 2007 and the contribution of factors like climate and R&D investment to changes in trend.

f Real public investment and research intensity in Australian agriculture: 1953 to 2007



Source: Derived from public financial statements of public research institutions and the ABS.

4 Methodology and estimation strategy

The CUSUM group of indices based on the cumulative sum of residuals (including CUSUM and CUSQ) has been used to identify the stability of statistical processes (Brown, Durbin and Evans 1975; Pagan and Schwert 1990; Tang and MacNeill 1993; Perron 2006; Deng and Perron 2008). To see how these indices work, note that any unanticipated upward or downward (trend) shifts of a statistical process will result in a uni-directional drift of its cumulative sum of variances or residuals obtained from a series of linear regressions of the time series variable on its regressors over time. Thus, the CUSUM procedures give an out-of-control signal when the absolute values of the cumulative sum indices exceed a critical value, indicating that the variable's values after a specific time point have been significantly different from their previously expected levels. When a significant out-of-control signal occurs, the point when the process starts to go out-of-control is determined and the relative magnitudes of trend shifts are also identified.[7]

The CUSUM-type index: a prototype model

Following Brown, Durbin and Evans (1975), a prototype model of structural change analysis generating a CUSUM index assumes there is a linear regression with k regressors $X_t' = (X_1, X_2, ..., X_k)$ such that

(1) $$y_t = X'_t b_{t-1} + u_t$$

where y_t is a time series vector (representing the statistical process to be examined), which can be explained by a group of factors, X_t and b_{t-1} is the estimated coefficients of X_{t-1} from the ordinary least square (OLS) regression with the previous $t-1$ observations.

If the total number of observations is T, the recursive residual e_t at time t can be estimated by using the $t-1$ observations.

(2) $$e_t = y_t - X'_t \hat{b}_{t-1}$$

where $X_t = (x_{1t}, x_{2t}, ..., x_{kt})$ contains factors that determine y_t. Thus, the variance of the predicted residual at time t can be written as: $\sigma^2_{ft} = \sigma^2[1 + x_t'(X'_{t-1} X_{t-1})^{-1} x_t]$.[8]

If a random time point r in the process is chosen such that $r \in T$, the r th standardised recursive residual from equation (1) can be defined as:

(3) $$w_r = \frac{e_r}{\sqrt{1 + x'_r (X'_{r-1} X_{r-1})^{-1} x_r}}$$

and the mean of this series of standardised residuals is given by $\overline{w} = \frac{1}{T-K} \sum_{r=K+1}^{r=T} w_r$ where K is the number of regressors.

If the trend of the statistical process (y_t) in the whole sample period remains constant, then $w_r \sim N[0, \sigma^2]$ is normally distributed, where w_r is independent of w_s (given $r \neq s$). These standardised residuals can be accumulated (deflated by their standard error) over the observation period (the CUSUM index) or the relative sum of squared recursive standardised residuals (the CUSQ index) can be estimated. The comparison between the estimated CUSUM/CUSQ index and their corresponding pre-determined criteria can be used to indicate a potential structural break in a time series y_t.

7 The CUSUM control schemes are designed to optimally detect (unknown) out-of-control states, and can therefore outperform other statistical techniques in this type of analysis. For a more detailed literature review, please refer to Perron (2006).

8 When there is no X_t, equation (1) can be written as $y_t = \overline{y}_{t-1} + u_t$ (where $\overline{y}_{t-1} = \frac{1}{T} \sum_{t-1} y_t$) and equation (2) as $e_t = y_t - \overline{y}_{t-1}$.

The CUSUM index can be defined as:

(4) $$CUSUM_t = w_t - \sum_{r=K+1}^{r=t} \frac{w_r}{\hat{\sigma}}$$

where w_r is the r th standardised recursive residual and $\hat{\sigma}^2 = \frac{1}{T-K-1}\sum_{r=K+1}^{T}(w_r - \overline{w})^2$ is the standard error of the series.

Under the initial assumption, the mean of the CUSUM index is zero and its variance is approximately equal to the values of accumulated residuals. The pre-determined boundary criteria are set at [$K - a\sqrt{T-K}$] and $K + 3a\sqrt{T-K}$ where a is the statistical significance level. If the CUSUM index (estimated with equation (4)) at time t lies outside these boundaries, it suggests there is a possible breaking point in time series (y_t) at time t.

The CUSQ index can be defined as:

(5) $$CUSQ'_t = \max_{K+1<r\leq T} | S_T^{(r)} - \frac{r-K}{T-K} | \text{ where } S_T^{(r)} = \frac{\sum_{r=K+1}^{t} w_r^2}{\sum_{r=K+1}^{T} w_r^2}$$

where the expected value of $S_T^{(r)}$ (or $E[S_T^{(r)}]$) approximates to $(t-K)/(T-K)$, which satisfies the Chi-square distribution. The pre-determined criteria is set between $E(S)-a$ and $E(S)+a$, where a is the statistical significance level. If there is a structural break, $S_T^{(r)}$ is likely to lie outside of the interval between $E[S_T^{(r)}]-a$ and $E[S_T^{(r)}]+a$.

