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Technology catch-up in agriculture among advanced economies

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Abstract

We examine whether countries with low initial levels of agricultural total factor productivity (TFP) tend to 'catch up' with the technology leaders. We first compare relative levels of agricultural TFP, capital services and labour input levels in agriculture for 17 OECD countries between 1973 and 2011. Then we apply (conditional) convergence analysis to the panel data to examine the speed of convergence and test whether the convergence is transitory or permanent by analysing TFP changes over the business cycle. Capital intensities, quality improvement of capital, factors such as human capital spillovers, and certain agricultural policies are conditioning variables. We examine how differences in relative capital intensities affect agricultural productivity convergence over the business cycle. We find evidence that the speed of convergence increases during periods of contraction in economic activity.

KEYWORDS

generalised method of moments, OECD agriculture, productivity convergence, the business cycle, total factor productivity

JEL classifications

Q16, Q17

1 | INTRODUCTION

With only modest increases in total factor input, productivity gains in agriculture over the past half-century have enabled growth in global agricultural output to outpace population growth. This has helped to mitigate global food insecurity. However, the rates of growth of productivity have been very uneven across countries, resulting in large differences in relative levels of productivity (Ball et al., 2001, 2010; Gollin et al., 2014; Herrendorf & Schoellman, 2015). In this paper, we examine whether countries with low initial levels of agricultural total factor productivity (TFP) tend to 'catch up' with (or show faster growth than) the technology leaders.

The uneven performance of agricultural productivity growth across countries could be related to improper accounting for quality improvement of capital input (Gollin et al., 2014), which generates a positive relationship between relative capital intensities and agricultural TFP growth. This is termed the *embodiment hypothesis* initially advanced by Jorgenson (1966) and recently was elaborated by Whelan (2007) and Caunedo and Keller (2021). This hypothesis states that the mis-measured improvements in capital accounting could lead to an ongoing productivity gap across regions. Our objective is to test this hypothesis by properly incorporating capital measures in the production accounts for agriculture across 17 OECD countries. The accounts underpin efforts to explore cross-country convergence of productivity in agriculture. We focus on capital accumulation as a vehicle for adopting advanced agricultural technologies.

We first compare relative levels of total factor productivity (TFP), capital service flows and labour input in agriculture for the 17 OECD countries between 1973 and 2011.[1] Then we apply (conditional) convergence analysis to the panel data to examine the speed of agricultural TFP convergence and test whether the convergence is transitory or permanent by analysing TFP changes over the business cycle. Capital intensities, quality improvement of capital, factors such as human capital spillovers, and certain agricultural policies such as the Common Agricultural Policy (CAP) of the European Union are conditioning variables. Since there are natural differences in capacity utilisation of capital input between periods of economic expansion and contraction (see Caunedo & Keller, 2021), we examine how differences in relative capital intensities affect productivity convergence over the business cycle.

Our results show that the countries with relatively low initial levels of agricultural TFP may exhibit faster productivity growth than the technology leaders when conditions such as capital intensities, human capital spillovers and certain agricultural policies are properly considered. Moreover, when the economy is in period of recession, the relationship between capital intensities and agricultural productivity growth becomes positive and significant (in particular, when land is used as numeraire). Since capital intensity is positively correlated with agricultural TFP growth, the embodiment hypothesis is still likely to hold even if capital inputs in agriculture are properly measured across countries. This contributes to differences in agricultural productivity over the business cycle.

This study makes at least two contributions to the literature. First, we use a newly developed dataset with quality-adjusted measures of capital, labour and intermediate inputs, including more countries and expanding the time period of Ball et al. (2001). This allows us to rigorously test the embodiment hypothesis for the 1973–2011 period. Second, we explore how capital deepening affects productivity convergence across countries over the business cycle. We find that capital accumulation is more likely to facilitate agricultural productivity catch-up across countries during contractions than during expansions in economic activity. This finding supports the embodiment hypothesis.

[1]The 17 OECD countries are including Australia, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, the United Kingdom and the United States.

