

Comparing Agricultural Total Factor Productivity between Australia, Canada, and the United States, 1961-2006

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ABSTRACT

This article provides a comparison of levels and growth of agricultural total factor productivity between Australia, Canada, and the United States for the 1961–2006 period. A production account for agriculture that is consistent across the three countries is constructed to estimate output, input and total factor productivity, and a dynamic panel regression is used to link the productivity estimates to potential determinants. We show that investment in public research and development and infrastructure plays an important role in explaining differences in productivity levels between countries. The findings provide useful insights into how public policy could be used to sustain agricultural productivity growth.

GLOBAL AGRICULTURAL OUTPUT HAS more than tripled over the past half century, driven by new technologies and increased input use. This output growth has helped to satisfy increasing demand for food and fibre as population and income per capita have increased, and has thereby stabilized global food prices. Agricultural productivity growth has contributed significantly to these gains (Fuglie and Wang, 2012).

One of the most important drivers of agricultural productivity growth is technological progress. This progress has followed two dis-

tinct paths in developed countries, depending on the initial endowment of resources. Those possessing relatively abundant capital and land, for example Australia, Canada and the United States, have been lead adopters of capital-intensive technologies such as reduced-till cropping, yield mapping and mechanised mustering, and thus have achieved high levels of output per worker. In contrast, land-scarce, labour-rich developed economies such as Japan, South Korea and Taiwan have adopted labour-intensive technologies such as green-housing and

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vertical farming technologies, and thus have achieved high yields per unit of land (Fuglie, Wang and Ball, 2012).

However, recent evidence suggests that agricultural productivity growth is either stagnant or slowing in many countries (Alston, Beddow and Pardey, 2010; World Bank, 2007; Sheng, Mullen and Zhao, 2011). This is particularly the case in countries such as Australia and Canada that have historically relied on the adoption of capital-intensive technologies to drive productivity growth, where the inelastic supply of natural resources (i.e. land) decreases the marginal benefits obtained from adopting the embodied technology. In turn, this creates concern about the sustainability of capital-intensive technological progress as a source of ongoing productivity growth, compared with labour-intensive technological progress. These concerns are heightened by decreasing marginal returns to capital and tightening agricultural land supply throughout the world.

To gather more empirical evidence on this issue, this article calculates and compares total factor productivity (TFP) levels and growth rates between Australia, Canada and the United States for the 1961–2006 period. Comparing output, input and productivity across countries requires data on relative output and input prices, based on purchasing power parity (PPP) estimates. We obtain these relative prices by combining output and input prices with their quantities in each country. In the estimation process, the Törnqvist index with the Caves-Christensen-Diewert formula for transitivity is employed. Productivity levels in each country are defined as the ratio of real output to real input, which in turn are constructed as their values divided by corresponding prices. Finally, we use a dynamic panel regression analysis to link these TFP measures to potential determinants in the three countries.

This article builds on previous research (for example, Ball *et al.*, 2001 and 2010) by con-

structing a consistent production account with which to compile price and quantity data for agricultural outputs and inputs in Australia, Canada, and the United States. In addition, the accounting identity (whereby total output value equals total input value) is used to derive unobserved returns to labour, enforcing the assumption of constant returns to scale. Finally, a quality adjustment has been applied to land and certain intermediate inputs to eliminate the undesirable impact of embodied technological progress when estimating TFP.

The article is organized into five sections. Section 1 provides a review of methods and data used in cross-country comparisons of agricultural productivity. Section 2 develops the data base for each country and describes the method used to develop comparable productivity estimates. Section 3 documents data sources for Australia, Canada, and the United States. Section 4 presents the results and compares agricultural productivity and its drivers between Australia, Canada, and the United States. Section 5 concludes.

Cross-Country TFP Comparison in Agriculture: A Literature Review

While many studies have used index number methods to estimate agricultural TFP in individual countries (Fuglie, Wang and Ball, 2012), international comparisons remain challenging. Obtaining data remains the most problematic issue, with some economists warning of ‘insurmountable data constraints’ in producing detailed commodity datasets for the agriculture industry in different countries (Craig, Pardey and Roseboom, 1997). Where established datasets are available, differences in the treatment of variables limits the comparability of input and output data (Capalbo, Ball and Denny, 1990).

Given these limitations, most cross-country comparisons have drawn on data from the

United Nations Food and Agriculture Organization (FAO). Although it lacks price information and does not cover all inputs, the FAO dataset covers many countries over a long time period. For example, Craig, Pardey and Roseboom (1994 and 1997) estimated agricultural land and labour productivity for 98 countries between 1961 and 1990 and found that input mix, input quality and public infrastructure were significant factors explaining agricultural productivity growth differences between countries. While such partial productivity measures are likely to overstate overall efficiency improvements (because they do not account for changes in the use of capital and intermediate inputs), they nonetheless provide some indication of factor-saving technical change (Fuglie, 2010).

Coelli and Rao (2005) used FAO data to compare agricultural TFP for 93 countries between 1980 and 2000 using a Malmquist index and data envelopment analysis (DEA). The Malmquist index method allows inputs and outputs to be aggregated through a distance function, without the need for price data. The results show that agricultural TFP growth was strong across all countries before 2000, with some evidence of catch-up between low and high performing countries. Ludena *et al.* (2007) also used the Malmquist index method to estimate TFP growth for subsectors of the agriculture industry (crops and ruminant and non-ruminant livestock) for 116 countries between 1961 and 2006. The study found that TFP growth in developing and developed countries was converging for crop and non-ruminant livestock production activities, and diverging in the ruminant livestock sector.

While the Malmquist index method has some advantages (for example, no price information is needed for TFP estimation), it also has disadvantages. In particular, it is sensitive to the set of countries compared, and the number of variables in the model (Lusigi and Thirtle, 1997).

Without a large cross-section of countries, TFP estimates are likely to suffer from measurement errors. Also, estimates from Malmquist index numbers often seem implausible (Coelli and Rao, 2005; Headey, Alauddin and Rao, 2010), possibly because of the unrealistic implicit shadow prices derived for aggregation (Coelli and Rao, 2005).

For these reasons, wherever reliable price data are available, 'superlative' index methods are preferred. Superlative index number methods are widely adopted by national statistical agencies and are recommended by the OECD (2001) for productivity statistics.

Fuglie (2010) used a Törnqvist index to estimate and compare agricultural TFP growth for 171 countries. While FAO data were used, and were augmented using a fixed set of average global prices from Rao, Maddison and Lee (2002) for revenue shares, and using input elasticities from country-level case studies for cost shares. Fuglie (2010) found that global agricultural TFP growth had accelerated in recent decades, particularly among developing countries such as China and Brazil. This contrasts with recent estimates of yield and labour productivity which indicate a global slowdown (Alston, Beddow and Pardey, 2010).

After considering various approaches for performing inter-region comparisons of agricultural prices, quantities and productivity, Ball *et al.* (1997) identified two suitable options: the Fisher index with an Eltetö-Köves-Szulc formula (Eltetö and Köves 1964; Szulc 1964) and the Törnqvist index with the Caves-Christensen-Diewert formula (Caves, Christensen and Diewert, 1982). Ball *et al.* (2001, 2010) conducted empirical studies to examine these approaches. To address the data challenges facing international comparisons of agricultural productivity, Ball *et al.* (2001, 2010) developed an internationally consistent production account system for collecting agri-

cultural input and output data from individual countries.

Ball *et al.* (2001) compared agricultural TFP between the United States and nine European Union countries. Using 1990 as the base year, Ball *et al.* (2001) derived bilateral Fisher price indexes adjusted by purchasing power parity and then by the Eltetö-Köves-Szulc (EKS) formula (for transitivity). Indirect quantity indexes of outputs (inputs) were then estimated as total output (input) value divided by the corresponding price index. The results showed that agricultural productivity converged between the United States and the nine European Union countries between 1973 and 1993. Accordingly, most of the observed disparity in output levels between these countries is caused by differences in input use.

Ball *et al.* (2010) further developed the method for comparing TFP across countries by applying Törnqvist price indexes and the Caves-Christensen-Diewert formula (to impose transitivity across countries). These studies compared competitiveness between the United States and eleven European Union countries over the period 1973 to 2002. Ball *et al.* (2010) found that the apparent catch-up of the European Union countries was reversed after the mid-1990s, and significantly weakened the competitiveness of European Union agriculture relative to that of the United States.

Using the method advanced by Ball *et al.* (2010), this article uses production account data for agriculture in Australia, Canada, and the United States to compare agricultural TFP between countries and identify its potential drivers.