The adjusted CUSQ test for multi-structural changes

The prototype model of the CUSUM/CUSQ test can be used to implement the structural change analysis of time series variables. However, it has been widely criticised for not being useful when there is a series correlation in u_t, when there are no regressors or when there is a strong correlation between X_t and u_t (in equation (1)). Specifically, when the above three situations occur, the OLS/recursive regressions would provide biased estimation of u_t and thus the CUSUM/CUSQ indexes. To address this issue, Tang and MacNeill (1993) adjusted the CUSUM test to account for serial correlation among error terms (u_t), while Deng and Perron (2008) adjusted the CUSQ test to account for the more general correlation between regressors and unobserved error terms. Also, Deng and Perron (2008) have addressed the potential effect of the conditional heterogeneity (of observations over different time periods) problem and proved that the adjusted CUSQ index is independent of regression technique (either recursive or non-recursive OLS regression) and sample size.

To see how the adjusted CUSQ index works, the description below follows Deng and Perron (2008, p. 2) by assuming that both $x_t u_t$ (where $x_t \in X_t$) and u_t^2 (in equation (1)) are short memory processes having bounded fourth moments. This assumption allows the regression to accommodate substantial conditional heteroscedasticity and autocorrelation such as the finite order stationary autoregressive models with bounded fourth moments and models with only exogenous regressors and stationary short memory errors, for example ARMA (p,q). Under this assumption, Deng and Perron (2008) found that u_t or $u_t^2 - \sigma_t^2$ can be used to replace $X_t u_t$ (where $\sigma^2 = \lim_{T\to\infty} T^{-1}\sum_{t=1}^{T} E(u_t^2)$) for calculating the CUSQ index and the adjusted results hold the same limit distribution as if the true residuals were used. In other words, as long as the statistical process y_t is stable and there is no change in regression coefficients, there will be $\max_{K^*+1<r\leq T} T^{-1/2}(\sum_{t=1}^{r} u_t^2 - \sum_{t=K^*+1}^{r} \tilde{u}_t^2) \to_p 0$ (where $\tilde{u}_t^2$ denotes either the OLS ($K^* = 0$) or recursive residuals ($K^* = K$)) whether or not there is a correlation between regressors and unobserved error terms (or $E(X_t u_t) \neq 0$). Using this condition, a new index can be constructed based on the relative sum of squared residuals as below to analyse potential structural changes in time series of y_t :

(6) $$CUSQ^* = \max_{K^*+1 \le r \le T} \left| \frac{T^{-1/2}[\sum_{t=K^*+1}^{r} \breve{u}_t^2 - \frac{r}{T}\sum_{t=K^*+1}^{T} \breve{u}_t^2]}{[T^{-1}\sum_{j=-(T-K^*-1)}^{T-K^*-1} w(j,m)\sum_{t=|j|+1}^{T-K^*} \breve{\eta}_t \breve{\eta}_{t-j}]^{1/2}} \right|$$

with $\breve{\eta}_t = \breve{u}_t^2 - \hat{\sigma}^2$ and $\hat{\sigma}^2 = T^{-1}\sum_{t=1}^{T} \hat{u}_t^2$. $\hat{u}_t^2$ denotes either the OLS ($K^* = 0$), or the recursive residuals ($K^* = K$), and $w(j,m)$ is the quadratic spectral kernel and m some bandwidth which can be elected using one of the many alternative ways that has been proposed by Andrews (1991). Also, the pre-determined criteria at the 1 per cent, 5 per cent and 10 per cent levels can be set at 1.63, 1.36 and 1.22, respectively. If y_t is stable over time, the estimated CUSQ* would be close to zero. However, if there is a significant structural break in y_t at time r , the estimated CUSQ* would be out of the pre-determined criteria at different statistical significant levels.

Equation (6) is comparable in concept with equation (5), since both indices are using the sum of squared residuals to time r and T to construct the out-of-control signal mechanism (for identifying potential structural changes). However, the former is based on the assumption of $E(X_t u_t) = 0$ (where the correlation between regressors and unobserved errors is not allowed) while the latter is based on $\max_{K^*+1<r\le T} T^{-1/2}(\sum_{t=1}^{r} u_t^2 - \sum_{t=K^*+1}^{r} \breve{u}_t^2) \to_p 0$ (where the correlation between regressors and unobserved errors is allowed). In addition, the adjusted CUSQ* also adjusts for some conditional heteroscedasticity by using the weighted function system $w(j,m)$ to correct standard errors (see the denominator of equation (6)). This provides a new mechanism through which one can examine the stability of a time series statistical process accounting for non-normal errors, serial correlation and conditional heteroscedasticity.