The rest of the paper is organised as follows. Section 2 reviews conditional convergence analysis and its use in testing the embodiment hypothesis in agriculture. Section 3 develops the production accounts for agriculture of 17 OECD countries for the period 1973–2011, including estimates of real output and real factor input. In Section 4, we examine changes in relative agricultural TFP levels across countries and over the business cycle. Section 5 provides an empirical model specification and discusses the empirical results of testing the embodiment hypothesis and technology catch-up over the business cycle. Section 6 discusses the conclusions and policy implications.

2 | CROSS-COUNTRY PRODUCTIVITY CONVERGENCE, THE BUSINESS CYCLE AND THE EMBODIMENT HYPOTHESIS

The neoclassical growth model (Solow, 1956) assumes that production is subject to diminishing returns to capital. This implies absolute convergence, or that labour productivity may converge to the same steady-state as capital intensity increases. For agriculture, this is particularly true because of the constrained supply of land or other natural endowments for each country. However, for agricultural TFP (rather than labour productivity) convergence to occur, all countries would have to share the same steady-state of technology (rather than income per capita). Absolute convergence usually does not happen due to the individual characteristics of each country (soil, climate, institutions, preferences, laws and other idiosyncratic characteristics). Therefore, conditional convergence is more likely since it reflects the different steady states to which each country or region trends (Barro & Sala-i-Martin, 1992, 1995; Quah, 1993).

According to the predictions of the (conditional) convergence model, investments in innovation accelerate the rate of TFP growth, allowing less productive farms to 'catch up' through increasing technology spillovers. However, investments in physical capital may not necessarily facilitate TFP convergence across countries unless technology spillovers embodied in physical capital are correctly priced. This is termed the 'embodiment hypothesis' as initially proposed by Jorgenson (1966). Only when quality improvements from capital accumulation are not properly measured will capital intensity and its embodied technology spillovers affect the TFP (or technology) catch-up process (Whelan, 2007). However, if physical capital is properly measured, it is unknown whether capital intensity in agriculture will still significantly contribute to the disparities in TFP growth across countries (Jorgenson, 1966).

Two groups of recent studies extended Barro and Sala-i-Martin (1992, 1995) by linking productivity convergence patterns with the business cycle. The first explanation is based on the procyclical nature of the innovation process (Basu & Fernald, 2001; Geroski & Walters, 1995) and the time lags between technological innovations and diffusion processes (Jovanovic & MacDonald, 1994). According to this argument, productivity leaders tend to innovate more during periods of expansion in response to positive demand shocks. However, due to the existence of informational barriers, productivity followers (who tend to learn by imitation) postpone the adoption of innovations made by the technology leaders until economic downturns. The second explanation is based on the relationship between competition and productivity. Productivity followers have a greater incentive to reduce their costs during downturns when adverse demand shocks increase the probability that these firms will exit the industry (Caunedo & Keller, 2021; Escribano & Stucchi, 2014).

Technology adoption in agriculture is related to changes in capital intensities over time and across the business cycle (Ball et al., 2014; Escribano & Stucchi, 2014). For example, McCunn and Huffman (2000) found evidence of conditional convergence in levels of agricultural TFP across the US States. The embodiment hypothesis suggests that mis-measured improvements in capital accounting could explain the persistent productivity gap across regions

(Jorgenson, 1966; Whelan, 2007). Comparisons either across countries or US States show that countries/regions with lower initial levels of TFP achieve faster growth. More recently, Caunedo and Keller (2021) also showed that accounting for technological advances embodied in capital played an important role in explaining differences in agricultural productivity across countries. We test whether embodiment and technology catch-up among the 17 OECD countries over the business cycle can explain the observed cross-country differences in agricultural productivity.

3 | PRODUCTION ACCOUNTS FOR AGRICULTURE IN OECD COUNTRIES

We construct the production accounts for each of the 17 OECD countries following Ball et al. (2008, 2010). Data on production patterns for each country are generated by a gross output model of agricultural production. Output is defined as gross production leaving the farm, as opposed to real value added. Inputs are not limited to labour and capital but include intermediate inputs as well. A constant efficiency model is used to derive capital services from capital stock and distinguish capital input from land, with the adjustment for the purchasing power parities. This newly constructed measure of capital input allows us to account for quality improvement of capital inputs in agriculture to exploring the role of capital deepening in affecting productivity catch-up across countries, as in Caunedo and Keller (2021). This section provides an overview of methods and data.

