The role of communication technologies in broadacre agriculture in Australia: An empirical analysis using panel data

Ruhul Salim[*1] , Shamsul Arifeen Khan Mamun[2] and Kamrul Hassan[3]

[1] School of Economics & Finance
Curtin Business School
Curtin University, Perth, WA 6845
Australia

[2] School of Commerce &
Australian Digital Futures Institute
University of Southern Queensland
Australia
Email: msarifeenkhan.mamun@usq.edu.au

and

[3]Department of Finance
School of Management and Governance
Murdoch University
90 South Street, WA 6150
Australia
K.Hassan@murdoch.edu.au

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* Corresponding author: School of Economics & Finance, Curtin Business School (CBS), Curtin University, P. O. Box U1987, Perth, WA 6845, Australia. e-mails: Ruhul.Salim@cbs.curtin.edu.au

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Abstract

This paper examines the role of communication technologies (CTs) in Australian broadacre agricultural production using data over the period of 1990-2013. Allowing for cross-sectional independence in the data, the Pooled Mean Group (PMG) and Augmented Mean Group (AMG) techniques are applied to estimate dynamic relationships among variables. The empirical results demonstrate that CTs affect agricultural output positively in the long run. The estimated elasticity is 0.237. This result suggests that government policies that lift investment in telecommunication facilities are shown to contribute to an increase of output in Australia's broadacre agriculture in the long run.

Keywords: Information and communication technology; agriculture production; pooled mean group regression; cointegration

JEL classification: O33, Q1

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1. Introduction

Information and communication technologies (ICTs) have been transforming economic activities in all sectors, including agriculture. Generally, Australian farmers' perceptions are positive about computers and the Internet, and these communication devices are useful to them (Rolfe *et al.* 2003). These perceptions are consistent with the theory of access to ICTs and agricultural growth (Adesina and Zinna 1993). The rapid expansion of ICTs and the concomitant proliferation of new communication devices and applications open avenues for increasing output in agriculture. The Australian government has been expanding ICTs, by, for example, providing high-speed Internet infrastructure facilities for all Australian businesses, homes, and schools under the National Broadband Network (NBN) since 2010. The new links have improved broadband Internet and mobile telephone facilities in urban and regional Australia where agricultural firms have been operating (Lamb 2013). The extended facilities increase the use of communication technologies (CTs) in the agriculture sector, thereby facilitating knowledge sharing among the farming communities. Thus, farmers are able to make informed and efficient decisions in agricultural production. Indeed, the systematic dissemination of information contributes to agricultural output.

Theoretically, farmers can expect two types of benefits from their access to ICTs (World Bank 2011). One type of benefit includes reduction in production costs, reduction in transaction costs, improvement in market participation, and gains from sales, while the other type of benefit entails technological innovation and improvement in agricultural output (Rolfe *et al*. 2003; World Bank 2011). The theoretical relation between the agricultural ICTs and yield technologies states that access to CTs, such as radio, mobile telephones, and the Internet provides farmers with information regarding the use of appropriate agricultural technologies (World Bank 2011). The information is used by the farmers when they have (yield-enhancing) technologies, such as organic fertilizer instead of chemical fertilizer, but no information on how to use the technology. Access to CTs results in more optimal use of these inputs, which consequently improves the output per unit of labor and capital. Other broad applications of ICTs in agriculture include pest and weather information management (World Bank 2011). Finally, CTs also facilitate the dissemination of information about factor and product markets and price information that significantly contribute to agricultural revenue growth. Therefore, it is worth investigating the impact of the expansion of CTs on broadacre agriculture in Australia.

The influence of ICTs on productivity in manufacturing and service sector firms has been extensively studied in developed countries (Cardona *et al.* 2013). However, the role of ICTs in agriculture is under-researched globally. This lack of research may be because the contribution of ICTs in agriculture is rapidly changing and not well understood. In developing countries, particularly in South Asia and Africa, some studies have examined the role of expansion and the access to communication technologies (CTs), such as mobile telecommunication facilities, in various agricultural activities (Bayes 2001; Silva and Dimuthu 2008; Muto and Yamano 2009; Rashid and Islam 2009; Aker 2010; Ali and Kumar 2011; Ali 2012; Fafchamps and Minten 2012; Aker and Fafchamps 2013; Dey *et al.* 2013; Zanello 2012). These studies find positive influences of the access to mobile telephones on agricultural activities, such as decreased transaction and travel costs associated with product marketing (Rashid and Islam 2009), increased sales (Muto and Yamano 2009), increased participation in the market and surplus food production (Zanello 2012), decreased price dispersion (Aker 2010), increased output prices and decreased input costs (Bayes 2001). The above studies analyzed the partial effect of CTs, particularly mobile telephones, on agricultural crop production in the Asian and African regions; however, at the aggregate level, the effects of CTs on agricultural output have yet to be ascertained.

Some cross-country studies show contrasting relationships between investment in information technology (IT) and agricultural productivity. For example, Lio and Liu (2006) demonstrate small effects of ICT use on farmers' productivity in both rich and poor countries. In contrast, Dewan and Kraemer (2001) find differences in the returns (measured by gross domestic product) from investment in IT between developed and developing countries. Although both studies used panel data and Cobb-Douglas type production functions, the differences in the measurement of IT perhaps contributed to the contrasting research findings. For example, Lio and Liu (2006) use an ICT adoption index at the country level as a measure of ICT, whereas Dewan and Kraemer (2001) use investment in IT at the country level as a measure of ICT. However, both studies suffer from a number of shortcomings in relation to the use of conventional (panel data) estimation techniques, such as a lack of attention to potential cross-section (country) correlation for cross-country study. If covariates are correlated with the source of interdependence, least square estimators are biased; hence estimators are inefficient (Andrews 2005).