Finally, Zhou and Perron (2008) further extended the CUSQ* test (defined in equation (6)) to cover the multiple structural changes identification issue. In doing so, Zhou and Perron (2008) assume that the potential break dates are $T_r^0 = [T\lambda_r]$ where $0 < \lambda_1 < \lambda_2 < \ldots < \lambda_m < 1$ and are asymptotically distinct. Since break date estimates with limit distributions are not independent, all break dates should be estimated jointly. Thus, the updated version of the CUSQ* can be written as (Zhou and Perron, 2008):

(7) $$CUSQ^* = \max_{\lambda \in [0,1]} \left| \frac{T^{-1/2}[\sum_{t=K^*+1}^{[T\lambda]} \breve{u}_t^2 - \frac{[T\lambda]}{T}\sum_{t=K^*+1}^{T} \breve{u}_t^2]}{[T^{-1}\sum_{j=-(T-K^*-1)}^{T-K^*-1} w(j,m)\sum_{t=|j|+1}^{T-K^*} \breve{\eta}_t \breve{\eta}_{t-j}]^{1/2}} \right|$$

with $\breve{\eta}_t = \breve{u}_t^2 - \hat{\sigma}^2$ and $\hat{\sigma}^2 = T^{-1}\sum_{t=1}^{T} \hat{u}_t^2$. $\hat{u}_t^2$ denotes either the OLS ($K^* = 0$), or the recursive residuals ($K^* = K$), and $w(j,m)$ is the quadratic spectral kernel and the bandwidth parameter m is selected using Andrews' (1991) method with a first-order auto regression approximation (or AR(1)). Although the CUSQ* index in equation (7) has relatively weaker power in specifying the number of breaks compared with other tools such as the super LM test and the LR test, it has good properties for monitoring the global behaviour of the statistical process (Perron 2006). This is important in examining the trend of agriculture productivity in Australia since it should be less volatile over time. In this paper, equation (7) will be applied to carry out the structural break analysis.

Estimation strategy for identifying agriculture TFP structural changes

To examine structural changes in Australian broadacre TFP and its determinants, a multi-step testing procedure based on equation (7) was adopted. The first scenario was to regress the logarithm of estimated broadacre TFP on a time trend (i.e. year), and use the residuals obtained from the regression to calculate the adjusted CUSQ* index. This scenario gives a baseline against which the other scenarios can be compared. The regression function can be written as:

(8) $$\ln(TFP_t) = \beta_0 + \beta_1 T_t + e_t$$

where $\ln(TFP)_t$ is the logarithm of broadacre TFP at time t, and T_t is a time variable.

The second scenario was to incorporate variables representing climate and a knowledge stock into the OLS regression and re-calculate the adjusted CUSQ index. The regression function can be written as:

(9) $$\ln(TFP_t) = \beta_0 + \beta_1 T_t + \beta_2 \ln WS_t + \beta_3 \ln K_t^i + u_t$$

where $\ln WS_t$ is the climate variable (approximated by using the waterstress index for the cropping industry), and $\ln K_t^i$ is the knowledge stock (approximated as the weighted sum of public investment in agricultural R&D where i can be 35 or 16 representing different time lags over which new technologies become available and are used by farmers). Since there is little known about the length of lags between R&D and adoption of technology by farmers, the rate of technology depreciation and about the shape of the research lag profile, Mullen (2007) has been followed in testing two alternative knowledge stock variables. A log-linear specification was also adopted in this estimation to examine the effect of agricultural R&D investment on agricultural productivity. Comparing results obtained from the first and second steps shows the extent to which climate change and agriculture R&D investments have affected the stability of agriculture productivity.

The third scenario was to incorporate education and terms of trade variables into the structural break analysis so that the effect of these factors on the stability of productivity growth could be examined. The regression function can be written as:

(10) $$\ln(TFP_t) = \beta_0 + \beta_1 T_t + \beta_2 \ln WS_t + \beta_3 \ln K_t^i + \beta_4 educ_t + \beta_5 \ln tot_t + v_t$$

where $educ_t$ is the education index, which is defined as the ratio of school attendance to the total population aged four to 19 (a proxy for the education status of farmers), and $\ln tot_t$ is the logarithm of terms of trade for Australian broadacre agriculture.

Based on Perron (2006, p. 9), a time trend is included in all three scenarios, rather than directly using the variance of the time series variable especially in the first step, to increase the power of the adjusted CUSQ* test for structural changes. All data used came from either ABARE's AAGIS survey or the ABS.[9]

9 Refer to appendix A for detailed descriptions.

3 OLS estimation results for the adjusted CUSQ procedure

	Base model		R&D 35 year lag			R&D 16 year lag		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year	0.020***	0.019***	0.008***	0.007**	0.004	0.012***	0.010***	0.009***
	-0.001	-0.001	-0.002	-0.003	-0.003	-0.002	-0.002	-0.003
lnWS	-	0.277***	0.279***	0.276***	0.271***	0.287***	0.284***	0.262***
	-	-0.052	-0.043	-0.044	-0.042	-0.043	-0.043	-0.042
K^{35}	-	-	0.196***	0.200***	0.144***	-	-	-
	-	-	-0.041	-0.041	-0.047	-	-	-
K^{16}	-	-	-	-	-	0.185***	0.189***	0.122***
	-	-	-	-	-	-0.038	-0.038	-0.044
educ	-	-	-	0.010	-0.234**	-	0.010	0.009
	-	-	-	-0.011	-0.108	-	-0.011	-0.010
lntot	-	-	-	-	-3.208***	-	-	-0.213**
	-	-	-	-	-1.007	-	-	-0.106
constant	0.015	-1.243***	-3.320***	-4.111***	-3.208***	-3.222***	-4.035***	-1.935
	-0.027	-0.237	-0.473	-0.950	-1.007	-0.450	-0.936	-1.254
R-square	0.906	0.938	0.957	0.957	0.960	0.957	0.957	0.962
Number of Obs.	55	55	55	55	55	55	55	55

Note: Standard errors in parentheses, and "***", "**" and "*" represent the significance at 1 per cent, 5 per cent and 10 per cent level, respectively.
Source: Authors' own calculation.