We construct translog price indices and implicit quantities of output and capital, land, labour and intermediate inputs for each of the 17 OECD countries over the period 1973–2011. The data on the value of the economic aggregates are reported in national currencies. To convert to a common currency (i.e. US dollars), we construct translog multilateral price indices over the 17 OECD countries (see Ball et al., 1997, 2010; Caves et al., 1982). These price indices are referred to in the international comparisons literature as purchasing power parities (PPP) (e.g. see Eithorn & Voeller, 1983; Voeller, 1981). The dimensions of the purchasing power parities are the same as exchange rates. However, unlike exchange rates, the purchasing power parities reflect the relative prices of the goods and services that make up the sector's output and capital, land, labour and intermediate inputs in each country. These are relative prices in each country expressed in terms of national currencies per dollar. We divide relative prices by the exchange rate to translate the purchasing power parities into relative prices in dollars. This allows us to decompose nominal values into price and quantity components.

We calculate directly the purchasing power parities for 2005. We then extend the estimates backward and forward in time using time-series price indices for each country. The result is a true panel dataset that can be used in cross-sectional or time-series analysis.

3.1 | Output and intermediate input

Our measure of agricultural output includes deliveries to final demand and to intermediate demand in the nonfarm sector. We include deliveries to intermediate farm demand so long as these deliveries are intended for different production activities (e.g. crop production intended for use in animal feeding). We also include output of certain nonagricultural or secondary activities in our measure of sectoral output. These activities are defined as activities whose costs cannot be observed separately from those of the primary agricultural activity. Two types of secondary activities are distinguished. The first represents a continuation of the agricultural activity, such as the processing and packaging of agricultural products on the farm, while services relating to agricultural production, such as machine services for hire, are typical of the second.

The total output of the sector represents the sum of output of agricultural goods and the output of goods and services from secondary activities. We evaluate sectoral output from the point of view of the producer. Subsidies are added, and indirect taxes are subtracted from market values. In those countries where a forfeit system prevails, the difference between payments and refunds of the tax on value added (or VAT) is also included in the value of output.

Intermediate input consists of all goods and services consumed during the accounting period, excluding fixed capital. Those goods and services that are produced and consumed within the agricultural sector are included in intermediate input so long as they also enter the farm output accounts. The value of intermediate input includes taxes (other than the deductible VAT) less subsidies, whether paid to suppliers of intermediate goods or to agricultural producers.[2]

3.2 | Capital input

The measurement of capital input begins with data on the stock of capital and capital rental price for each asset type in each country.[3] At each point of time, 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, $S(\tau)$.

$$K(T) = \sum_{\tau=0}^{\infty} S(\tau) I(T-\tau) \tag{1}$$

To estimate the capital stock, we must introduce an explicit description of the decline in efficiency. This function, S, may be expressed in terms of two parameters, the service life of the asset L and a curvature or decay parameter β. One possible form of the efficiency function is given by

$$\begin{aligned} S(\tau) &= (L-\tau)/(L-\beta\tau), \quad && (0 \leq \tau \leq L) \\ S(\tau) &= 0, && (\tau < L) \end{aligned} \tag{2}$$

This function is a form of a rectangular hyperbola that provides a general model incorporating several types of depreciation as special cases. The value of β is restricted only to values less than or equal to one. For values of β greater than zero, the function S approaches zero at an increasing rate. For values less than zero, S approaches zero at a decreasing rate.

There is little empirical evidence to suggest a precise value for β. However, a number of studies provide evidence that efficiency decay occurs more rapidly in the later years of service, corresponding to a value of β in the zero–one interval. Utilising data on expenditures for repairs and maintenance of 745 farm tractors covering the period 1958–1974, Penson et al. (1977) found that the loss of efficiency was very small in the early years and increased rapidly as the end of the asset's life approached. Romain et al. (1987) compare the explanatory power of alternative capacity depreciation patterns for farm tractors in a model of investment behaviour. They found that the concave depreciation pattern better reflects actual investment decisions. Beutel (1997), Baldwin

[2]The data on output and intermediate input for the European countries are from the Economic Accounts for Agriculture NewCronos database http://epp.eurostat.ec.europe.eu/. Comparable data for the United States, Canada and Australia are available from the Economic Research Service, US Department of Agriculture, Statistics Canada, and the Australian Bureau of Statistics, respectively.