Despite theoretical and empirical evidence from the developing countries, no reliable study examines the relation between ICTs (either information technology (IT) or communication technology (CT)) and agricultural output in the developed countries, particularly Australia. The absence of such a study may be due to an assumption that as a primary sector of the economy, agriculture has no gain from ICTs (Rolfe *et al.* 2003). It may also be that researchers do not yet understand how farmers' access to the non-traditional factors of production, such as ICTs, affects agricultural output. This research aims to extend the existing body of literature by adding new evidence based on the dynamic relationship between CT expenditure and Australian broadacre agricultural production in the short and long terms. We use the Pooled Mean Group (PMG) method of Pesaran *et al*. (1999) after time demeaning of variables to control for cross-sectional dependence (CSD) to achieve the main objective of this paper. For robustness of our results, we also use the Augmented Mean Group (AMG) method of Bond and Eberhardt (2009) and Eberhardt and Teal (2010) accounting for the cross-sectional dependence in panel data. This study is significant because agriculture and farming will play an important role in Australia's digital economic future, which will be characterized by an increase in the importance of digital communications through the Internet, mobile telephones, and smartphones.

The rest of this article is structured as follows. Section 2 presents an overview of Australian broadacre agriculture, followed by a presentation of the data sources and information on the variables in Section 3. Section 4 presents econometric methodologies, followed by an analysis of the empirical results in Section 5. Conclusions and policy implications are provided in the final section.

2. Australian Broadacre Agriculture: An Overview

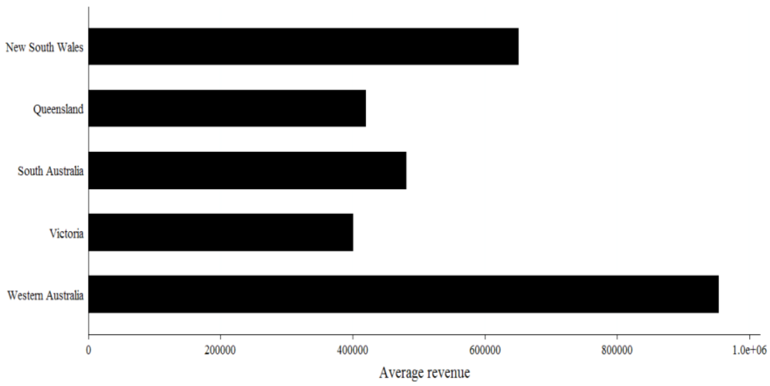
Australia has a very strong agricultural sector. The National Farmers' Federation (NFF) Annual Review of 2013-14 shows that the gross value of Australian farm production in 2012-13 was $48 billion, an increase of 3 percent from 2011-12. As of June 2013, this sector employed 278,000 people, approximately 3 percent of the total labor force in 2013 (NFF 2014). However, including the food and fiber industries, this sector provides over 1.6 million jobs to the Australian economy. More than 15 percent of Australia's total value of merchandise exports comes from the farm sector. In 2012-13, this sector earned $38 billion, approximately 15.5 per cent of Australian merchandise exports (ABS Cat No 5368.0). The broadacre sector of Australian agriculture consists of 5 industries: wheat and other crops, mixed livestock-crops, sheep, beef, and the sheep-beef industry (DAFF 2012), generating over 85 percent of the country's gross agricultural output (Khan *et al*. 2014). Wheat is the major crop in broadacre agriculture based on the market value of the total output, and wheat exports account for a larger share of total exports (food items only) than any other broadacre crop (ABARES 2013), with other large exportable crop items including barley, sorghum, rice, cotton, canola, oats, lupins, and sugarcane. Table 1 presents an overview of the total agricultural land, total cultivated land, and total agricultural business units in the six Australian states and the Northern Territory.

Table 1: Distribution of agricultural resources by state, 2011-12

States	Total agricultural land (million hectares)	Total agricultural business units	Total cultivated agricultural land (million hectares)	Actual use of agricultural land (in percent)
1	2	3	4	5 = (4 ÷ 2) × 100
New South Wales	60.6	44 000	4.20	6.93
Northern Territory	55.1	500	n.a.	n.a.
Queensland	137.0	28 200	1.80	1.31
South Australia	49.7	13 900	2.40	4.82
Victoria	12.7	32 500	2.10	16.53
Western Australia	88.4	12 500	5.20	5.88
Tasmania	1.7	4100	0.087	5.11

Note: n.a. = 'Not available'. Data are sourced from the website of the Australian Bureau of Statistics.

Figure 1: Average agricultural revenue in Australia, 1990-2012



Source: Ministry of Agriculture. Available at http://apps.daff.gov.au/AGSURF/.

The states vary in their agricultural outputs. Figure 1 presents the interstate differences in cash receipts by farms (hereafter agricultural revenue) for the years 1990-2012. It is evident from this graph that Western Australian agricultural farms had been receiving more revenue than their counterparts in the other states. Physical and economic characteristics, such as climate, soil type, water drainage patters, and access to services and facilities, all combine to contribute to variation in agricultural farms' output and revenue within and among states.

Hooper *et al.* (2002) suggest that farm size is an important factor in inter-farm differences in agricultural income (total revenue minus total costs) in 2000-2001. They also suggest that large agricultural farms that have been engaged in cropping gain an advantage from the use of technologies. Sheng *et al.* (2014), however, note that larger firms achieved higher productivity not by increasing their scale but by changing production technology. The precise nature of the mapping from ICTs to agricultural revenue (outputs) is the subject of the following section.

3. Data sources and preliminary data analysis

3.1 Data sources

The data used in this study are mainly drawn from the website of the Department of Agriculture, Fisheries and Forestry (DAFF) of the Government of Australia: http://apps.daff.gov.au/AGSURF/. The website contains data on Australian broadacre agriculture at the state level covering the period 1990-2012, and all financial data are expressed in constant 2012 dollars. However, a complete dataset is not available for Tasmania and the Northern Territory, hence these regions are excluded from the analysis. This study includes five states: New South Wales, Victoria, Queensland, South Australia, and Western Australia. We use cross-section and time series data covering the period 1990-2012 for this study. We have a dataset with N equals 5 and T equals 22 years. The total number of observations is 115.