5 Estimation results

Structural change in Australian broadacre TFP: baseline scenario

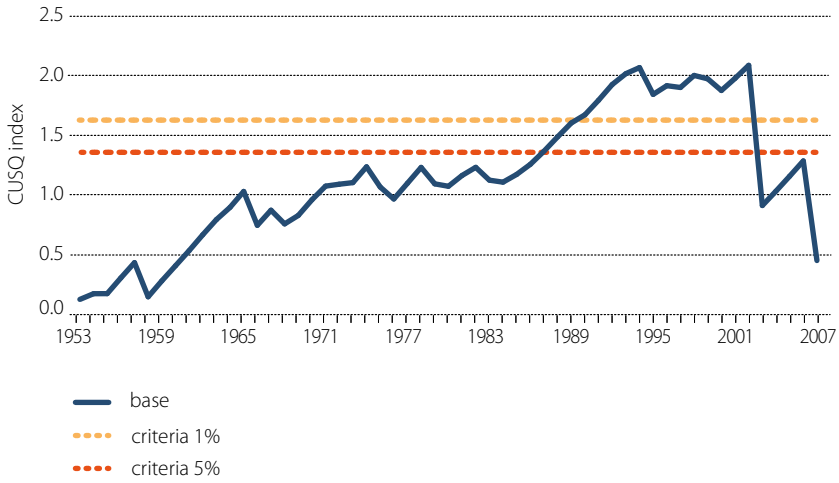
Figure g shows the estimated CUSQ index from the first scenario, with both the 1 per cent and 5 per cent Andrews criteria, for the period 1953 to 2007.[10] There is an obvious trend in the estimated CUSQ index with a global peak of 2.09 occurring in 2002 after a decade of monotonic increase. This value easily exceeds the Andrews 5 per cent and 1 per cent critical values, 1.36 and 1.63, and the hypothesis of no structural break in the TFP series for Australian broadacre agriculture was rejected.

Given that evidence of structural breaks was found, the next step was to determine how many breaks there were and when they occurred. To identify the number of breaks, figure g shows that there have generally been three waves of systematic changes in estimated CUSQ index over time, occurring in the early 1960s, the 1970s and the 1990s, respectively. The first wave of change reaches a high of 1.03 in 1965, while the second and third reach highs of 1.24 in 1974 and 2.07 in 1994 (or 2.09 in 2002). All of these can be treated as candidate structural breaks. However, when compared with the Andrews 5 per cent and 1 per cent critical values, only the potential structural break in the 1990s exceeded the criteria, suggesting there was just one significant structure break from 1953 to 2007.[11]

10 These critical values are asymptotic and estimated with chi-square values from sequential Chow tests.
11 Using the earlier broadacre TFP series, Mullen found some evidence supporting Stoeckel and Miller's (1982) view that TFP grew more quickly (2.5 per cent up from 2 per cent) after 1967 but this hypothesis was not supported by the present TFP series, though a potential structural break was found around 1965.

There are different views in the literature on the dating of the turning points of structural changes. Some studies, including Bai (1994) and Bai and Perron (1998), tend to use the criteria method. This uses the time when the CUSQ index breaks through the critical value as the break date. In this case, this would be 1987 at the 5 per cent level and 1990 at the 1 per cent level. Other studies, including Chong (1995), Bai (1997) and Hansen (2001), prefer to use the local or global peak point to identify the change in structure. In this study, the latter view was taken because of the limited sample size by using the time when the CUSQ index reaches its first peak out of the criteria boundary as the break date. Thus, the turning point for broadacre TFP (in figure g) was identified as 1994 when the CUSQ index reached its first peak of 2.07. This result suggests that the growth patterns of broadacre productivity were significantly different before and after 1994. Although our finding from this analysis seems to contradict what might be concluded from a visual inspection of the TFP series (figure b), which appears to show the structural change in productivity occurred after 2000, substantial year to year fluctuation in productivity makes accurate visual identification of its long-term trend difficult.

g Testing for TFP structural change in Australian broadacre industry 1953 to 2007: A baseline scenario



Source: Authors' own estimation.

Finally, since the annual TFP growth rate for the period from 1953 to 1994 (2.2 per cent) was significantly higher than that for the period from 1994 to 2007 (0.4 per cent), the identified structural change reflected a slowing in TFP growth for the broadacre industry (table 2).

The role of climate, R&D investment and other factors

Severe climate conditions and a decline in public R&D investment are widely believed to be related to the slowdown of agricultural productivity growth in the broadacre industry in recent years. To investigate further, the estimation of the CUSQ index was extended by accounting for possible effects from climate (crop water stress index), real agriculture R&D investment[12] with 35 and 16 year lag structures (obtained and updated from Mullen (2007)), education and the terms of trade facing broadacre agriculture. The estimated CUSQ indexes are shown in figures h, i and j, along with the baseline scenario. Figures h, i(1) and i(2) focus on climate and R&D. Figures j(1) and j(2) focus on education and the terms of trade. The '1' figures are for the 35 year lag research profile and the '2' figures are for the 16 year lag research profile.