[3]Data on investment for the European countries are from *Capital Stock Data for the European Union* (Beutel, 1997). The series was extended through 2011 using Eurostat's NewCronos database http://europa.eu.int/comm/eurostat/newcronos/. Data for the United States are from Fixed Reproducible Tangible Wealth in the United States (U.S. Dept. of Commerce). Data for Canada come from Canadian Statistics and Agri-Food and Agriculture Canada, while for Australia come from Australian Bureau of Statistics.

et al. (2015) and Australian Bureau of Statistics (2018) provide further empirical evidence to support using the concave decay pattern. For purposes of this study, it is assumed that the efficiency of a structure declines very slowly over most of its service life. The decay parameter for machinery and transportation equipment assumes that the decline in efficiency is more uniformly distributed over the asset's service life. Given these assumptions, the final β values chosen were 0.75 for structures and 0.5 for machinery and transportation equipment.

The other variable in the efficiency function is the asset life $\boldsymbol{L}$. For each asset type, there exists some mean service life $\overline{L}$ around which there exists a distribution of actual service lives. In order to determine the amount of capital available for production, the actual service lives and the relative frequency of assets with these lives must be determined. It is assumed that this distribution may be accurately depicted by the normal distribution truncated at points two standard deviations before and after the mean service life.

Once the frequency of a true service life L is known, the decay function for that particular service life is calculated using the assumed value of β. This process is repeated for all other possible values of L. An aggregate efficiency function is then constructed as a weighted sum of individual efficiency functions using as weights the frequency of occurrence.[4]

This function not only reflects changes in efficiency, but also the discard distribution around the mean service life.

To construct measures of the user cost of capital, we draw on the literature on investment behaviour (see Coen, 1975; Penson et al., 1977; Romain et al., 1987). Firms undertaking investment decisions should add to capital stock if the present value of the net revenue generated by an additional unit of capital exceeds the purchase price of the asset. Stated algebraically, this condition is

$$\sum_{t=1}^{\infty}\left(P\frac{\partial Y}{\partial K}-W_K\frac{\partial R_t}{\partial K}\right)(1+r)^{-t}>W_K \tag{3}$$

where P is the price of output, W_K is the price paid for a new unit of capital, R_t is replacement investment, and r is the real discount rate.

To maximise net worth, firms will add to capital stock until equation (3) holds as an equality

$$P\frac{\partial Y}{\partial K}=rW_K+r\sum_{t=1}^{\infty}W_K\frac{\partial R_t}{\partial K}(1+r)^{-t}=c \tag{4}$$

where c is the implicit rental price of capital. The rental price consists of two components. The first term, rW_K, represents the opportunity cost associated with the initial investment. The second term, $r\sum_{t=1}^{\infty}W_K\frac{\partial R_t}{\partial K}(1+r)^{-t}$, is the present value of the cost of all future replacements required to maintain the productive capacity of the capital stock.

We can simplify the expression for the rental price in the following way. Let F denotes the present value of the stream of capacity depreciation on one unit of capital according to the mortality distribution m

$$F=\sum_{\tau=1}^{\infty}m(\tau)(1+r)^{-\tau} \tag{5}$$

where $m(\tau)=-[S(\tau)-S(\tau-1)],(\tau=1,2,\ \dots,L)$. It can be shown that.

$$\sum_{t=1}^{\infty}W_K\frac{\partial R_t}{\partial K}(1+r)^{-t}=\frac{F}{1-F}, \tag{6}$$

so that $c=\frac{rW_K}{1-F}$.

[4]The mathematical model that underpins our estimates of capital stock can be found in Ball et al. (2008).

The real rate of return r is calculated as the nominal yield on government bonds less the rate of inflation as measured by the implicit deflator for gross domestic product.[5] An ex ante rate is obtained by expressing observed real rates as an ARIMA process.[6] We then calculate F holding the required real rate of return constant for that vintage of capital goods. In this way, implicit rental prices c are calculated for each asset type.