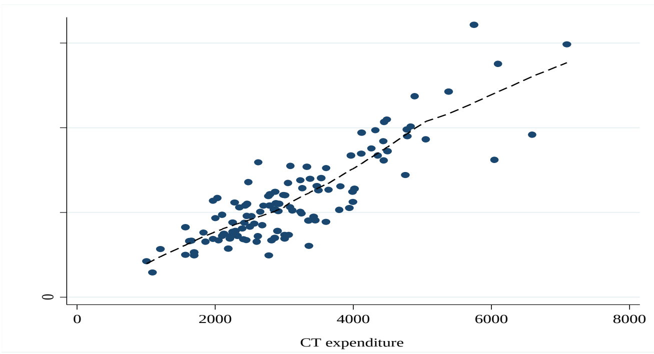
Our dataset includes the following variables: agricultural revenue (Y), non-ICT capital (K), communication technology (CT) capital, expenditure for labor (L), agricultural land rent (Lr) and fertilizer (F). Y is the measurement of aggregate revenue, including cash receipts from the sale of crops, livestock, livestock products, royalties, rebates, refunds, plant hire, contracts, share farming, insurance claims and compensation, and government assistance payments. The variable 'non-ICT' capital includes physical capital expenditures for machinery, equipment, fuel and irrigation facilities. The variable CT measures expenditure for farmers' use of telecommunications, including telephone and Internet. Because this CT expenditure also serves as an estimate of real functioning (McGregor and Borooah 1992), this variable represents an aggregate measure of the adoption or use of CTs. Because climatic conditions influence broadacre agriculture in Australia, we include rainfall (RF) as an important input of broadacre agriculture in our analysis. Rainfall data are gathered from the

Australian Bureau of Meteorology. The period for measuring rainfall is chosen to match the growing season in each state (for details, please see Khan et al. 2014). The remaining unobserved variables are subsumed in the error term in the production function.

3.2 Preliminary data analysis

Locally weighted scatter plot smoothing (LOWESS), a non-parametric regression (local mean smoothing), is used to determine the actual functional relationship between the main explanatory variable (CT expenditure) and the dependent variable in the dataset without imposing any assumption of their functional relationship. Figure 2 presents the LOWESS curve. The LOWESS curve shows a positive linear relationship between the two categories of variables.

Figure 2: Scatter plots of agricultural revenue and CT expenditures



Source: authors' calculations.

In addition to the LOWESS analysis presented above, a simple correlation analysis is presented in Table 2. This correlation analysis confirms that CT expenditures and agricultural revenue are correlated positively and significantly in the five Australian states.

Table 2: Correlation between CT expenditure and agricultural revenue

NSW	Victoria	Queensland	South Australia	Western Australia
0.607	0.477	0.651	0.539	0.782
(0.002)	(0.021)	(0.000)	(0.008)	(0.000)

Note: Figures in the parentheses are *p* values.

Furthermore, Table 3 presents descriptive statistics of all the variables to be used for empirical analysis. The table shows that the actual use of inputs differs substantially among the states over the years.

Table 3: Descriptive statistics

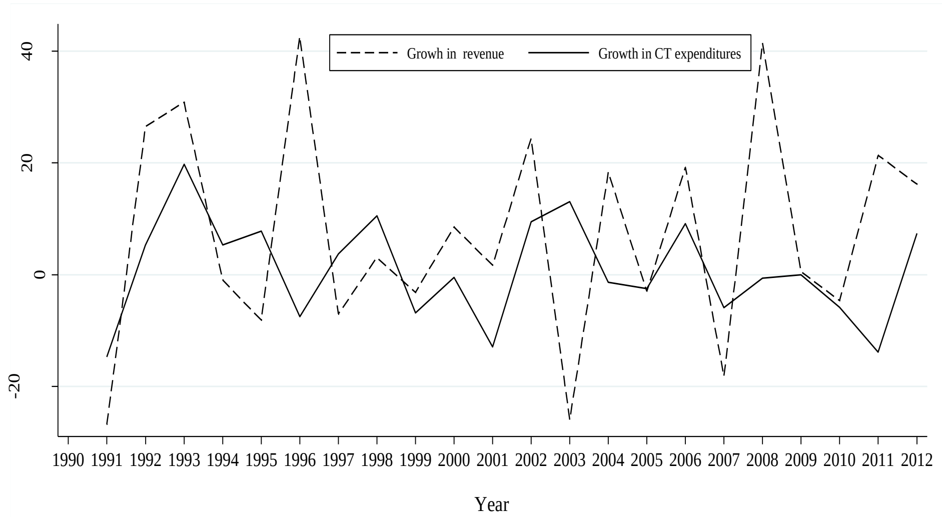
Variable	Description	Mean	Std. Dev.	Min	Max

		New South Wales (NSW)			
logY	Log of cash receipts	5.801	0.100	5.557	6.000
logL	Log of wages paid for labor	4.281	0.172	3.916	4.643
logF	Log of expenditures for fertilizer	4.707	0.197	4.150	5.015
logLr	Log of rental payments for land	3.591	0.312	2.933	4.183
logK	Log of payment for capital	4.053	0.172	3.693	4.329
logCT	Log of CT expenditures	3.537	0.084	3.358	3.677
logRF	Log of rainfall	6.260	0.225	5.743	6.703
		Victoria			
logY	Log of cash receipts	5.582	0.147	5.160	5.784
logL	Log of wages paid for labor	3.747	0.227	3.186	4.089
logF	Log of expenditures for fertilizer	4.540	0.212	3.923	4.834
logLr	Log of rental payments for land	3.757	0.236	3.292	4.188
logK	Log of payment for capital	3.549046	0.2374538	3.037426	3.994229
logCT	Log of CT expenditures	3.332	0.143	3.003	3.537
logRF	Log of rainfall	6.180	0.210	5.678	6.528
		Queensland			
logY	Log of cash receipts	5.601	0.139	5.390	5.886
logL	Log of wages paid for labor	4.052	0.230	3.593	4.511
logF	Log of expenditures for fertilizer	4.511	0.170	4.118	4.713
logLr	Log of rental payments for land	3.372	0.365	2.496	4.000
logK	Log of payment for capital	2.584	0.546	1.724	3.801
logCT	Log of CT expenditures	3.415	0.108	3.219	3.581
logRF	Log of rainfall	6.441	0.251	5.951	7.036
		South Australia			
logY	Log of cash receipts	5.669	0.111	5.394	5.900

logL	Log of wages paid for labor	3.843	0.238	3.228	4.208
logF	Log of expenditures for fertilizer	4.674	0.161	4.357	4.947
logLr	Log of rental payments for land	4.947	0.520	2.012	4.425
logK	Log of payment for capital	3.135	0.204	2.620	3.410
logCT	Log of CT expenditures	3.395	0.080	3.195	3.525
logRF	Log of rainfall	5.032	0.350	4.295	5.635
		Western Australia			
logY	Log of cash receipts	5.961	0.127	5.731	6.204
logL	Log of wages paid for labor	4.358	0.161	4.003	4.694
logF	Log of expenditures for fertilizer	5.119	0.189	4.737	5.455
logLr	Log of rental payments for land	3.937	0.389	3.264	4.670
logK	Log of payment for capital	2.854	0.414	1.857	3.332
logCT	Log of CT expenditures	3.657	0.114	3.391	3.850
logRF	Log of rainfall	5.297	0.329	4.488	5.769