Measuring Output, Input and TFP in Agriculture

In this section, we briefly discuss the index number method used for multilateral comparison of agricultural productivity levels. When using this method, the TFP index is defined as the ratio of the index of real output to real input,

which in turn are obtained from the nominal values of output and input by the corresponding price indexes. The construction of the output and input price indexes takes into account prices and quantities of the individual components in each country, and is adjusted for cross-country comparability. To identify its underlying drivers, measures of TFP are then regressed against factors such as climate conditions, public R&D knowledge stock, and infrastructure.

Index Method for TFP Estimates

Theoretically, TFP is measured as real output, Y_t , divided by real input, X_t , and its growth is measured as the difference between output and input growth rates (estimated using logarithmic differentials to time t).

$$(1) TFP_t = \frac{Y_t}{X_t}$$

$$(2) \frac{d \ln(TFP_t)}{dt} = \frac{d \ln(Y_t)}{dt} - \frac{d \ln(X_t)}{dt}$$

where X_t includes land, capital, labour and intermediate inputs.

Both direct and indirect methods can be used to derive real output and input. In practice, an indirect approach is usually preferred, whereby real output and input quantities are measured as the gross value of outputs or inputs divided by a corresponding price index, since value data for most outputs and inputs are more readily available than quantity data. Assuming perfect competition and a linearly homogenous production function, direct and indirect quantity estimates are equivalent when using a superlative index that satisfies the factor reversal test (Diewert, 1992). In this sense, the estimation of real output, real input and productivity is converted into the estimation of output and input relative prices.

For each country, output and input price indexes can be obtained by using a Törnqvist

index to approximate a linearly homogeneous translog function, such that

$$(3) \ln\left(\frac{P_t}{P_{t-1}}\right) = \frac{1}{2} \cdot \sum_i (R_{i,t} + R_{i,t-1}) \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

$$(4) \ln\left(\frac{W_t}{W_{t-1}}\right) = \frac{1}{2} \cdot \sum_j (S_{j,t} + S_{j,t-1}) \ln\left(\frac{W_{j,t}}{W_{j,t-1}}\right)$$

where R_i is the revenue share of the i th output and S_j is the cost share of the j th input. P_i and W_j are the prices of the i th output and j th input, respectively.

We use the Törnqvist index for two reasons. First, although the Törnqvist index only satisfies the weak factor reversal test (which states that the product of price and quantity indexes should yield the expenditure), it nonetheless provides a reasonable second-order approximation.² Second, Ball *et al.* (1997) also showed that the Törnqvist index retains a high degree of characteristicity when combined with the Caves-Christensen-Diewert (CCD) formula for transitivity (Drechsler, 1973). This means that a price index estimated when using this method is not dependent on the basket of goods in one particular country that is used in the comparison.

Purchasing Power Parity Adjustment

To enable cross-country level comparisons, output and input price indexes measured in domestic currencies must be converted to a common ‘international’ currency. The common currency estimates of relative input and output price levels produced by market exchange rates do not necessarily represent the purchasing power parity estimates. Instead, relative price

indexes for agricultural output and input were constructed to capture each country’s purchasing power parity (PPP). For example, the PPP of wheat in Australia was defined as the amount of Australian dollars required to purchase the same quantity of wheat as one 2005 U.S. dollar.

In this article, we used the CCD formula (Caves, Christensen and Diewert, 1982), derived from the geometric average of bilateral Törnqvist indexes, to compare output and input prices between countries in a given base year (2005). Compared with the Fisher index adjusted by the EKS formula, this method has the advantage that a complete matrix of bilateral Törnqvist indexes is not required, but instead a man-made country average can be used as a numeraire.

Specifically, the difference between logarithms of the price of output for any two countries can be expressed as weighted averages of the differences between logarithms of the component prices and the geometric average of component prices for the three countries. Therefore, relative to the United States in the base year, the output price for other countries in the same year can be written as:

$$(5) \ln P^d = \ln P^{US} + \sum_i \tilde{R}_i^d [\ln P_i^d - \overline{\ln P_i}] - \sum_i R_i^{US} [\ln P_i^{US} - \overline{\ln P_i}]$$

$$\text{where } \tilde{R}_i^d = \frac{1}{2} \cdot \left[R_i^d + \frac{1}{c} \sum_d R_i^d \right], \overline{\ln P_i} = \frac{1}{c} \cdot \sum_d \ln P_i^d$$

and R_i^d is the value share of the components in the output aggregates. $d = AU, CA, US$ denotes Australia, Canada, and the United States, and C is the number of countries in the comparison.

Similarly, we can also write the input price for other countries relative to the United States as:

2 When the factor reversal test is satisfied, the direct and indirect methods will lead to the same results. Under certain assumptions, Diewert (1978) showed that the failure to satisfy the factor reversal test is not a major problem when the Fisher or Törnqvist indexes are used to estimate the price index.

$$(6) \ln W^d = \ln W^{US} + \sum_j \tilde{S}_j^d [\ln W_j^d - \overline{\ln W_j}] - \sum_j S_j^{US} [\ln W_j^{US} - \overline{\ln W_j}]$$

$$\text{where } \tilde{S}_j^d = \frac{1}{2} \cdot \left[S_j^d + \frac{1}{c} \sum_d S_j^d \right],$$

$\overline{\ln W_j} = \frac{1}{c} \cdot \sum W_j^d$ and S_j^d is the cost share of the components in the input aggregates.

The price indexes in Equations (5) and (6) represent the PPP between the currencies of the two countries expressed in terms of agricultural output and input respectively. Finally, the Törnqvist index was used to chain-link the 2005 cross-country comparable prices to construct a time series in each country.

Data Sources

In this section, we briefly discuss the two types of data used in this paper. Data used for productivity measures were sourced from Australia, Canada, and the United States. A cross-country consistent production account was developed for agriculture and the same definition and method was used to derive each variable, although data were collected from different sources (a complete list of variables is provided in Appendix A). Most variables were collected for the period from 1961 to 2006, except for capital investment and asset prices, for which a longer time series was used.³ Data used to construct independent variables for the productivity regression were obtained from internationally consistent databases such as the World Bank's World Development Indicator database and the Global Historical Climatology Network.

Australia

Agricultural output quantity and value data were sourced primarily from the Australian

Bureau of Agricultural Research Economics and Sciences' (ABARES) Agricultural Commodity Statistics. For some smaller commodity items price data were not available, and so an ABARES index of farm prices received was used instead.

Capital investment data were taken from the Australian Bureau of Statistics (ABS) National Accounts Database from 1960, and backcast to 1860 using data from Butlin (1977) and Powell (1974). Since no data are available for the deflator for transportation vehicles between 1920 and 1960, it is assumed to be the same as that for plant and machinery.

Data from the ABS Agricultural Census was used to estimate the land area used for agricultural production. Land prices were estimated using ABARES' Australian Agricultural and Grazing Industry Survey data after 1978 and backcast to 1960 using a GDP deflator. For the base year (2005), more detailed data on land area and prices across 226 statistical local areas were collected for a hedonic regression analysis.

Data on intermediate inputs (including total expenditure and price indexes) were sourced from ABARES' Agricultural Commodity Statistics.

The labour input quantity was estimated as the total number of hours worked each year, calculated by multiplying the number of workers by the average number of hours worked in a week, and the number of weeks worked each year. The average number of hours worked was obtained from the ABS Population Census and it is assumed there are 52 weeks of work each year.

Canada

Output quantity data were not directly available for Canada, but were estimated from total

3 We use the perpetual inventory method to estimate the capital stock and capital input for depreciable assets. Depending on the service life of each capital asset, this method requires a long time-series of data on investment and the purchasing price of each capital asset before the starting period. For example, the average service life of non-residential buildings and structures is 40 years. Given that the real service life of most assets is distributed within two standard deviations of the average service life, to construct the capital stock of non-residential buildings and structures in 1960, we needed investment data for at least 80 years prior to 1960.

income from sales to processors, consumers, exporters and farm households (including within-sector use, waste, dockage, loss in handling and changes in closing stocks). Output price data were available from Statistics Canada CANSIM tables. Some non-separable forestry outputs were included in the aggregate output estimates.

A capital investment data series was compiled for the period 1926 to 2006. Data were not available for some early of this period, and so imputations were applied at the beginning of the investment series. Investment deflators (i.e. a price index) were constructed for the period 1926 to 1935 using import price data taken from CANSIM tables. For other years, disaggregated deflators for each asset grouping were taken directly from the national account statistics.

Land area data were sourced from the Canadian Agricultural Census, while land price data were obtained from the Canadian Agricultural Value-Added Account. All data series started from 1981, and were backcast using a fixed proportion of agricultural land in the total land, which was derived from the Census.