Although we estimate the decline in efficiency of capital goods for each component of capital input separately for all 17 countries, we assume that the relative efficiency of new capital goods is the same in each country. The appropriate purchasing power parity for new capital goods is the purchasing power parity for the corresponding component of investment goods output (OECD, 2001, p. 62). To obtain the purchasing power parity for capital input, we multiply the purchasing power parity for investment goods output for any country by the ratio of the price of capital input in that country relative to the United States.

3.3 | Land input

To estimate the stock of land in each country, we construct translog price indices of land in farms. The stock of land is then constructed implicitly as the ratio of the value of land in farms to the translog price index.

Spatial differences in land characteristics or quality prevent the direct comparison of observed prices. To account for these differences, indexes of relative prices of land are constructed using hedonic regression methods in which a good is viewed as a bundle of characteristics that contribute to the productivity derived from its use. According to the hedonic framework, the price of a good represents the valuation of the characteristics that are bundled in it, and each characteristic is valued by its implicit price. These prices are not observed directly and must be estimated from the hedonic price function.

A hedonic price function expresses the price of a good or service as a function of the quantities of the characteristics it embodies. Thus, the hedonic price function for land may be expressed as

$$\ln\left(w_j^i\right) = \sum_{i=1}^{I} \delta_i D_i + \sum_{c=1}^{C} \beta_c x_j^i c + \varepsilon_{ij} \tag{7}$$

where w_j^i is the price of land in region j of country i, x_j^i is a vector of land characteristics, and D_i is a dummy variable equal to unity for the corresponding country and zero otherwise, and ε_{ij} is a stochastic error term.

Sanchez et al. (2003) introduced a soil taxonomy that is used to identify attributes relevant for crop production. The attributes most common in major agricultural countries are loamy topsoil (particularly in the United States, Portugal and Spain) and moisture stress (particularly in Australia, Greece, Italy, Portugal and Spain). In areas with moisture stress, agriculture is not possible without irrigation. Hence, irrigation (i.e. the percentage of cropland that is irrigated) is included as a separate variable. We also include the interaction between moisture stress and irrigation in the hedonic regression.

In addition to environmental attributes, we also include a 'population accessibility' score for each region in each country. This index is constructed using a gravity model of urban development, which provides a measure of accessibility to population concentrations (Shi et al., 1997). A gravity index accounts for both population density and distance from that

[5]The nominal rate was taken to be the average annual yield over all maturities.

[6]Ex ante real rates are expressed as an AR(1) process. We use this specification after examining the correlation coefficients for autocorrelation, partial and inverse autocorrelation and performing the unit root and white noise tests.

population. The index increases as population increases and/or distance from the population centre decreases.

Other variables (denoted by D) are also included in the hedonic equation, and their selection depends not only on the underlying theory but also on the objectives of the study. If the main objective of the study is to obtain price indexes adjusted for quality, as in our case, the only variables that should be included in D are country dummy variables, which will capture all price effects other than quality. After allowing for differences in the levels of the characteristics, the part of the price difference not accounted for by the included characteristics will be reflected in the country dummy coefficients.

Several methods have been used to calculate price indexes adjusted for quality using hedonic functions, including characteristics prices and dummy variable techniques. The latter is used in this study because it is simpler and because Triplett (1989) has provided extensive evidence of the robustness of the hedonic price indexes to the method of calculation. Using the dummy variable approach, quality-adjusted price indexes are calculated directly from the coefficients on the country dummy variables D in the hedonic regression.

3.4 | Labour input

Data on labour input in agriculture consist of hours worked disaggregated by hired and self-employed and unpaid family workers (Ball et al., 2010; Sheng et al., 2017). Compensation of hired farm workers is defined as the average hourly wage plus the value of perquisites and employer contributions to social insurance. The compensation of self-employed workers is not directly observable. These data are derived using the accounting identity where the value of total product is equal to total factor outlay. Our index of labour input will then reflect differences in marginal products of hired and self-employed and unpaid family workers.