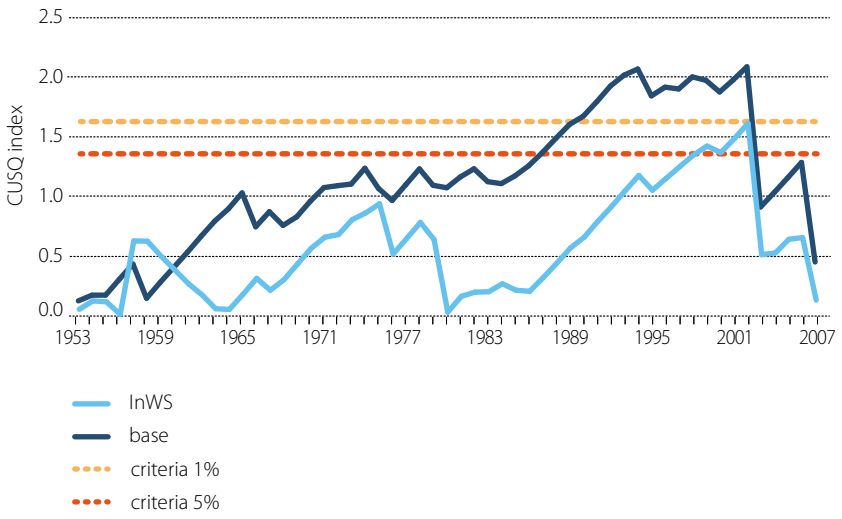
12 Details of four independent variables used in this study—crop waterstress index, real agricultural R&D investment, farmer's education and terms of trade—are provided in appendix A.

When the effect of climate was considered (figure h), the CUSQ index became more stable for the period 1953 to 2007. Compared with the baseline model, it was generally lower throughout the whole period and reached a peak of 1.62 in 2002 (smaller than 2.09 in 2002 and less than the 1 per cent significance criteria). This result implies that, as expected, climate (in particular, drought) in recent years was an important factor contributing to the instability of the productivity trend. However, since the CUSQ index after controlling for climate (in 2002) was still more than the Andrews 5 per cent and close to the 1 per cent critical values, drought may not fully explain the slowing of broadacre productivity in the most recent decade.

Regarding the date of the breaking point after controlling for climate, the first peak of CUSQ index approaching the 1 per cent Andrews boundary occurred in 2002 (with the value of 1.62) rather than in 1994 (with the value of 2.07) as in the baseline model. The statistics suggest that, if there had not been a run of poor climate conditions (including severe droughts) since the mid-1990s, broadacre TFP would have kept growing at its trend rate until 2002. A possible explanation for this phenomenon is that the drought in the mid-1990s had an adverse impact on farmers' outputs (given inputs) and dragged down their productivity growth, which has not fully recovered because of many years of poor seasonal conditions since. However, climate alone does not account for the change in trend in TFP because, after accounting for climate, there remains a change in structure in 2002.

The 16 year and 35 year knowledge stock variables assembled from real public R&D investment in Australian broadacre agriculture were then added into the structural change analysis (with climate still included in the

h Effect of climate on agricultural productivity structural change



Source: Authors' own estimation.

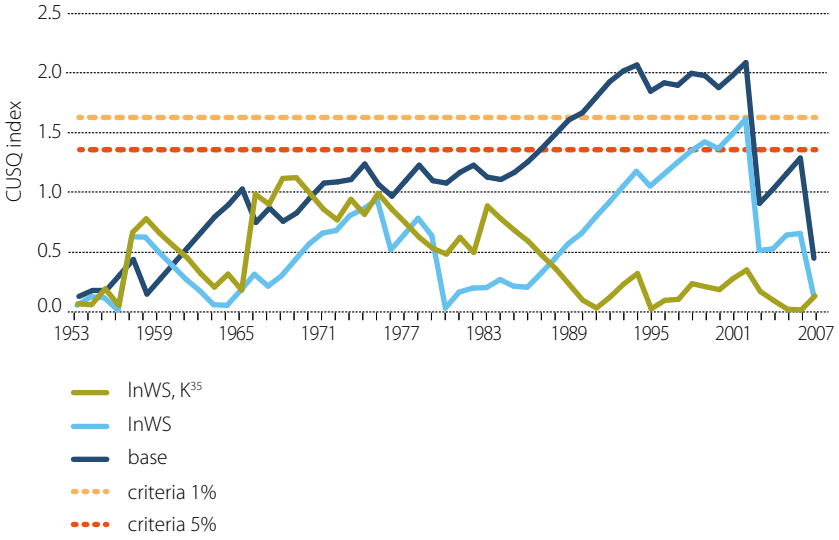
model), and the adjusted CUSQ index re-estimated. This was undertaken to assess whether the effect of stagnant real agriculture R&D investment has further exacerbated the slowdown in broadacre productivity

Figures i(1) and i(2) compare the adjusted CUSQ index obtained from the scenario, accounting for both climate and a knowledge stock. After controlling for the effects of real agricultural R&D investments, the variability in the CUSQ index further decreased, especially for the past two decades. Throughout the whole period of 1953 to 2007, the CUSQ index for the 35 year lag profile reached peaks of 1.13 (or 1.80 for the 16 year lag research profile) in 1969 and 0.89 (or 1.47 for the 16 year lag research profile) in 1983, which is less than the Andrews 5 per cent value. There was no longer a significant out-of-control pattern for the CUSQ index, which implies there was no strong evidence of structural change in productivity growth in recent years after controlling for real agricultural R&D investments and climate. Comparing this result with those obtained from both the baseline model and the

model accounting for climate (where statistically significant structural changes were identified), it can be said that real agriculture R&D investment is an important factor affecting the stability of broadacre productivity in the past two decades. In particular, it contributes to explaining the recent trend of a slowing down of broadacre productivity growth since 2002.