Figure 3 presents the time series plot of growth of agricultural revenue and CT expenditures for the years 1990-2012. The figure shows that both series follow each other closely, except for three breaks, in 1996, 2003, and 2008. The growth in CT expenditures outpaced the growth in agricultural revenue at different points, such as for the years 1994-1995, 1997-1999, and 2003. In the remaining years, the growth in agricultural revenue outpaced the growth of CT expenditures. There were three droughts in Australian agriculture during the periods of 1982-83, 1994-95, and 2002-2003, which might be the cause of fluctuations in these series.

Figure 3: Time series plot of growth of agricultural revenue and CT expenditures, 1990-2012



Source: Department of Agriculture, Fisheries and Forestry (DAFF) of the Government of Australia: http://apps.daff.gov.au/AGSURF/.

4. Methodology

4.1 Theoretical framework

Aggregate Cobb-Douglas production function have been used widely in the past to examine the causal link between ICTs and productivity at the macro level (Cardona *et al.* 2013). There are two measures of productivity measurement in the production literature: a physical quantity-based measure and a revenue-based measure (Foster *et al.* 2008). Both measures have strengths and weaknesses. One strand of literature identifies that the physical quantity based measure is extremely problematic because the measurement of physical output is represented by a single number of collection of heterogeneous objects, such as labor and capital, which is factious (Felipe and Fisher 2003). Another strand of literature identifies that the revenue-based measure of quantity is misleading because of differential product price related to differential product demand in the market (Katayama *et al.* 2009; Foster *et al.* 2008). Despite these weaknesses of both approaches, researchers are of the opinion that both physical and revenue measures of output are correlated and one can be used as a proxy for the other (Katayama *et al.* 2009). In an academic exercise, Mairesse and Jaumandreu (2005) compared two sets of estimates derived from a production function based on physical measure and revenue measures using panel data and thereafter suggest 'estimating the revenue function (using nominal output measure) or the production function (using a real output measure) make very little difference' (p.651).

Furthermore, because price level change causes the changes in the measurement of revenue, some researchers suggest incorporating deflated revenue in the revenue function (Kato 2012).

Another issue is the likely impact of exchange rate fluctuations or of price changes in international market on the income of Australian farmers, who export approximately 60 percent of their production. Australia is a small open economy, so it cannot influence price in international market. Movements in exchange rate can affect the cash flows of farms, exposed to international trade, as almost 80 percent of Australia's merchandise trade is denominated in foreign currency (Rush *et al.* 2013); however, because we use revenue as our dependent variable, any fluctuation in exchange rate is accommodated in the fluctuation of revenues through our input data. As such, we can assume that exchange rate fluctuations do not have significant impact on agricultural revenue. Following the suggestion we have used deflated agricultural revenue to measure agricultural output. Because we use a revenue-based measure of output, product heterogeneity[1] is not a major concern in our study.

The variable capital enters into agricultural revenue function through two channels: ICT-capital and non-ICT capital (otherwise called physical capital). CT-capital includes expenditures for CT, and physical capital includes capital such as machinery, equipment, irrigation facilities and fuel. A similar approach was used by researchers in the past (for details, please see Cardona *et al.* 2013). We begin with an aggregate production function of the following form:

$$Y_{it} = AK_{it}^{\alpha} L_{it}^{\beta} T_{it}^{1-(\alpha+\beta)} \tag{1}$$

where Y_{it} is the agricultural revenue of state i in year t; K_{it} is the non-ICT physical capital, including irrigation facilities, of state i in year t; L_t is the labor expenditure of state i in year t and T_t is in fact CT that is non-physical capital expenditures of state i in year t.

The expected relationships between CT expenditure and revenue are as follows. Farmers' expenditure on CTs, such as land telephones, mobile telephones and Internet, determine the intensity of use of communication technologies and digital connectivity to the local and global knowledge hubs. This connectivity facilitates the use of existing knowledge and improved technology (World Bank 2011) and thereby increases agricultural output and thereafter sales revenue in the market. This study has used the log-log form of revenue function, which makes the estimation of elasticity convenient. This strategy is frequently used in empirical research. The log form of Equation (1) is re-written as:

[1] Barkley and Barkley (2013) note: 'Majority agricultural products are homogenous products: wheat, corn, and soybeans are identical across all producers' (p: 275). In the crop industry, hundreds of firms (crop producers) produce thousands of tons of wheat, rice or barley and thereafter sell products in a perfectly competitive product market. Thus, by using revenue function, we can overcome any potential problem of heterogeneity.

$$\log Y_{it} = \theta + \theta_1 \log K_{it} + \theta_2 \log L_{it} + \theta_3 \log CT_{it} + \mu i_t \quad (2)$$

where θ_1, θ_2 and θ_3 measure elasticities of capital, labor and CT expenditure.

Weather conditions significantly affect Australian agriculture, particularly broadacre agriculture (Salim and Islam 2010). To capture the effects of seasonal weather conditions on Australia's agricultural productivity, we augment Equation (2) by adding the variable of rainfall (*RF*) as an important input of broadacre agriculture production. We also add land rental (*Lr*) expenditure as an additional control variable in Equation (2):

$$\log y_{it} = \theta + \theta_1 \log K_{it} + \theta_2 \log L_{it} + \theta_3 \log CT_{it} + \theta_4 \log RF_{it} + \theta_5 \log Lr_{it} + \theta_6 \log F_{it} + u_{it} \quad (3)$$

Because we are working with time series data for 5 states, the appropriate expression of Equation (3) is:

$$\log y_{it} = \theta + \theta_1 \log K_{it} + \theta_2 \log L_{it} + \theta_3 \log CT_{it} + \theta_4 \log RF_{it} + \theta_5 \log Lr_{it} + \theta_6 \log F_t + u_t \quad (4)$$

Here, the numbers of groups are i= 5 states and t = 1…..23 years.