Data on intermediate input quantities and values were taken from the Statistics Canada publication *Supply Disposition Balance Sheets*, and other industry statistics. Individual price indexes were obtained from Statistics Canada or were imputed using a combination of prices. Finally, for inputs where data were unavailable, values were estimated to be 1 to 3 per cent of total costs and were added into the production account of agriculture.

The hired labour input was estimated using data from the Canadian Labour Force Survey and the Population Census of Canada. Estimates of the self-employed labour input (defined as the number of hours worked) were based on data from the Canadian Agricultural Census. The number of days worked were then converted into number of hours worked assuming 10 hours a day

worked for 1961 to 1991, and using actual hours worked (obtained from the Canadian Labour Force Survey) for 1991 onwards. The input of unpaid family members was estimated as a proportion of the self-employed labour input.

United States

Agricultural output values were constructed by aggregating state-level data on farm cash receipts compiled by the United States Department of Agriculture Economic Research Service (USDA ERS). Price data were sourced from the USDA for most outputs and intermediate inputs.

Capital investment data were sourced from the Bureau of Economic Analysis, and deflators for transport vehicles were obtained from the Bureau of Labor Statistics. For non-dwelling buildings and structures, the implicit price deflator from the US National Accounts was used.

County-level land area data were collected from the US Census of Agriculture with interpolation between census years using spline functions and prices were obtained from the annual USDA survey on agricultural land values.

Intermediate input data were sourced from the USDA state farm income database. Price data were sourced from the National Accounts, the US Monthly Energy Review and the USDA agricultural prices database.

Labour input data for hired and self-employed workers were sourced from the US Census of Population and the US Current Population Survey.

Variable Definition for Potential Productivity Drivers

Estimating equation (7) requires data for a series of variables that reflect potential productivity drivers. These variables include the stock of research and development (R&D) knowledge, the capital-labour ratio, rural infrastructure lev-

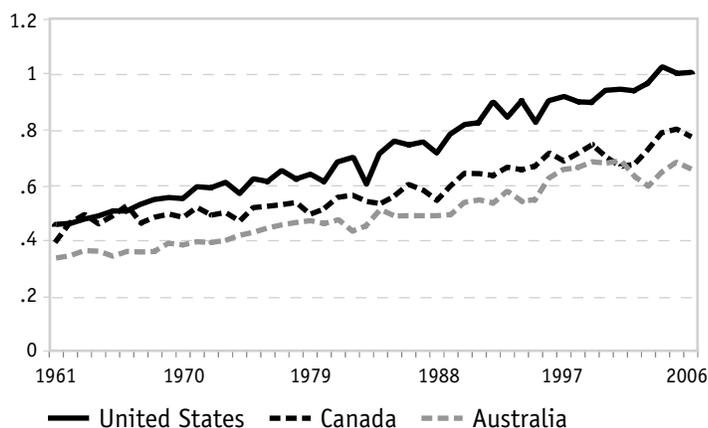
els, the urbanisation rate, temperature, and rainfall. These variables are defined below.

The knowledge stock of R&D in agriculture is considered to be a better indicator of disembodied technological progress than R&D investment. This is because there are often long lags before farmers begin accessing the outputs of R&D investment. We define the R&D knowledge stock as the weighted average of past public investments in agricultural R&D following the methods used by Alston *et al.* (2010a) and Sheng *et al.* (2011). Specifically, weights are obtained from an assumed R&D lag profile that reflects the dynamics of knowledge creation, use and depreciation. For all the three countries, we assumed that the R&D lag profile takes the form of a gamma distribution with the length of average service life of 35 years. Data on public R&D investment in agriculture are obtained from ABARES for Australia, USDA ERS for the United States and Statistics Canada for Canada.

To capture differences between countries in the extent of capital deepening and therefore in associated embodied technology, we use the capital-labour ratio as a control variable.⁴ This variable is defined as the aggregate capital input divided by the labour input. For all three countries, the capital input is consistently defined and derived from the stock of three depreciable assets, namely non-dwelling buildings and structures, transportation vehicles and other plant and machinery. The labour input is defined as the total number of hours worked by both hired workers and unpaid proprietors, adjusted by their age, education and experience.

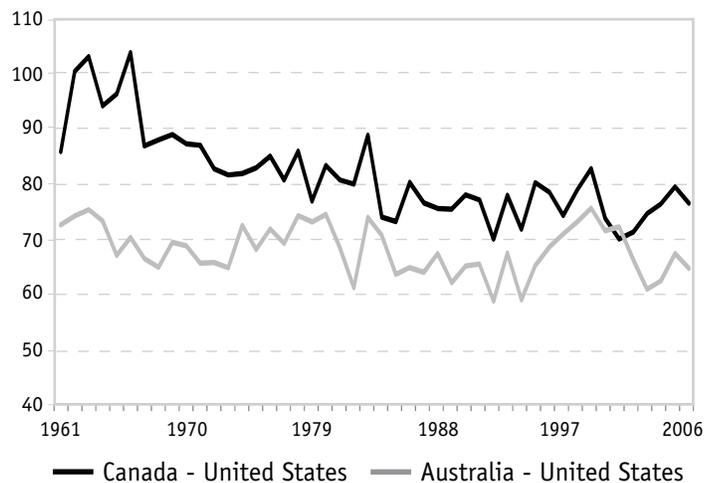
Road transport plays an important role in agricultural production in all three countries, and so we used the average per-capita length of roads in

Chart 1
Comparable Agricultural TFP Levels, Australia, Canada and the United States, 1961-2006
(US=100 in 2005)



Note: Detailed results are shown in Table 1.
Source: Authors' calculations.

Chart 2
Agricultural TFP Levels Relative to the United States, 1961-2006
(per cent)



Source: Authors' calculations.

⁴ Theoretically, embodied technological change (in capital) should have little effects on TFP if the associated adoption costs equal to the benefits (or being well considered from the input or cost perspective). However, in practice, the situation could be more complex depending on the interactive relationship between the embodied and disembodied technological progress (Kohli 2015). Specifically, if the embodied technology progress brings more benefits than the adoption costs (or it is positively correlated to the disembodied technology progress), TFP would be higher; and vice versa.

rural areas to approximate the level of rural infrastructure available to farmers. Specifically, this variable was defined as the total length of roads in the rural areas of each country divided by the rural population. In addition, we also used the urbanisation ratio, defined as the proportion of the urban population in the total population, as a control variable to represent changing economic development levels in each country. Data used to construct those variables were obtained from the World Bank World Development Indicator database, which provides cross-country consistent measures of these variables.⁵

Finally, all three countries have significant shares of non-irrigated cropping and grazing in their agriculture sectors, hence changes in rainfall and temperature will affect agricultural productivity from year to year. To consider these effects, we used total precipitation and average temperature for the crop growing season in each country. Reflecting the difference in seasons between the Northern and Southern hemispheres, the growing season for Australia is defined as September to April while for Canada and the United States it is defined as March to October. Data used to construct these two variables were obtained from the Global Historical Climatology Network.

Agricultural TFP Estimates

Using the index method and production account data, we estimate and compare agricultural TFP between Australia, Canada, and the United States. A dynamic panel regression technique is then used to link the productivity differences between countries to some of its potential drivers.

Productivity Comparison Between Australia, Canada, and the United States

Australian agricultural TFP was generally below the level achieved by the United States and Canada from 1961 to 2006 (although in 2001 Australia's TFP level briefly exceeded the level achieved by Canada) (Chart 1), but its growth was relatively strong. Between 1961 and 2006, the annual growth rate of agricultural TFP in Australia was 1.6 per cent a year on average, higher than in Canada (1.2 per cent a year),⁶ and only slightly lower than in the United States (1.8 per cent a year). Australia's relatively strong TFP growth allowed it to improve its TFP level relative to Canada and to maintain its TFP level at around 70 per cent of the United States (Chart 2).

While Canada and the United States had similar levels of agricultural TFP during the 1960s, they have since diverged. The average level of agricultural productivity in Canada fell to 70 per cent of that in the United States in 2001, before rebounding to about 80 by the mid-2000s (Chart 2). A further analysis of productivity growth in the most recent decade of the dataset showed that Canada experienced a downturn in agricultural productivity associated with drought in the early 2000s, but this slowdown was not sustained. In contrast, Australia experienced a slowdown in agricultural productivity growth from 1998 onwards. This slowdown widened the TFP gap between Australian agriculture and its North American competitors, particularly between 2002 and 2006. This finding is consistent with Sheng, Mullen and Zhao (2011) who identified a turning point in broadacre agricultural productivity in Australia after the mid-1990s, associated with poor seasonal conditions and a decline in the intensity of public R&D investment.