We have constructed indices of prices of aggregate output relative to the United States and the corresponding implicit quantities. Similarly, we calculated indices of relative input prices defined over capital, land, labour and intermediate inputs and implicit quantities of total factor input. Finally, we have constructed indices of relative levels of total factor productivity as the ratio of output for each country relative to the United States divided by the index of total factor input.[7]

4 | AGRICULTURAL TFP GROWTH AND POSTCRISIS (WORLD FINANCIAL CRISIS) ACCELERATION

Using the newly developed data, we compare agricultural TFP levels and their growth across the 17 OECD countries for the 1973–2011 period and link them to the business cycles. Figures 1–5 graphically illustrate the differential impacts of economic contractions on TFP growth from 1973 to 2011. We especially note the impact of the financial crisis of 2008–09. We also compare the economic expansion 1973–2008 and the economic contraction 2008–2011 periods. These figures illustrate how business cycles affect TFP growth and convergence. Countries with below average TFP levels converge to the mean level at a faster rate than nations with high average TFP levels.

Table 1 provides summary statistics for the main variables for the 1973–2011 period. Over the entire study period, the United States continues to be the leader in TFP level (see Figures 1 and 2)

[7]These data are reported in the Appendix S2.

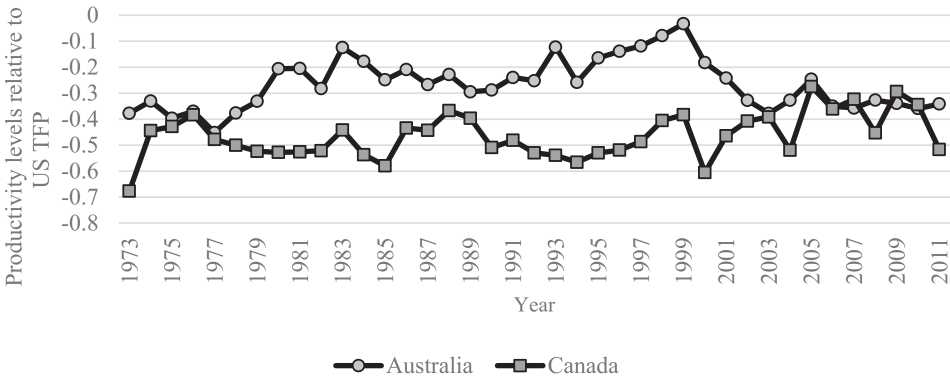

FIGURE 1 Trends in relative levels of productivity. Australia and Canada versus the United States ($TFP_{us} = 0$). *Source*: Authors' own estimation.