4.2 Econometric approach

Panel heterogeneity is assumed in our study. This heterogeneity arises particularly in cross-country analyses (Pesaran *et al*. 1999). Because Australia is a continent where the states are very diversified in terms of the distribution of land, weather conditions, and people, the panel heterogeneity assumption is justified in the present case. This study presumes that region-specific or time-specific effects must exist in this situation. If region-specific heterogeneity is not captured by the explanatory variables in the model, parameter heterogeneity may result in the specified model. In these cases, Pesaran, *et al.* (1999) suggest two different estimators to resolve the bias due to heterogeneous slope in dynamic panels: Pooled Mean Group (PMG) and Mean Group (MG) estimators.

By using the PMG, we can allow for the short-term impacts of the inputs but constrain the long-term impacts to be equal. We can address the problem of non-stationarity, which may result in spuriously significant estimates in the absence of actual relationships between the dependent and independent variables (Kangasniemi *et al.* 2012). Several studies use this techniques in various settings. For example, Kangasniemi *et al.* (2012) use the PMG to estimate the parameter coefficients in studies in which they investigated IT expenditure and firm-level productivity issues and migration and national level productivity issues. The advantage of the PMG technique is that it can estimate efficiently even in the presence of endogeneity (Kangasniemi *et al.* 2012). The PMG approach is modeled as an autoregressive distributed lag (ARDL) model. The ARDL (p, q_1, q_2,....q_k) dynamic panel model is specified as follows:

$$y_{it} = \sum_{1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta_{ij}^{/} \mathbf{X}_{i,t-j} + \mu_i + \varepsilon_{it} \tag{5}$$

where the number of cross-section units i = 1,2,….N; the number of period t = 1,2,….T; $\mathbf{X}_{it}$ is a k x 1 vector of explanatory variables; δ_{it} is the k x 1 coefficient vector; λ_{ij} are scalars and μ_i is the cross-section specific effect. For convenience, Equation (5) can be re-parameterized as follows:

$$\Delta y_{it} = \phi_i \left(y_{i,t-1} - \theta_i^{/} \mathbf{X}_{it} \right) + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta y_{i,t-1} + \sum_{j=0}^{q-1} \delta_{ij}^{/*} \Delta \mathbf{X}_{i,t-j} + \mu_i + \varepsilon_{it} \tag{6}$$

where, $\phi_i = -\left(1 - \sum_{j=1}^{p} \lambda_{ij}\right)$; $\theta_i = \dfrac{\sum_{j=0}^{q} \delta_{ij}}{\left(1 - \sum_{k} \lambda_{ik}\right)}$; $\lambda_{ij}^{*} = -\sum_{m=j+1}^{p} \lambda_{i,m}$, $j = 1,2,..,p-1$, and

$\delta_{ij}^{/*} = -\sum_{m=j+1}^{q} \delta_{i,m}$, $j = 1,2,..,q-1$.

The parameter ϕ_i is the error-correction speed of adjustment term. Rejection of the null of $\phi = 0$ is the evidence of a long-run equilibrium relationship, that is, the variables are co-integrated. In this case, the parameter value is expected to be significantly negative. The vector $\theta^{/}$ contains the long-run relationships among the variables. Equation (6) can be expressed in terms of our model in Equation (4) as follows:

$$\Delta \ln y_{it} = \phi_i \left(\ln y_{i,t-1} - \theta_i^{/} \mathbf{X}_{it} \right) + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta \ln y_{i,t-1} + \sum_{j=0}^{q-1} \delta_{ij}^{/*} \Delta \mathbf{X}_{i,t-j} + \mu_i + \varepsilon_{it} \tag{7}$$

where **X** is the vector of log$K$, log$L$, logCT, log$F$, logLr, and logRF.

One potential problem with the PMG estimator is its inability to address cross-sectional dependence. Because five Australian states are the cross-section units in this study, cross-sectional dependence will likely be an issue in the estimation process.

4.3. Test statistics

4.3.1. Cross-sectional dependence

A growing concern with panel data model is the likely presence of substantial cross-sectional dependence (CSD), which may be caused by the common shocks and unobserved components. If CSD is present in data and is not accommodated in the estimation, the estimators will not be consistent and panel estimation may have little advantage over single-equation estimation (Phillips and Sul 2003). To examine this dependence, we employ the CSD test proposed by Pesaran (2004). The Pesaran CSD test employs the correlation-coefficients between the time-series for each panel member. In our case N = 5, this test will give 5×4 = 20 correlations between state i and all other states, for i=1 to N-1.

4.3.2. Panel unit root test

Many different types of unit root tests are available in the literature to examine whether all variables are integrated with the same order. The most widely used tests are the Levin-Lin (LL) test, Im-Pesaran-Shine test (hereafter the IPS test) and Maddala-Wu test; all are first-generation tests. These tests ignore cross-sectional dependence that “arises from unobserved common factors, externalities, regional and macroeconomic linkage, and unaccounted residual interdependence” (Bangake and Eggoh 2012 p 10). The second-generation tests are Pesaran’s (2007) tests, which represent Cross-sectional Augmented IPS (CIPS) tests and allow for cross-sectional dependence heterogeneity in the autoregressive coefficient of the Dickey-Fuller regression. Thus, this study uses Maddala and Wu’s test and Pesaran’s Cross-sectional Dependence IPS (CIPS) statistics to examine the panel unit root tests.