⁵ More details about the database are available at <http://data.worldbank.org/data-catalog/world-development-indicators> (World Bank, 2015).

⁶ This TFP growth rate is consistent with the TFP estimate of 1.0 per cent annually in Canadian crop and animal production over the 1961-2006 period based on Statistics Canada's official TFP estimates available in CANSIM Table 383-0022.

Table 1
Comparison of Relative Agricultural TFP Levels in Australia,
Canada and the United States, 1961-2006
 US = 100 in 2005

Year	Australia	Canada	United States	Year	Australia	Canada	United States
1961	0.329	0.389	0.452	1984	0.504	0.527	0.710
1962	0.338	0.457	0.455	1985	0.482	0.554	0.754
1963	0.356	0.486	0.471	1986	0.482	0.596	0.740
1964	0.354	0.454	0.482	1987	0.483	0.576	0.750
1965	0.337	0.481	0.499	1988	0.483	0.540	0.713
1966	0.353	0.519	0.500	1989	0.487	0.590	0.780
1967	0.351	0.457	0.525	1990	0.532	0.637	0.814
1968	0.353	0.477	0.542	1991	0.540	0.635	0.821
1969	0.383	0.489	0.549	1992	0.529	0.629	0.895
1970	0.377	0.477	0.546	1993	0.571	0.568	0.843
1971	0.388	0.512	0.588	1994	0.536	0.650	0.902
1972	0.386	0.484	0.584	1995	0.541	0.663	0.825
1973	0.393	0.494	0.604	1996	0.620	0.710	0.901
1974	0.411	0.464	0.566	1997	0.652	0.682	0.915
1975	0.422	0.512	0.617	1998	0.658	0.709	0.897
1976	0.438	0.517	0.607	1999	0.679	0.742	0.895
1977	0.449	0.523	0.646	2000	0.674	0.695	0.939
1978	0.459	0.530	0.616	2001	0.683	0.662	0.943
1979	0.465	0.489	0.634	2002	0.624	0.670	0.937
1980	0.454	0.507	0.607	2003	0.591	0.723	0.965
1981	0.467	0.550	0.680	2004	0.643	0.785	1.024
1982	0.428	0.557	0.695	2005	0.677	0.797	1.000
1983	0.446	0.535	0.601	2006	0.652	0.770	1.003

Source: Authors' calculations.

Sensitivity Check

To examine the sensitivity of our agricultural TFP estimates for the three countries, we compare them with those obtained from Fuglie and Rada (2013) for the period 1961–2006 and those from Coelli and Rao (2005) for the period 1980–2000. Differences in estimated TFP growth rates between studies reflect differences in both methodology and data, and provides some useful insight into cross-country comparisons of agricultural productivity.

Table 2 presents the comparison results. Generally, the magnitude of TFP growth rates estimated in this article are similar to those obtained in earlier studies during both periods, but our estimates are closer to those of Fuglie (2010). Since both Coelli and Rao (2005) and

Fuglie (2010) used the Malmquist index with FAO data, this result reflects (to some extent) the relatively weak performance of the Malmquist index for generating cross-country consistent estimates of agricultural productivity compared with the Fisher or Törnqvist indexes. Given the Malmquist index only uses the quantity information for outputs and inputs, this highlights the importance of collecting price information when performing cross-country comparisons of agricultural productivity.

In addition, there were significant differences between countries in the variation in estimated TFP growth across studies. In particular, the difference in TFP growth rates across studies for Canada was around three times larger than that of Australia and the United States (Table 2).

Table 2
Agricultural TFP Growth Rates
(per cent)

	Australia	Canada	United States
Time period for comparison: 1961-2006			
Fuglie (2010)	1.53	1.57	1.67
Our estimates	1.64	1.24	1.80
Relative difference to our estimates	-0.07	0.27	-0.07
Time period for comparison: 1980-2000			
Coelli and Rao (2005)	2.60	3.30	2.60
Our estimates	2.14	1.73	1.99
Relative difference to our estimates	0.21	0.91	0.31

Note: TFP growth rates are estimated using the regression method.

This difference might reflect the use of different data sources in earlier studies, which reinforces the importance of constructing a production account that is comparable across countries when performing international comparisons of agricultural productivity.

Agricultural TFP Drivers Estimation Strategy for TFP Driver Analysis

To investigate cross-country differences in agricultural productivity, we use a dynamic panel data regression to analyse the relationship between TFP measures and some potential drivers. Following Alston *et al.* (2010a), Ball *et al.* (2001, 2010) and OECD (2012), we focus on three such drivers, namely technological progress, capital deepening and the availability of infrastructure, while controlling for the impacts of climate conditions and the market environment. The empirical specification is, for simplicity, assumed to take the log-linear form so that we can interpret coefficients in terms of percentage changes in TFP:

$$(7) \ln TFP_{it} = \beta_0 + \sum_j \beta_j \ln X_{it}^j + \sum_k \gamma_k \ln Z_{it}^k + \varepsilon_{it}$$

where $\ln TFP_{it}$ is the logarithm of agricultural TFP of country i at year t . $\ln X_{it}^j$ denotes the logarithm of potential drivers of productivity across countries, $\ln Z_{it}^k$ denotes the control variables and ε_{it} are the residuals. β_j and γ_k are the coefficients associated with productivity drivers and control variables respectively, which capture their marginal effects on agricultural productivity. The null hypothesis is that β_j is insignificant, suggesting that there is no causal relationship between the potential drivers and cross-country productivity growth and vice versa.

Implementing equation (7) may encounter potential endogeneity problems because of possible correlation between independent variables and the residual. To avoid this problem, we use a flexible combination of lagged independent variables and the differential of rainfall and temperature as instruments,⁷ and adopt the generalized method of moments (GMM) to perform the estimation. A difference GMM is used as it elim-

7 Our argument for using the differential of exogenous climate change conditions as a valid instrument is based on the observation of significant amount of efforts having been put into dealing with adaptation to climate change at the national levels for all the three countries. Specifically, lagged and differential of those variables generally will not directly affect agricultural productivity of the current period when land quality is well controlled (when TFP are estimated). But, they are correlated to rainfall and temperature in the current period, given that the climate is gradually evolving over time (or time-contingent). In addition, when observing rainfall and temperature in the previous period, farmers are willing to adapt to the situation through changing R&D knowledge stock, infrastructure, capital-labor ratio to adapt to the new environment.

inates country-specific fixed effects. In addition, we have also use the Arellano-Bond test to examine autocorrelation of the error terms⁸ and the Sargan/Hansen test to examine the identification issues.⁹

Three scenarios are specified. In scenario one (Model 1), we consider a baseline model which only incorporates the variables that represent climate conditions into the regression. Scenario two (Models 2-4) individually adds disembodied technological progress, the capital-labour ratio and infrastructure-related variables into the baseline model to explore their roles in explaining cross-country productivity differences. Scenario three (Model 5) adds all these factors together into the baseline model and investigates their combined effects.

A Dynamic Panel Data Regression Analysis

Many factors have been used to explain differences in agricultural productivity between countries. These include climate conditions, technological progress and innovation, public infrastructure and domestic policies (Alston, Beddow and Pardey, 2010; Ball *et al.*, 2010; OECD 2012). In this research, a dynamic panel regression analysis was used to estimate the relative contribution of these factors to agricultural productivity growth based on annual data for the 1961-2006 period for Australia, Canada, and the United States. Reflecting concerns on the limited sample size, standard errors were corrected (by using the finite-sample regression procedure) to avoid the potential for downward bias (Windmeijer, 2005) and country-specific cluster effects were accounted for. The results obtained from different scenarios, and the corresponding

Arellano-Bond test and the Sargan/Hansen tests are reported in Table 3. Three main findings are discussed below.

First, R&D spending has played an important role in promoting agricultural productivity growth across the three countries. After controlling for climate conditions and services from public infrastructure, the coefficients associated with R&D knowledge stocks (which generate the service flow of disembodied technologies) are 0.34 and 0.35, which are positive and significant at the 1 per cent level. The results are consistent throughout different scenarios (Models 2 and 5), implying that a one per cent increase in the R&D knowledge stock tends to raise the agricultural TFP level by more than 0.3 per cent. Similar results were also obtained in Alston *et al.* (2000), Pardey *et al.* (2006) and Alston (2010), which showed productivity improvements in agriculture were strongly associated with lagged R&D investments. This suggests that further increasing agricultural R&D investment remains an effective way for policy makers to achieve long-term productivity growth in agriculture.