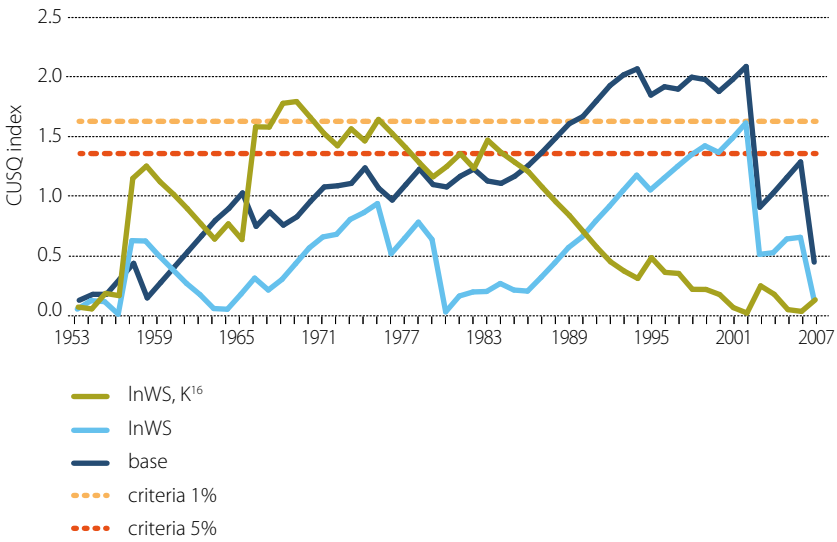
Comparing the relative effect of the 16 to 35 year research profiles, our analysis lends support to the view that the lags involved in agricultural research are more likely to be in the order of 35 years than 16 years. This is because the pattern of the estimated CUSQ index with the 35 year lag profile in agricultural research is more stable than that with the 16 year lag profile, which indicated a statistically significant change in trend in 1969.

i1 Effect of climate and R&D investment (35 year lag) on agricultural productivity structural change



Source: Authors' own estimation.

i2 Effect of climate change and R&D investment (16 year lag) on agricultural productivity structural change

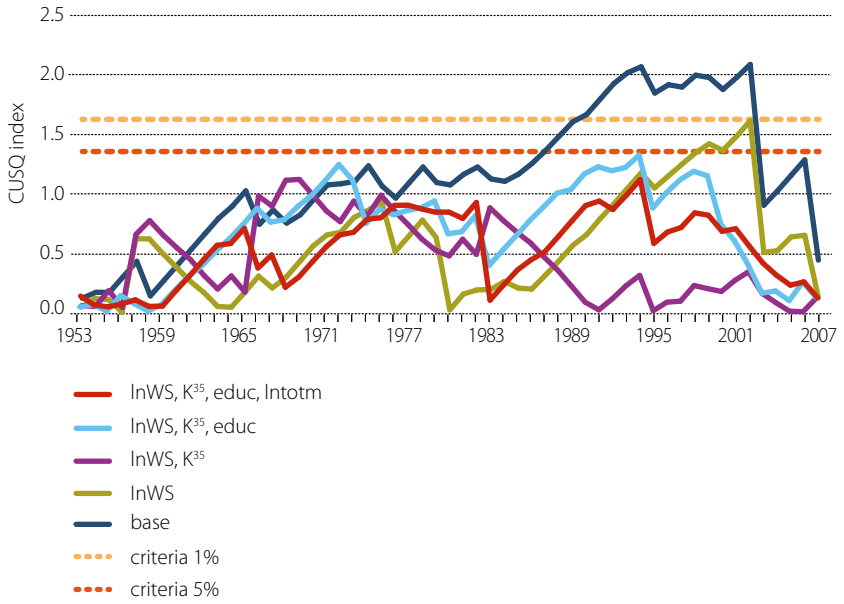


Source: Authors' own estimation.

Productivity growth after controlling for climate and real agriculture R&D investment was expected to be more stable over time and similar to a random process given the nature of technology progress. Of course, the above statistical results are only valid if the strict assumptions about the effect of agricultural R&D on productivity represented by the alternative lag profiles remain unchanging over time.

The effects of some other factors, such as farmers' education and terms of trade[13], on the slowdown in Australian broadacre productivity were also examined. Figures i(1) and i(2) show the estimated CUSQ index under the assumption of real agricultural R&D investments with 35 year and 16 year lags, respectively, with these variables added. Compared with the model only accounting for climate and real agriculture R&D investment, the estimated CUSQ indexes from the model that includes the education and terms of trade indexes are less stable especially since the mid-1980s. This result, combined with the observation of continuing education-level improvement and flattening terms of trade in the past two decades (figures m and n), suggests that changes in education and the terms of trade contributed to weakening the structural change in productivity and favouring broadacre productivity growth in recent years. However, since the estimated CUSQ indexes were not out of the 5 per cent and 1 per cent Andrews boundaries, it can be concluded that, statistically, they were not as important as climate and real agricultural R&D investment in affecting broadacre productivity.