4.2.3. Co-integration test

Although the PMG estimator examines the long-run equilibrium relationships among variables, we employ an additional co-integration test introduced by Westerlund (2007), which is robust when there is cross-sectional dependence. In this cointegration test, four test statistics are proposed; two are designed to test the alternative that the panel is cointegrated as a whole, while the other two are designed to test the alternative that variables in at least one cross-section unit are cointegrated. The former two statistics are referred to as *group statistics*, while the latter two are referred to as *panel statistics.* The data-generating process in this test is assumed to be as follows:

$$y_{it} = \phi_{1i} + \phi_{2i}t + z_{it} \tag{8}$$

$$x_{it} = x_{it-1} + v_{it} \tag{9}$$

where t and i represent the time and space dimensions of the data, respectively. In this formulation, the vector x_{it} is modeled as a pure random walk and y_{it} is modeled as the sum of the deterministic term $\phi_{1i} + \phi_{2i}t$ and a stochastic term z_{it} . This term is modeled as follows:

$$\alpha_i(L)\Delta z_{it} = \alpha_i(z_{it-1} - \beta_i' x_{it-1}) + \gamma_i(L)' v_{it} + e_{it} \tag{10}$$

where $\alpha_i(L) = 1 - \sum_{j=1}^{p_i} \alpha_{ij} L^j$ and $\gamma_i(L)' = \sum_{j=0}^{p_i} \gamma_{ij} L^j$

Now, substituting Equation (8) into Equation (10) gives the following error correction model for y_{it}:

$$\alpha_i(L)\Delta y_{it} = \delta_{1i} + \delta_{2i} t + \alpha_i(y_{it-1} - \beta_i' x_{it-1}) + \gamma_i(L)' v_{it} + e_{it} \tag{11}$$

where, $\delta_{1i} = \alpha_i(1)\phi_{2i} - \alpha_i\phi_{1i} + \alpha_i\phi_{2i}$ and $\delta_{2i} = -\alpha_i\phi_{2i}$

In Equation (11) above, the vector β_i defines a long-run equilibrium or cointegrating relationship between the variables *x* and *y*. However, in the short run, there may be disequilibrium, which is corrected by a proportion $-2 < \alpha_i \leq 0$ each period. Here, α_i is called the error correction parameter. If $\alpha_i < 0$, then there is error correction and the variables are co-integrated, and if $\alpha_i = 0$, then there is no error correction and the variables are not cointegrated. The test statistics are given by[2]:

Group test statistics:

$$G_\tau = \frac{1}{N}\sum_{i=1}^{N} \frac{\hat{\alpha}_i}{SE(\hat{\alpha}_i)} \tag{12.a}$$

$$G_\alpha = \frac{1}{N}\sum_{i=1}^{N} \frac{T\hat{\alpha}_i}{\hat{\alpha}_i(1)} \tag{12.b}$$

Panel statistics:

$$P_\tau = \frac{\hat{\alpha}}{SE(\hat{\alpha})} \tag{13.a}$$

$$P_\alpha = T\hat{\alpha} \tag{13.b}$$

5. Analysis of empirical results

Before applying the unit root test, we examine whether there is any cross-sectional dependence by using Pesaran's (2004) CSD test. The results (Table A1 in Appendix) indicate that the null hypothesis of cross-sectional independence is rejected at the 1 percent significance level for all the variables except the non-ICT capital variable, in which case the

[2] For derivation of these statistics, please see Westerlund (2007).

null is rejected at the 10 percent level. We therefore must take corrective measures to account for cross-sectional dependence in applying the PMG estimator.

Table 4 reports the unit roots tests results. The null hypothesis is I(1). The choice of lag lengths is based on Akaike Information Criteria (AIC). The test results show that Pesaran's test rejects the null of unit root for three variables (log*Y*, log*Lr* and log*C*T) at level, whereas the Maddala and Wu test rejects the null of unit root for five variables (log*Y*, log*L*, log*F*, log*Lr*, and log*CT*). The findings indicate that Maddala and Wu's (1999) test procedure is not robust to detect unit roots when common factors influence the underlying process of the test (Mohammadi and Parvaresh 2014). The overall findings of the unit root test results indicate that most of the variables are I(*1*) when cross-sectional dependence is taken into account.

Table 4: Panel unit root tests

Variable	Test statistic at level		Test statistic at first difference	
	Pesaran test	Maddala & Wu test	Pesaran test	Maddala & Wu test
log*Y*	-2.992 (0.050)**	26.447 (0.003)*	-3.804 (0.000)*	64.701 (0.000)*
log*CT*	-3.557 (0.001)*	23.049 (0.010)*	-3.776 (0.000)*	77.836 (0.000)*
log*L*	-2.070 (0.718)	21.940 (0.015)**	-4.634 (0.000)*	67.165 (0.000)*
log*F*	-2.681 (0.186)	26.848 (0.003)*	-3.695 (0.001)*	61.531 (0.000)*
log*Lr*	-3.989 (0.001)*	22.346 (0.013)**	-4.569 (0.000)*	94.264 (0.000)*
log*K*	0.708 (0.760)[3]	13.321 (0.206)	-3.658 (0.000)*	53.204 (0.000)*
log*RF*	-1.565 (0.963)	4.503 (0.921)	-4.065 (0.000)*	116.850 (0.000)*

Note: *t-statistics* is with time trend. * and ** indicate 1% and 5% levels of significance, respectively.

Next, we examine the possibility of co-integration between the CT expenditures and agricultural revenue through Westerlund's co-integration test (Westerlund 2007). The test is carried out under the null hypothesis of no cointegration. For each series, this study has chosen an optimal lag and lead lengths, and the Barlett kernel window is set equivalent to three according to $4(T/100)^{2/9}$. Table 5 reports the results.

Table 5: ECM-based panel co-integration test

Statistic	Value	Z-value	*p*-value	Bootstrap *p*-value
G_t	-2.504	-3.284	0.001	0.010
G_α	-10.200	-3.146	0.001	0.010
P_t	-5.772	-3.967	0.000	0.000
P_α	-10.157	-7.052	0.000	0.000

[3] This series is unbalanced; therefore, instead of the *t* statistic, the standardized *z* statistic is reported.

Note: Dependent variable = Y; null hypothesis of the test: no cointegration.

It is apparent from Table 5 regarding the test results of G_t and G_a that the rejection of null hypothesis is taken as evidence of cointegration of at least one of the cross-sectional units, and regarding P_t and P_α, the rejection of null hypothesis is taken as evidence of cointegration of the panel as a whole. The co-integration test statistics imply the existence of a long-run equilibrium relationship between the CT expenditure and agricultural revenue. When no error correction hypothesis is rejected, it is practically important to determine the speed of adjustment in the short run. This determination can be made by calculating the value of α_i, the error correction parameter. The estimated value of this error correction parameter is found from Equation (13b). The value of P_α is -10.157 (Table 5), and the time period T is 23; therefore, the value of α is $\hat{\alpha} = \frac{P_\alpha}{T} = \frac{-10.157}{23} = -0.442$, that is, the speed of adjustment of short-term departure toward the long-run equilibrium is 0.442 per year. This finding means that 44.2 per cent of the deviation from the long-run relation between CT expenditure and agricultural revenue is adjusted each year; that is, it takes slightly more than 2 (two) years to restore the equilibrium relation.