Second, simply increasing the capital-labour ratio without adopting new technology and changing farm practices does not necessarily increase agricultural TFP in the three countries. In our regressions, the coefficients attached to the capital-labour ratio are not significant at the 10 per cent level and become negative when other factors are accounted for (Column 5 in Table 3). This implies that increasing the capital-labour ratio through making more investment does not necessarily contribute to improved TFP levels.¹⁰ For example, to implement reduced-till technology in the cropping industry, farmers in Australia, Canada, and the

8 The Arellano-Bond test is designed to examine whether there is autocorrelation in the idiosyncratic disturbance term, and helps to identify which periods of lagged variables could be used to obtain instruments. The null hypothesis is that once fixed effects are removed, the disturbance term is not autocorrelated.

9 The Sargan/Hansen tests are designed to examine whether the model is over-identified, and tests for the joint validity of the moment conditions in the GMM framework. The null hypothesis of these tests are that the chosen moments (or instruments) are jointly valid.

Table 3
Dynamic Panel Regression on Agricultural TFP Levels, Difference GMM Estimation Results

	Scenario 1	Scenario 2		Scenario 3	
	Model 1	Model 2	Model 3	Model 4	Model 5
Dependent variable: lnTFP					
ln_rainfall (growing seasons)	0.056** (0.027)	0.054** (0.027)	0.058** (0.028)	0.056** (0.004)	0.051*** (0.005)
ln_average_temp	0.068*** (0.013)	0.064*** (0.015)	0.071*** (0.010)	0.069*** (0.007)	0.068*** (0.009)
ln_R&D knowledge stock	-	0.337*** (0.082)	-	-	0.349*** (0.112)
ln_capital_labour_ratio	-	-	0.061 (0.065)	-	-0.001 (0.039)
ln_infrastructure_index	-	-	-	0.179*** (0.013)	0.196*** (0.013)
urbanisation ratio	-	-	-	0.059* (0.031)	0.031** (0.014)
Number of observations	135	135	135	135	135
F-statistics	417	1,148	262	217	321
Arellano-Bond test for AR(1)	0.191	0.164	0.196	0.111	0.119
Arellano-Bond test for AR(2)	0.331	0.235	0.308	0.461	0.406
Sargan test of overid. restrictions	1.000	0.424	0.426	0.388	0.341
Hansen test of overid. restrictions	1.000	1.000	1.000	1.000	1.000

Note: the numbers in parenthesis below coefficients are “robust” standard errors taking into consideration of heteroskedasticity $H(1)$, and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Statistics for Arellano-Bond test for autocorrelation and Sargan/Hansen test for over identification are p-values.

United States invested heavily in more powerful tractors/machinery and larger pieces of land during the 1980s and 1990s. By the 2000s, however, this technology was widely adopted, and further investment in powerful tractors/machinery encountered decreasing marginal rates of return, particularly on farms with relatively modest size (Sheng *et al.*, 2015).

Although this finding appears inconsistent with that of Ball *et al.* (2001), who found that an increase in the capital-labour ratio significantly contributed to reducing the difference in agricultural productivity between European countries and the United States, it is nonetheless a reasonable result. On one hand, all three countries in this analysis have been widely adopting capital-intensive technologies such as minimum

or no tillage and yield mapping for some time, and accordingly, further investment in physical capital may lead to decreasing marginal returns to capital. As such, labour and land productivity can still increase with more investment, but total factor productivity will decline. On the other hand, a positive correlation between a change in the capital-labour ratio and agricultural TFP in Ball *et al.* (2001) could result from the interaction between the capital-labour ratio and other productivity drivers (i.e. R&D knowledge stock), which have not been well considered in this study. Empirically, this follows from the observation that the marginal effects of the capital-labour ratio on productivity become negative when other variables are controlled for (Models 3 and 5 in Table 2).

10 Of course, increased capital intensity boosts labour productivity. For example, de Avillez (2011) showed that capital deepening accounted for just under one half of the 3.77 per cent increase in output (value added) per hour in Canadian agriculture between 1961 and 2007.

Table 4
Robustness Checks on Estimation Method and Variable Choices

	Scenario 1	Scenario 2	
	Panel Fixed Effect	Panel Fixed Effect	Difference GMM
Dependent variable: lnTFP			
ln_rainfall (growing seasons)	0.098*** (0.008)	0.135*** (0.008)	0.138*** (0.008)
ln_average_temp	0.062*** (0.005)	0.063*** (0.004)	0.062*** (0.005)
R&Dknowledgestock	0.316*** (0.057)	0.213*** (0.039)	0.231*** (0.038)
ln_capital_labour_ratio	-0.018 (0.043)	-0.050 (0.046)	-0.053 (0.046)
ln_infrastructure_index	0.304*** (0.059)	0.350*** (0.050)	0.354*** (0.050)
urbanisation_ratio	0.043*** (0.010)	-0.037*** (0.010)	0.037*** (0.009)
similarity_index	-	0.838*** (0.154)	0.885*** (0.155)
Constant	1.586*** (0.450)	0.458*** (0.028)	-
Number of observations	138	138	135
Adjusted R-squared	0.883	0.901	-
Arrellano-Bond test for AR(1)	-	-	0.150
Arrellano-Bond test for AR(2)	-	-	0.101
Sargan test of overid. restrictions	-	-	0.350
Hansen test for overid. restrictions	-	-	1.000

Note: the numbers in parenthesis below coefficients are “robust” standard errors that account for heterochasticity H(1), and *** p<0.01, ** p<0.05, * p<0.1. Statistics for Arrellano-Bond test for autocorrelation and Sargan/Hansen tests for over identification are p-values.

Third, climate conditions and public policies targeted to improve the supply of public infrastructure services may also contribute to explaining cross-country differences in TFP growth. In all scenarios, the coefficients estimated for growing-season rainfall and temperature are positive and significant at the 1-5 per cent level (Models 1 and 5 in Table 3). This suggests that agricultural TFP is sensitive to average growing-season rainfall and temperature in the three countries, which implies that differences in climate condition could be causes of differences in TFP growth. In addition, the results also show that the availability of public infrastructure and the urbanisation ratio (a proxy for the level of economic development) appear to have posi-

tive impacts on productivity. For example, the coefficients associated with the rural infrastructure index and the urbanisation ratio are all positive and significant at the 1-10 per cent level (Models 4 and 5 in Table 3).

Robustness Check

To establish whether or not the findings obtained from the analysis of productivity drivers are sensitive to the choice of methods and the independent variables included, we carried out two robustness tests.

First, with respect to the choice of regression methods, it has been argued that the dynamic panel data regression technique is less efficient than the standard panel data regression technique when a long time-series of data is available (Zilak,

1997; Wooldridge, 2010). To check the sensitivity of our finding to the regression method used, we re-estimated equation (7) using a panel data regression with fixed effects (for Scenario 1 in Table 4). The results obtained from this regression are similar to those obtained from the dynamic panel data regression.

Second, with respect to the choice of independent variables, it could be argued that the three countries produce different mixes of output, and produce some country-specific products, which may bias the regression results. For example, Canada and the United States produce a large amount of maize and soybeans in the crop sector and beef and cattle in the livestock sector while Australia produces more canola in the crop sector and more sheep and wool in the livestock sector. Without accounting for this disparity in output mix between countries, the estimated contribution of various productivity drivers would be biased since TFP could vary between farms. To examine the sensitivity of our findings to this possibility, we added an index of output similarity to the regression.¹¹ The results are similar to those obtained from the basic model, although model fit is higher.

Conclusion

This article has estimated and compared agricultural total factor productivity in Australia, Canada and the United States between 1961 and 2006. To

do this, a consistent production account for the agriculture sector in all three countries was developed, and a multilateral index was applied to construct comparable price and quantity estimates for output and input in each country.

Our results show that these countries have experienced different TFP levels and growth patterns over the past four decades, despite primarily using capital-intensive technologies and possessing similarly well-developed production systems. In particular, Australian agriculture has experienced rapid productivity growth over four decades, which has improved Australia's productivity level relative to Canada and maintained it relative to the United States. In recent years however, Australia's productivity growth rate has slowed relative to that of Canada and the United States.

Further empirical analysis shows that agricultural productivity differences are likely to be related to each country's capacity for investing in R&D and the availability of infrastructure. Differences in climate conditions are also found to be important causes of differences in agricultural TFP between Australia, Canada, and the United States. These findings provide useful insights into the importance of public policies in promoting public R&D investment in agriculture and providing infrastructure to the farm sector to sustain productivity growth.