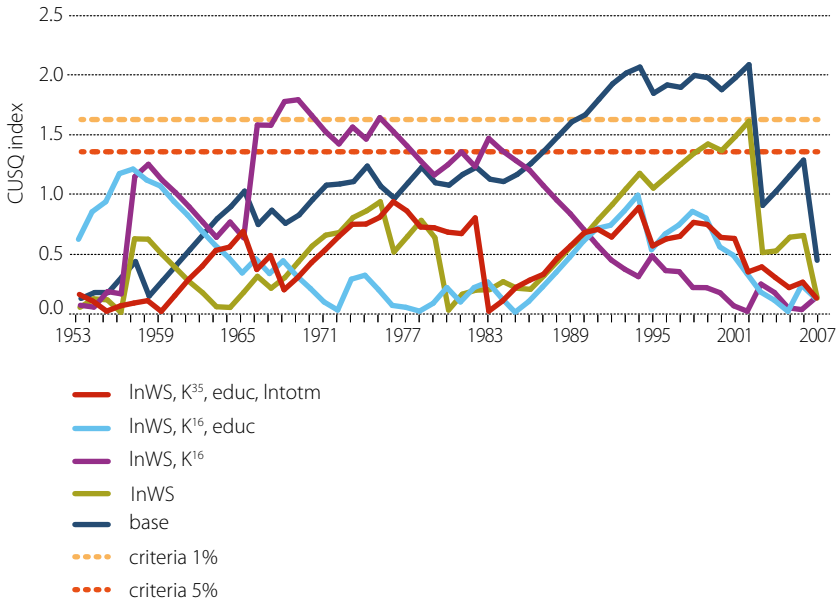
j1 Effect of education and terms of trade on agricultural productivity structural change (35 year lag for R&D)



Source: Authors' own estimation.

13 Details of the two variables are provided in Appendix A.

j2 Effect of education and terms of trade on agricultural productivity structural change (16 year lag for R&D)



Source: Authors' own estimation.

6 Conclusions

There was little growth in productivity in broadacre agriculture over the decade to 2007. For cropping specialists, TFP grew at a rate of 4.8 per cent a year from 1980 to 1994 but declined at -2.1 per cent a year for the 10 years to 2007. For the past decade, TFP for all broadacre agriculture fell at the rate of -1.4 per cent a year. There is much less evidence of a slowing in TFP growth for beef and sheep specialists. The reasons for this slowdown are uncertain, although poor seasons and little growth in public investment in agricultural R&D appear to have been prime contributors.

Using the structural change analysis, the stability of the trend in broadacre TFP growth for the period of 1953 to 2007 was examined. There is statistical evidence of a significant structural change in broadacre productivity in the mid-1990s. A further comparison of productivity growth before and after this turning point in the 1990s shows this structural change led to a decline in the rate of productivity growth. The analysis undertaken here suggests that, while climate has had an important effect on lowering growth in broadacre TFP over the past decade, it alone did not fully account for the slowdown. Only when the reduction in investment in public R&D extending back to the 1970s was taken into account was there a return to a stable path for broadacre TFP growth.

Appendix A: Definition of four independent variables

In this study, four independent variables were used in the OLS regressions to examine their effect on the stability of productivity growth over time.

Crop waterstress index

$\ln WS_t$ is the logarithm of an index of crop waterstress used to account for the effect of seasonal conditions[14]. For the period 1953 to 1988, an index at aggregate level was obtained directly from the Agricultural Production System Research Unit (APSRU), CSIRO. For the period 1989 to 2004 this index was not available and the authors derived a waterstress index at the farm level and aggregated it up to the industry level, using sheep equivalents carried as weights. In the post-2004 period, water stress index at the farm level was unavailable. The authors used a weighted average of the total rainfall at the farm level and aggregated the data to the industry level.

Agricultural R&D expenditure

There is little by way of theory or empirical evidence to guide the construction of knowledge stock variables representing the technology available to farmers except that most empirical work suggests that these lags are long (Alston et al. 2008). Mullen (1995 (with Cox) 2007) used a trapezoidal 35 year lag research profile, K_t^{35} and a 16 year inverted V profile, K_t^{16}, to proxy the effect of public investment in research and development. Mullen's database on R&D investment has been updated to 2007 from ABS sources.

Farmer's education

$educ_t$ is defined as the percentage of enrolled students in schools in the total population aged between four and 19. The index was initially used by Hastings (1978), then updated by Mullen and Cox (1995). The same methodology was used in this study. Enrolment is defined as school attendance or the number of school students at the national level, obtained from ABS 4102.0 (various years: 2005, 2009) for the period 1995 to present. The population data came from ABS 3201.0 Population by Age and Sex, Australian States and Territories (TABLE 9.1 Estimated Resident Population by single year of age, Australia). To smooth the trend, a five year moving average of the dataseries was taken.