Having found a co-integrating relation between CT expenditure and agricultural revenue, we next estimate the model specified in Equation (4) using PMG as proposed by Pesaran (1999). To account for cross-section dependence, the variables are transformed by time de-meaning the data, in which case a panel model takes the following form:

$$\left(y_{it} - \bar{y}_t\right) = \left(\alpha_i - \bar{\alpha}\right) + \beta'\left(\mathbf{x_{it}} - \bar{\mathbf{x}}_t\right) + \left(\mu_{it} - \bar{\mu}_t\right) \tag{14a}$$

$$\left(\mu_{it} - \bar{\mu}_t\right) = \left(\phi_i - \bar{\phi}\right) f_t + \left(\varepsilon_{it} - \bar{\varepsilon}_t\right) \tag{14b}$$

where $\bar{y}_t = \frac{1}{N}\sum_i^N y_{it}$ and so on.

The error structure is given by $\mu_{it} = \phi_i f_t + \varepsilon_{it}$, where f_t represents the unobserved factor that generates cross-sectional dependence and ϕ_i is factor loading. In this transformation, disturbances are expressed in terms of deviations from time-specific averages; therefore, we essentially remove the mean impact of f_t. In addition to PMG, we also estimate the model with the Augmented Mean Group (AMG) technique proposed by Eberhardt and Bond (2009) and Eberhardt and Teal (2010). Both AMG and the Common Correlated Estimator (CCE) of Pesaran (2006) account for cross-section dependence; however, unlike CCE, AMG provides an estimate of the common dynamic process that gives rise to cross-sectional dependence. The empirical model considered in AMG is as follows:

$$y_{it} = \beta_i^{/} x_{it} + u_{it} \tag{15a}$$

where x_{it} is a vector of observable independent variables, which is modeled as linear functions of unobserved common factors (f_t) and state-specific factor loadings (g_t) as follows:

$$x_{mit} = \pi_{mi} + \boldsymbol{\delta}_{mt}^{/}\mathbf{g}_{mt} + \rho_{1mi} f_{1mt} + ... + \rho_{nmi} f_{nmt} + \upsilon_{mit} \tag{15b}$$

where $m = 1,\ldots.k$; $\mathbf{f}_{.mt} \subset \mathbf{f}_t$; $\mathbf{f}_t = \varphi^{/}\mathbf{f}_{t-1} + \epsilon_t$ and $\mathbf{g}_t = \boldsymbol{\kappa}^{/}\mathbf{g}_{t-1} + \epsilon_t$ (15c)

The error term u_{it} in Equation (15a) is composed of group-specific fixed effects (α_i) and a set of common factors (f_t) with country-specific factor loadings (λ_i) as follows:

$$u_{it} = \alpha_i + \boldsymbol{\lambda}_{\mathbf{i}}^{/}\mathbf{f}_t + \varepsilon_{it} \tag{15d}$$

To obtain the AMG estimator, estimation is performed in two stages. In the first stage, the model (15a) is estimated by OLS in the first difference with T-1 year dummies as follows:

$$\Delta y_{it} = b^{/}\Delta x_{it} + \sum_{t=2}^{T} c_t \Delta D_t + e_{it} \tag{16a}$$

In the second stage, the estimated coefficient of year dummy ($\hat{c}_t$) is included in each of the N state regressions. These individual state regressions may include linear time trend to 'capture omitted idiosyncratic processes which evolve in a linear fashion over time' (Eberhardt and Bond 2009; p.3) as follows:

$$y_{it} = a_i + \mathbf{b}_{\mathbf{i}}^{/}\mathbf{x}_{\mathbf{it}} + \eta_i t + d_i \hat{c}_t + e_{it} \tag{16b}$$.

Following Pesaran and Smith's (1995) Mean Group (MG) approach, the AMG estimates are derived as averages of the individual state estimates as follows:

$$\hat{\mathbf{b}}_{AMG} = N^{-1}\sum_{i=1}^{N}\hat{\mathbf{b}}_i \tag{17}$$

In what follows, we first examine the long-run relationship between agricultural revenue and its determinants as estimated by PMG and AMG and then examine the short-run relations. Table 6 reports the PMG (with time de-meaned variables) and AMG estimation results. The table shows that the standard errors of AMG (both with and without trend) estimators are smaller than those of the PMG estimators. Additionally, the residuals from these three estimations are examined for autocorrelation and normality assumptions. Wooldridge's (2002) test for first-order autocorrelation in panel data (Table A2 in Appendix A) indicates that the null hypothesis of 'no first-order autocorrelation' is not rejected, that is, the residuals of these models are free from autocorrelation. However, the residuals from PMG estimation fail to pass the normality assumption. In Figure A1 in Appendix A, a normal distribution is superimposed on the kernel density of the residuals. Kernel density graphs of the residuals from AMG (with and without trend) almost coincide with the normal distribution, which indicates that residual normality cannot be rejected; however, the kernel density graph of the PMG residuals differs significantly from the normal distribution graph. This finding indicates that the PMG residuals are not normally distributed. From the viewpoint of estimate precision and residual normality, one should therefore rely on AMG estimators. Another advantage of the AMG estimator is that it provides the numerical value of the common dynamic process, which in the present case is approximately 0.90 and highly significant.

Table 6: Pooled Mean Group (PMG) and Augmented Mean Group (AMG) estimation results

	PMG	AMG (with trend)	AMG (without trend)
log*CT*	0.238* (0.125)	0.209*** (0.077)	0.197** (0.079)
log*L*	-0.028 (0.057)	0.044 (0.058)	0.019 (0.070)
log*F*	0.642*** (0.085)	0.571*** (0.054)	0.542*** (0.062)
log*Lr*	0.045 (0.039)	0.073*** (0.018)	0.072*** (0.024)
log*K*	-0.031 (0.024)	0.012 (0.026)	0.015 (0.028)
log*RF*	0.178* (0.106)	0.073** (0.037)	0.072* (0.038)
Error correction term	-0.762*** (0.111)	—	—
Trend	—	-0.002 (0.002)	—
Constant	—	1.828*** (0.219)	2.094*** (0.329)
Common dynamic process	—	0.891*** (0.236)	0.901*** (0.226)

Note: Figures in parentheses are standard errors.