Although our estimates measure agricultural output, input and TFP in the three countries, a shortcoming is that the time series ends at 2006

11 An output similarity index relative to the US at the base year (i.e. 2005) was estimated for Australia, Canada, and the United States based on all agricultural outputs. The output similarity index (ω) is given by

$$\omega = \frac{\sum_{m=1}^M f_{im}f_{jm}}{\sum_{m=1}^M (f_{im}^2)^{1/2} \sum_{m=1}^M (f_{jm}^2)^{1/2}}$$

where f_{im} and f_{jm} are the value of production of output m , expressed as a

share of the total value of agricultural output in country i (that is, Australia, Canada or the United States) at time t and country j (that is, the United States at the based year 2005) where there is a total of M different commodity categories for Australia (or Canada) and the United States, and $M = 16$. Data on f_{im} for Australia, Canada and the United States, and data on f_{jm} for the United States at the base year are obtained from the output value estimates at current prices. For a more detailed technical discussion, see Alston, Beddow and Pardey (2010).

because of data constraints. Additional studies could better inform policy-makers by updating the series, and by applying additional regression analysis to examine the sources of the various productivity experiences of these countries.

References

- Alston, J.M., M.C. Marra, P.G. Pardey, and T.J. Wyatt (2000) "A Meta-Analysis of Rates of Return to Agricultural R&D: Ex Pede Herculem?" IFPRI Research Report No. 113.
- Alston, J. M. (2010) "The Benefits from Agricultural Research and Development, Innovation, and Productivity Growth," OECD Food, Agriculture and Fisheries Working Papers No. 31, OECD Publishing.
- Alston, J. M., J. M. Beddow and P.G. Pardey (2010) 'Global Patterns of Crop Yields and Other Partial Productivity Measures and Prices', in J. Alston, B.A. Babcock and P. Pardey (eds.), *The Shifting Patterns of Agricultural Production and Productivity Worldwide*, Midwest Agribusiness Trade Research and Information Center, Iowa State University, Ames, Iowa.
- Alston, J.M., M.A. Andersen, J.S. James and P.G. Pardey (2010a) 'Shifting Patterns of Agricultural Production and Productivity in the United States', in J. Alston, B.A. Babcock and P. Pardey (eds.), *The Shifting Patterns of Agricultural Production and Productivity Worldwide*, Midwest Agribusiness Trade Research and Information Center, Iowa State University, Ames, Iowa.
- Alston, J.M., M. Andersen, J.S. James and P.G. Pardey (2010b) "Revisiting the Returns to U.S. Public Agricultural Research: New Measures, Models, Results and Interpretation," University of Minnesota, Department of Applied Economics Staff Papers, Staff Paper P10-8.
- Andersen, M.A., J.M. Alston and P.G. Pardey (2011) "Capital Services in US Agriculture: Concepts, Comparisons, and the Treatment of Interest Rates," *American Journal of Agricultural Economics*, Vol. 93, pp. 718–38.
- Ball, E., J.C. Bureau, J.P. Butault and R. Nehring (2001) "Levels of Farm Sector Productivity: An International Comparison," *Journal of Productivity Analysis*, Vol. 15, pp. 5–29.
- Ball, V.E., A. Barkaoui, J.C. Bureau and J.P. Butault (1997) "Aggregation Methods for Intercountry Comparisons of Prices and Real Values in Agriculture: a Review and Synthesis," *European Review of Agricultural Economics*, Vol. 24, pp. 183–206.
- Ball, V.E., J.P. Butault, C. Mesonada and R. Mora (2010) "Productivity and International Competitiveness of Agriculture in the European Union and the United States," *Agricultural Economics*, Vol. 41, pp. 611–27.
- Box, G.E.P. and D.R. Cox (1964) "An Analysis of Transformations," *Journal of the Royal Statistical Society, Series B*, Vol. 26, pp. 211–52.
- Butlin, M.W. (1977) "A Preliminary Annual Database, 1900–01 to 1973–74," Research Bank of Australia, Research Discussion Paper, May.
- Capalbo, S.M., V.E. Ball and M.G.S. Denny (1990) "International Comparisons of Agricultural Productivity: Development and Usefulness," *American Journal of Agricultural Economics*, Vol. 72, pp. 1292–97.
- Caves, D., L.R. Christensen and E. Diewert (1982) "Multilateral Comparisons of Output, Input, and Productivity using Superlative Index Numbers," *Economic Journal*, Vol. 92, pp. 73–86.
- Coelli, T. & D.S.P. Rao (2005) "Total Factor Productivity Growth in Agriculture: A Malmquist Index Analysis of 93 Countries, 1980–2000," *Agricultural Economics*, Vol. 32, pp. 115–34.
- Craig, B.J., P.G. Pardey and J. Roseboom (1994) "International Agricultural Productivity Patterns," University of Minnesota, CEFAP Working Paper No. WP94-1.
- Craig, B.J., P.G. Pardey and J. Roseboom (1997) "International Productivity Patterns: Accounting for Input Quality, Infrastructure, and Research," *American Journal of Agricultural Economics*, Vol. 79, pp. 1064–77.
- de Avillez, Ricardo (2011) "A Half Century of Productivity Growth and Structural Change in Canadian Agriculture: An Overview," *International Productivity Monitor*, Number 22, Fall, pp. 82–99.
- Diewert, W.E. (1978) "Superlative Index Numbers and Consistency in Aggregation," *Econometrica*, Vol. 46, pp. 883–900.
- Diewert, W.E. (1992) "Fisher Ideal Output, Input and Productivity Indexes Revisited," *Journal of Productivity Analysis*, Vol. 3, pp. 211–48.
- Drechsler, L. (1973) "Weighting of Index Numbers in Multilateral International Comparisons," *Review of Income and Wealth*, Vol. 19, pp. 17–34.
- Eltető, O. and P. Köves (1964) "On a Problem of Index Number Computation Relating to International Comparison," *Szatistikai Szemle*, Vol. 42, pp. 507–18.
- Eswaran, H., F. Beinroth and P. Reich (2003) "A Global Assessment of Land Quality," in K. Weibe (ed.), *Land Quality, Agricultural Productivity and Food Security* (Edward Elgar: Cheltenham, UK.)
- Fuglie, K. and S. Wang (2012) "New Evidence Points to Robust but Uneven Productivity Growth in Global Agriculture," *Amber Waves*, September, Vol. 10, pp. 1–6.