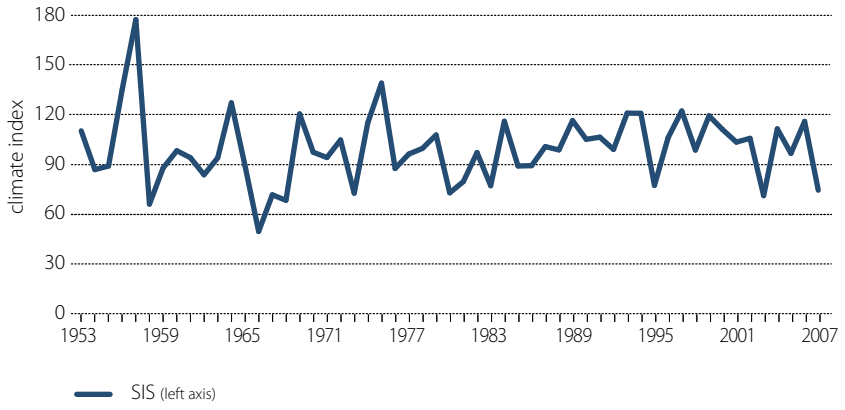
Terms of trade

$\ln tot_t$ is defined as the logarithm of terms of trade for broadacre agriculture derived from ABARE data.

Finally, some descriptive statistics of the four variables are shown in Figures k to n.

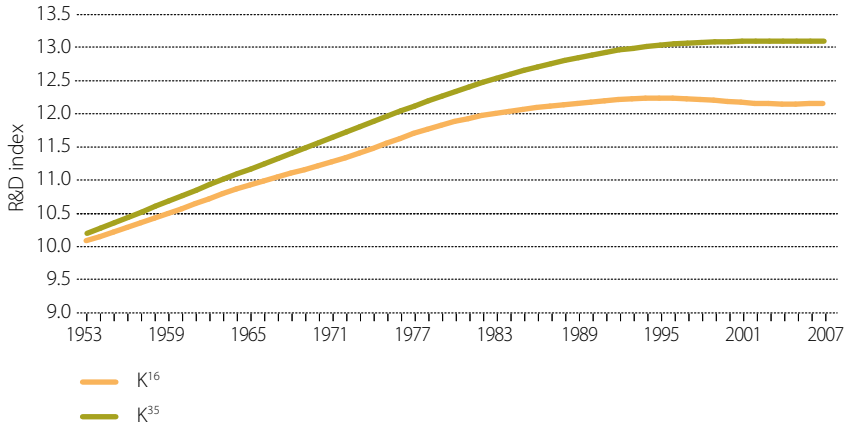
14 An alternative climate variable is a pasture growth index but the crop waterstress index is likely to better represent climate experienced during the growing season for the cropping industry (given that TFP for cropping specialists seems to have slowed more than that for other industries).

k Crop waterstress index: 1953 to 2007



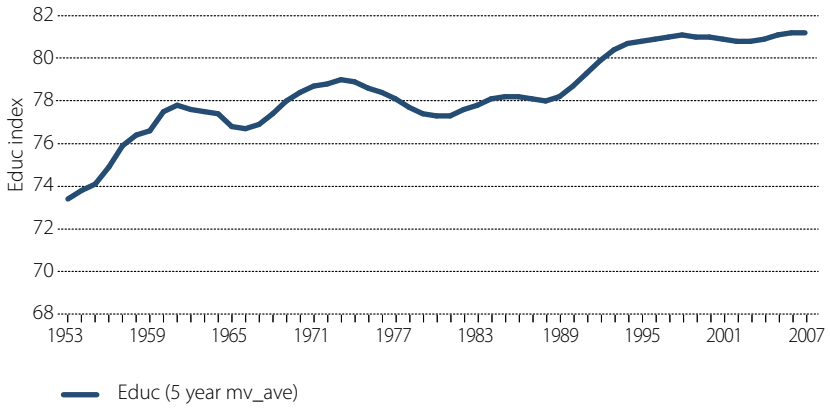
Source: Authors' own calculation.

l Trends in public real R&D investment in agriculture with 35 year and 16 year lags: 1953 to 2007



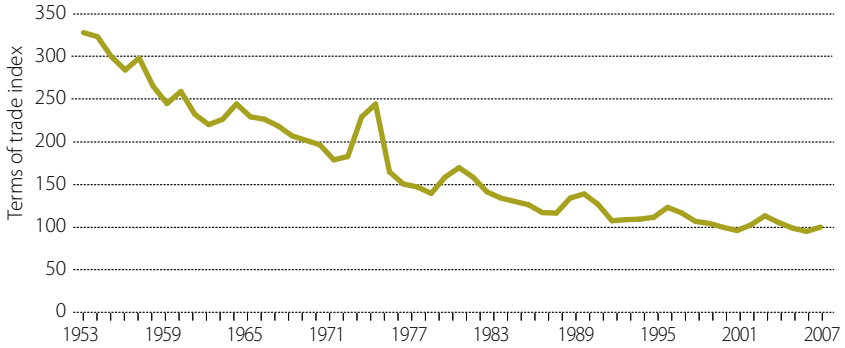
Source: Authors' own calculation.

m Trends in education index in Australia: 1953 to 2007



Source: Authors' own calculation.

n Trends in terms of trade for Australian broadacre agriculture: 1953 to 2007



Source: Derived from ABARE data.

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