Comparing the results in Table 6, we see that all three coefficients of CT expenditure are significant and that they are close in value. The PMG coefficient value is slightly higher than those of the AMG coefficients; however, the AMG coefficients are more precise than that of PMG for the reason noted above. A 10 percent increase in CT expenditure in the long run causes agricultural revenue to increase by approximately 2 percent. The weather variable (rainfall) is found to have significant impact on revenue in the long run. A 10 percent increase in rainfall would increase agricultural revenue by more than 0.70 percent (AMG) and 1.78 percent (PMG) in the long run. In all three estimations, fertilizer has the largest impact on revenue in the long run. Among the other variables, the land rental coefficient in AMG estimation is found to have a significant impact on revenue in the long run. The error correction term in PMG estimation is highly significant and has a negative sign as expected, which further confirms Westerlund's (2007) above results, that is, that the variables are cointegrated in the long run.

One limitation of AMG estimator is that it gives only long-run coefficients; however, we can obtain an idea of the short-run impacts of the variables on revenue from the PMG estimation results. PMG also gives the state-wise values of the short-run coefficients. Table 7 reports these short-run coefficients.

Table 7: Short-run coefficients (Pooled Mean Group estimation)

Regressor (1)	Average coefficient (2)	NSW (3)	Victoria (4)	Queensland (5)	South Australia (6)	Western Australia (7)
Δlog*CT*	-0.039	0.069	-0.149	0.114	-0.196	-0.036
	(0.060)	(0.148)	(0.268)	(0.176)	(0.144)	(0.194)
Δlog*L*	0.089***	0.042	0.052	0.135*	0.150***	0.066
	(0.022)	(0.071)	(0.073)	(0.078)	(0.042)	(0.128)
Δlog*F*	0.064	0.158	-0.058	0.040	0.335***	-0.154
	(0.085)	(0.110)	(0.219)	(0.149)	(0.103)	(0.179)
Δlog*Lr*	0.018	-0.008	0.079	0.045	-0.023	-0.005
	(0.019)	(0.038)	(0.054)	(0.035)	(0.023)	(0.060)
Δlog*K*	0.043***	0.059	0.048	0.027	0.080**	0.004
	(0.013)	(0.048)	(0.056)	(0.018)	(0.034)	(0.033)
Δlog*RF*	-0.043	-0.227*	0.003	0.129	0.056	-0.176
	(0.068)	(0.128)	(0.192)	(0.121)	(0.073)	(0.121)
constant	-0.005	0.035	-0.044	0.023	0.010	-0.045
	(0.017)	(0.024)	(0.032)	(0.023)	(0.018)	(0.038)

Note: Figures in parentheses are standard errors.

The short-run coefficients from PMG estimation reported in Table 7 (column 1) make it clear that CT has no significant impact in the short run. Among the other variables, only payment to labor and non-ICT capital have significant (at 1% level) positive impacts on revenue. The state-specific short-run results (columns 2 through 7) provide more or less similar results. In none of the cases is CT found to have a significant influence in the short run. These findings are not unexpected because CT brings changes in the structure of an economy and its benefit is realized in the long run. New technology is not adopted immediately, and agents take time to adopt it (Christiansen 2008). It diffuses slowly throughout the economy (David 1990; Rogers 1995; and Hall 2004).

Conclusions and policy implications

This article aims to examine the effects of CTs on agricultural revenue in Australia in the short and long runs during the period of 1990-2012. An aggregate Cobb-Douglas revenue function is estimated incorporating the expenditures for traditional factors plus telecommunication. Accounting for cross-sectional dependence, the results of cointegration tests indicate the existence of a long-run equilibrium relationship between the variables. The empirical results show that the long-run elasticities of CT expenditure are significant and positive; however, in the short run, CT expenditure does not have any significant influence on agricultural revenue. The Pooled Mean Group estimate of long-run elasticity is 0.237, and the Augmented Mean Group estimates with and without trend are 0.209 and 0.197, respectively. These findings imply that holding other things constant, an increase in CT expenditure by 10 percent will increase a firm's revenue earnings by an average of approximately 2 percent in the long run. Statistically, zero elasticity of CT expenditure in the short run is not unusual because technology takes time to exert its impact. The positive and significant relationship between CT expenditure and agricultural revenue in the long run demonstrates that CT capital will remain a critical driving force for raising broadacre agricultural output and revenue in Australia.

The empirical findings have some policy implications. If other factors remain the same, the ongoing national broadband network expansion to the regional areas will bring about benefits for the farming communities in terms of increasing connectivity. Like developing countries, Australian farmers will increasingly be connected digitally to the local and global knowledge hubs, which will enable the farmers to obtain and use a wide variety of information in relation to production technology and production marketing. Thus, Australian farmers' average earnings are expected to rise substantially. However, the impact of communication technology requires a 'critical mass' before it is felt (Röller and Waverman 2001); therefore, the achievement of a critical mass in the regional areas should be a policy priority of the government of Australia. Furthermore, an effective regional-specific public policy intervention entailing skill development (for example, training) is required for the farmers so that the farmers can acquire necessary skills in using CTs in regional areas along with the diffusion of NBN facilities.

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Appendix A

Table A1: Cross-section dependence test

Variable	CSD test stat (*p* value)	Correlation
log*Y*	8.31 (0.000)	0.548
log*CT*	10.24 (0.000)	0.675
log*L*	6.91 (0.000)	0.456
log*Lr*	9.75 (0.000)	0.643
log*I*	1.78 (0.075)	0.210
log*F*	10.41 (0.000)	0.686
log*RF*	9.22 (0.000)	0.621

Table A2: Wooldridge test for autocorrelation

	AMG (with trend)	AMG (without trend)	PMG
Test statistic	0.211	0.293	0.420
(*p* value)	(0.6699)	(0.61730	(0.5522)

Null hypothesis: no first-order autocorrelation

Figure A1: Kernel density estimates of residual normality

With trend (AMG) | Without trend (AMG) | PMG