- Fuglie, K.O. (2010) "Total Factor Productivity in the Global Agricultural Economy: Evidence from FAO Data," in J. Alston, B.A. Babcock and P. Pardey (eds.), *The Shifting Patterns of Agricultural Production and Productivity Worldwide*, Midwest Agribusiness Trade Research and Information Center, Iowa State University, Ames, Iowa, pp. 63–95.
- Fuglie, K.O., S. Wang and E. Ball (2012) "Productivity Growth in Agriculture: An International Perspective," (CAB International: Cambridge, MA.)
- Headey, D., M. Alauddin and D.S.P. Rao (2010) "Explaining Agricultural Productivity Growth: An International Perspective," *Agricultural Economics*, Vol. 41, pp. 1–14.
- Huffman, W.E. and R.E. Evenson (2006) "Do Formula or Competitive Grant Funds Have Greater Impacts on State Agricultural Productivity?" *American Journal of Agricultural Economics*, Vol. 88, pp. 783–98.
- Jorgenson, D.W. and P. Schreyer (2012) "Industry-Level Productivity Measurement and the 2008 System of National Accounts," *Review of Income and Wealth*, Vol. 59, pp. 185–211.
- Ludena, C.E., T.W. Hertel, P.V. Preckel, K. Foster and A. Nin (2007) "Productivity Growth and Convergence in Crop, Ruminant and Non-Ruminant Production: Measurement and Forecasts," *Agricultural Economics*, Vol. 37, pp. 1–17.
- Lusigi, A. and C. Thirtle (1997) "Total Factor Productivity and the Effects of R&D in African Agriculture," *Journal of International Development*, Vol. 9, pp. 529–38.
- OECD (2001) "Measuring Productivity: Measurement of Aggregate and Industry-Level Productivity Growth," OECD Manual, OECD, Paris.
- OECD (2012) "Cross Country Analysis of Farm Performance," Trade and Agriculture Directorate, Committee for Agriculture, OECD, Paris.
- Pardey, P.G., N. Beintema, S. Dehmer and S. Wood (2006) "Agricultural Research: A Growing Global Divide?" Agricultural Science and Technology Indicators Initiative, International Food Policy Research Institute, Washington, DC.
- Penson, J. B., D. W. Hughes and G. L. Nelson (1987) "Measurement of Capacity Depreciation Based on Engineering Data," *American Journal of Agricultural Economics*, Vol. 35, pp. 321–29.
- Powell, R. A. (1974) "Technological Change in Australian Agriculture, 1920–21 to 1969–70," Thesis, University of New England, Armidale.
- Rao, D. S. P, A. Maddison and B. L. Lee (2002) "International Comparison of Farm Sector Performance: Methodological Options and Empirical Findings for Asia-Pacific Economies, 1900–1994," in A. Maddison, W.F. Shepherd, and R. Prasada (eds.), *The Asian Economies in the Twentieth Century* (Edward Elgar, Northampton, MA), pp. 27–52.
- Romain, R., J.B. Penson and R. Lambert (1987) "Capacity Depreciation, Implicit Rental Prices, and Investment Demand for Farm Tractors in Canada," *Canadian Journal of Agricultural Economics*, Vol. 35, pp. 373–78.
- Sanchez, P.A., C.A. Palm and S.W. Buol (2003) "Fertility Capability Soil Classification: A Tool to Help Assess Soil Quality in the Tropics," *Geoderma*, Vol. 114, issues 3–4, pp. 157–85.
- Sheng, Y., E. Gray, J.D. Mullen and A. Davidson (2011) "Public Investment in Agricultural R&D and Extension: An Analysis of the Static and Dynamic Effects on Australian Broadacre Productivity," ABARES Research Report 11.7, Australian Bureau of Agricultural and Resource Economics and Sciences, Canberra.
- Sheng, Y., J.D. Mullen and S. Zhao (2011) "A Turning Point in Agricultural Productivity: Consideration of the Causes," ABARES Research Report 11.4 for the Grains Research and Research and Development Corporation, Australian Bureau of Agricultural and Resource Economics and Sciences, Canberra.
- Sheng, Y., S. Zhao, K. Nossal and D. Zhang (2015) "Productivity and Farm Size in Australian Agriculture: Reinvestigating the Returns to Scale," *Australian Journal of Agriculture and Resource Economics*, Vol. 59, pp. 16–38.
- Shi, U. J., T.T. Phipps and D. Colyer (1997) "Agricultural Land Values Under Urbanizing Influences," *Land Economics*, Vol. 73, pp. 90–100.
- Szulc, B. (1964) "Indices for Multiregional Comparisons," *Przegląd Statystyczny*, Vol. 3, pp. 239–54.
- World Bank (2007) *World Bank Development Report 2008*, World Bank, Washington, DC.
- World Bank (2015) World Development Indicator Database, World Bank, Washington, DC, available at the website of <http://data.worldbank.org/data-catalog/world-development-indicators>.
- Zilak, J. P. (1997) "Efficient Estimation with Panel Data When Instruments Are Predetermined: An Empirical Comparison of Moment-Condition Estimators", *Journal of Business and Economic Statistics*, Vol. 15, pp. 419–431.
- Wooldridge, J. (2010) *Econometric Analysis of Cross Section and Panel Data*, 2nd Edition, (MIT Press: Cambridge, MA).

Appendix A

Cross-Country Consistent Production Account for Agriculture: Methodology and Variable Definition

The agricultural production account is defined and collected consistently between countries, and data are obtained from a range of sources in each country. This appendix provides a definition for each output and input (summarized in Table A1). All data were collected on a calendar year basis. For Australia, this meant converting financial year data by taking a simple average of two consecutive financial years.

Outputs

Output variables were collected under three categories: crops, livestock and other outputs. Crop outputs included grains and oil seeds, vegetables, and fruits and nuts. Livestock outputs included slaughter livestock (red meat), poultry and eggs, and other animal products (dairy and wool). Other outputs included ‘non-separable secondary activities’ such as income from machinery hire and contract services.

Primary agricultural outputs included deliveries to final demand as well as intermediate demand and on-farm use. Primary output is approximated as total sales plus non-market transactions (that is, cross-industry transfers through long-term contracts and on-farm use such as animal feed). Where production statistics are not directly available, primary output is approximated from changes in inventory for each commodity.

Outputs from non-separable secondary activities are defined as goods and services whose costs cannot be observed separately from those of primary agricultural outputs. Two types of secondary activities are included: on-farm production activities such as the processing, packaging and marketing of agricultural products, and service provision such as machinery hire and land lease.

Government taxes are included in agricultural outputs, since the value of inputs is inclusive of indirect taxes. We recognise that differences in government subsidies or taxes between countries may create differences in the measured value of total output.

Equation (3) is used to aggregate output prices using their corresponding revenue shares. The implicit aggregate output quantity index is then defined as the total value of agricultural output divided by the aggregate price index.

Inputs

Input variables were collected under four categories: capital, land, labour, and intermediate inputs. Capital and land inputs are estimated as service flows.

Capital

Following Ball *et al.* (2001 and 2010), three types of capital input are distinguished: non-dwelling buildings and structures, plant and machinery, and transportation vehicles. While relevant, the inventory of crops, livestock, and other biological resources, such as vineyards and orchards, are not included because of inadequate value data. However, these capital inputs are likely to represent a relatively small proportion of total capital.

Measurement of the capital input begins with using investment data to calculate the stock of three types of capital goods. At each point in time t , the stock of capital $K(t)$ is the sum of all past investments, $I_{t-\tau}$, weighted by the relative efficiencies of capital goods of each age τ , S_τ .

$$(A1) K_t = \sum_{\tau=0}^{\infty} S_\tau I_{t-\tau}$$

When using equation (A1) to estimate the capital stock, the efficiencies of capital goods must be defined explicitly. Similar to Ball *et al.* (2010), this is done by using two parameters, namely service life of the asset, L , and a decay parameter, β , to specify the functional form, $S(\cdot)$ such that:

$$(A2) S(\tau) = (L - \tau)/(L - \beta\tau), \text{ if } 0 \leq \tau \leq L$$

$$S(\tau) = 0 \text{ if } \tau > L$$

Each type of capital asset has an assumed distribution of actual service life which provides a mean service life \bar{L} . In this analysis, the asset lives for non-dwelling buildings and structures, plant and machinery, and transport and other vehicles are assumed to be 40 years, 20 years and 15 years, respectively, with an assumed standard normal distribution truncated at points two standard deviations before and after the mean service life.

The decay parameter β can take values between 0 and 1, with $\beta = 1$ implying that the capital asset does not depreciate over its service life. Although there is little empirical evidence to define appropriate values of β , it is reasonable to assume that the efficiency of a capital asset declines smoothly over most of its service life. Following Ball *et al.* (2001), decay parameters are set to be 0.75 for non-dwelling buildings and structures and 0.50 for all other capital assets, reflecting an assumption that efficiency declines more quickly in the later years of service (Penson, Hughes and Nelson, 1987; Romain, Penson and Lambert, 1987).

The aggregate efficiency function was constructed as a weighted sum of individual efficiency functions where the weights are the frequency of occurrence.

Rental Rate

Assuming the sector invests when the present value of the net revenue generated by an additional unit of capital exceeds the purchase price of the asset, the farm sector will invest in capital stock formation until the output price P satisfies:

$$(A3) P = \frac{\delta Y}{\delta K} \\ = rW_K + r \sum_{t=1}^{\infty} W_K \frac{\delta R_t}{\delta K} (1+r)^{-t} = c$$

where c is the implicit rental price of capital, r is the real rate of return and W_K is the price of an additional unit of capital (or investment).

The rental price c consists of two components: the opportunity cost associated with investment, rW_K , and the present value of the cost of all future replacements required to maintain the productive capacity of the capital stock,

$$\sum_{t=1}^{\infty} W_K \frac{\delta R_t}{\delta K} (1+r)^{-t} s.$$

Let F denote the present value of the rate of capital depreciation on one unit of capital according to the mortality distribution m :

$$(A4) F = \sum_{t=1}^{\infty} m_t (1+r)^{-t}$$

where $m(\tau) = -[S(\tau) - S(\tau - 1)]$ for $\tau = 1, \dots, L$.

It can be shown that

$$\sum_{t=1}^{\infty} \frac{\delta R_t}{\delta K} (1+r)^{-t} = \sum_{t=1}^{\infty} F^t = \frac{F}{1-F}$$

such that

$$(A5) c = \frac{rW_K}{1-F}$$

Following Ball *et al.* (2010), the real rate of return, r , is approximated with an *ex-ante rate*, estimated as the nominal rate of return minus inflation. The nominal rate of return is obtained

using the exogenous approach, and is derived from returns on government bonds with a range of different maturities. The choice of interest rate is widely debated. Andersen, Alston and Pardey (2011) argued that use of a fixed interest rate generates more plausible estimates of capital services in the United States than annual market rates, while Jorgenson and Schreyer (2012) proposed using the residual of output value after deducting input costs to derive an endogenous real interest rate. To test the sensitivity of measured capital services to different real interest rates, both *ex-ante* and *ex-post* rates were estimated. The *ex-ante* rate was chosen for this study as it was less volatile than the *ex-post* rate.

Land

The value of land service flows is given by the product of the land stock and rental price. The stock of land was estimated from the total land areas operated. The rental price of land was obtained using Equation (9) with the assumption of zero depreciation, i.e. $c = rW_L$. As explained below, the land price, W_L , was derived from a hedonic function.

In particular, agricultural land prices can be affected by many factors unrelated to agricultural production, such as urbanisation pressures, distance to major cities and government land release policies. Also, spatial differences in land quality may prevent direct comparison of prices between regions and over time. To address these problems, comparable land price indexes for each country were constructed using the hedonic regression method.

In this article, the hedonic price of land is a generalised linear function of its characteristics relevant to agricultural production and some control variables. The function uses the Box-Cox (1964) transformation to represent the dependent variable and each continuous independent variable:

$$(A6) \quad W_L(\lambda_0) = \sum_n \alpha_n X_n \lambda_n + \sum_d \gamma_d D_d + \varepsilon$$

where the price of land, $W_L(\lambda_0)$, is the Box-Cox transformation of real observations, when $W_L > 0$, that is:

$$(A7) \quad W_L(\lambda_0) = f(x) = \frac{W_L^{\lambda_0}}{\lambda_0} \text{ if } \lambda_0 \neq 0$$

$$W_L(\lambda_0) = f(x) = \ln W_L \text{ if } \lambda_0 = 0$$

Similarly, $X_n(\lambda_n)$, a vector of land characteristics associated with agricultural production, is the Box-Cox transformation of the continuous quality variable X_n where:

$$(A8) \quad X_n(\lambda_n) = f(x) = \frac{(X_n^{\lambda_n} - 1)}{\lambda_n} \text{ if } \lambda_n \neq 0$$

$$X_n(\lambda_n) = f(x) = \ln X_n \text{ if } \lambda_n = 0$$

and D is a vector of country dummies used to control for external factors. For simplicity, D is approximated by a group of region and time dummy variables and not subject to transformation; λ , α and γ are unknown parameter vectors to be determined in the regression and ε is a stochastic disturbance term. This expression can assume linear, logarithmic and intermediate nonlinear functional forms depending on the transformational parameter.

To apply the hedonic regression model, regional land prices and land characteristics were observed for each country in 2005. Land characteristic data for 2005 were sourced from the USDA World Soil Resources Office and selected following Eswaran, Beinroth and Reich (2003) and Sanchez, Palm and Buol (2003). GIS mapping was used to overlay country and regional boundaries with land characteristics data relating to particular soil categories, including soil acidity, salinity, and moisture

stress. Across the three countries more than 18 common variables were used to capture environmental attributes.

Two additional attributes affecting the price of agricultural land should also be considered: irrigation and population accessibility. Irrigation (the percentage of cropland irrigated) was included as a separate indicator of production capacity in water-stressed areas, as well as an interaction term between irrigation and soil acidity. A population accessibility index could be used to control for the impact of urbanisation and economic development on land prices; however, it was not included in this analysis due to data constraints. Such indexes have been constructed in previous studies by using a gravity model of urban development, and provided a measure of accessibility to population concentrations (Shi, Phipps and Colyer, 1997).

Intermediate Inputs

Intermediate inputs comprise all materials and services consumed, excluding fixed capital, land and labour inputs. They include 10 categories, namely: fuel, electricity, fertilisers and chemicals, fodder and seed, livestock purchases, water purchases, marketing services, repairs and maintenance, plant and machinery hire, and 'other materials and services'.

Fuel (including lubricants) and electricity are estimated from the total quantity consumed and an index of prices paid by farmers for petrol, diesel, liquefied natural gas and electricity. A fuel price index was calculated using quantities of petrol, diesel and liquefied natural gas consumed as weights. The total quantity of fuel consumed was obtained by dividing total expenditure by this fuel price. The price of electricity was estimated separately and used to deflate electricity expenditure to obtain the quantity consumed.

Other intermediate inputs were estimated as implicit quantities. Price indexes were sourced domestically, except for pesticides and chemicals

where quality-adjusted price data from 2005 were sourced from the World Bank World Development Indicator database and FAO statistics. The quality-adjusted data for 2005 were used with domestic time-series prices to impute a trend.

Consistent with the treatment of output, intermediate inputs were valued at farm-gate prices, including direct taxes and excluding indirect taxes and subsidies.

Labour

Labour is defined as total hours worked by hired, self-employed and unpaid family workers. Because data were only available on the number of people employed in the agriculture industry, total hours worked were imputed by multiplying the number of workers by the average hours worked per week and the number of weeks. For consistency, we use 52 weeks a year for this imputation.

Wages were not used to estimate the value share of labour inputs. This is because hourly wages are unlikely to capture total compensation to farm workers, since additional employee benefits (such as lodging and superannuation contributions) are not included in wage statistics. In addition, compensation to self-employed workers is not directly observable.

Instead, the real cost of total labour use was derived using the accounting assumption that the value of total output equals the value of total input. This enabled real wages to be estimated as real labour compensation (or total output value minus capital, land, and intermediate input costs) divided by the total number of hours worked.

Finally, hired, self-employed, and unpaid family workers were distinguished, and differences in education levels and work experience were used to adjust prices for labour quality in all three countries.

Table A1
Summary List of Variables

Outputs					Inputs			
Crops			Livestock	On-farm activities	Land	Capital	Labour	Materials
Grains and oil seeds	Fruits and nuts	Vegetables						
Barley	Almonds	Asparagus (fresh, processing)	Cattle and calves	Marketing	Land services	Buildings and structures (non-dwelling)	Operator labour	Chemicals
Canola	Apples	Snap beans	Ducks	Packaging				
Caster	Apricots	Bean (dry, processing)	Chickens and broilers	Processing	Contract services	Plant machinery	Hired labour	Fertiliser
Cottonseed	Avocadoes	Broccoli	Eggs	Services				
Flaxseed	Bananas	Cauliflower	Hogs	Machinery hire	Transportation and other vehicles	Unpaid workers	Fuel and lubricant	Livestock purchases
Hay and silage	Cherries (sweet)	Cabbage	Milk, butter, cheese	Land lease				
Maize	Cherries (tart)	Capsicum	Sheep and lambs	Other services	Marketing	Veterinary services	Water purchases	Other materials
Oats	Dates	Celery	Turkey					
Peanut	Cranberry	Cucumber (fresh, processing)	Wool		Services	Other services	Other purchases	Other materials
Rice	Dates	Corn (fresh, processing)						
Rye	Figs	Honeydew			Marketing	Plant and machinery hire	Repairs and maintenance	Veterinary services
Safflower	Grapefruit	Lettuce						
Sorghum	Grapes	Lentils			Marketing	Plant and machinery hire	Repairs and maintenance	Veterinary services
Soybean	Hazelnuts	Onions						
Sunflower	Lemons and limes	Peas (dry, green)			Marketing	Plant and machinery hire	Repairs and maintenance	Veterinary services
Triticale	Macadamias	Potatoes						
Wheat	Mandarins	Rock melon			Marketing	Plant and machinery hire	Repairs and maintenance	Veterinary services
Other crops	Mangoes	Spinach (fresh, processing)						
Cotton lint	Nectarines	Sweet potatoes			Marketing	Plant and machinery hire	Repairs and maintenance	Veterinary services
Tobacco	Olives	Tomatoes (fresh, processing)						
Horticulture	Oranges	Watermelon			Marketing	Plant and machinery hire	Repairs and maintenance	Veterinary services
Floriculture	Peaches	Other vegetables						
Greenhouse nursery	Pears				Marketing	Plant and machinery hire	Repairs and maintenance	Veterinary services
Sugar beet	Pecans							
Sugar cane	Plums				Marketing	Plant and machinery hire	Repairs and maintenance	Veterinary services
Mushrooms	Prunes							
Other crops not included elsewhere	Strawberries				Marketing	Plant and machinery hire	Repairs and maintenance	Veterinary services
	Tangelos							
	Tangerines				Marketing	Plant and machinery hire	Repairs and maintenance	Veterinary services
	Walnuts							
	Other fruit and nuts				Marketing	Plant and machinery hire	Repairs and maintenance	Veterinary services