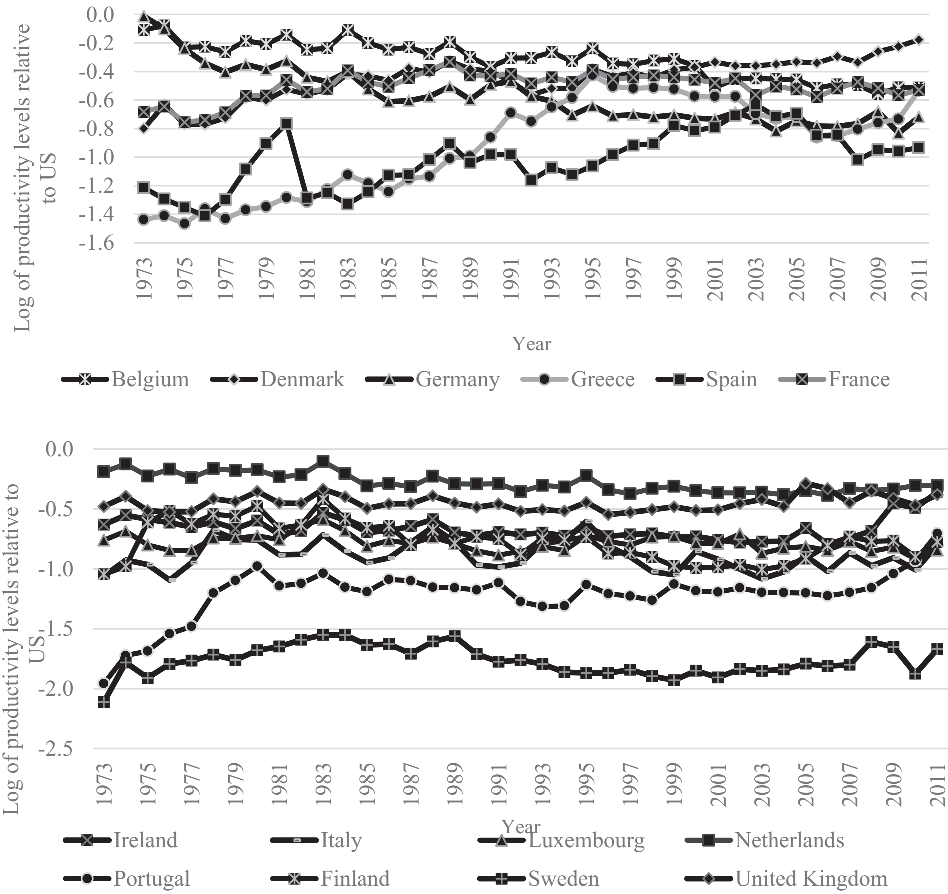

FIGURE 2 Trends of differences in relative levels of productivity: EU countries ($TFP_{us} = 0$). *Source*: Authors' own estimation.

but not in the average annual rate of growth. Moreover, for the United States, the average rate of growth from 1973 to 2011 is below the average of the 14 European Union and the 17 OECD countries (Figure 3). Australia was closing the gap in relative levels of productivity with the United

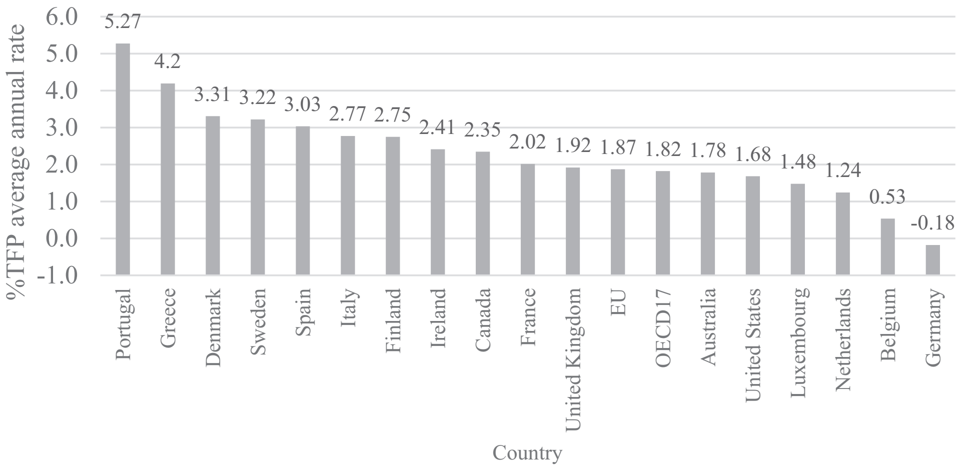

FIGURE 3 Ranking agricultural TFP growth across countries: 1973 to 2011 (%). *Source*: Authors' own estimation.

States until 1999 (Figure 1). However, after the decade-long 'millennium drought' in the 2000s, Australia's relative level of productivity fell to the level of Canada despite achieving a higher average growth rate than the United States between 1973 and 2011 (Figure 1).[8] Other variables also include openness to trade and agricultural output structure. In this paper, we measure openness to trade by using the ratio of total export and import value to total GDP, while agricultural output structure by using the proportion of cropping output value to total agricultural output value.

On average, the 17 OECD countries achieved a 1.82% rate of TFP growth for the entire period, but below the EU average annual rate of growth of 1.87%. The leaders, in the long run, were the Mediterranean and the Nordic countries. Canada's rate of productivity growth exceeded the average, but not that of Australia, the United States and the Netherlands (Figure 3). Belgium had the lowest growth rate in productivity other than Germany, whose growth rate became negative after the reunification.

Figure 4 further shows the scope of the restructuring of the 17 OECD country agricultural sectors after 2008. It compares the historic productivity trend versus the postfinancial crisis. The positive bars on the left hand of Figure 4 indicate an acceleration of the rate of productivity growth following the financial crisis of 2008–09. The postcrisis growth rates in Portugal, Ireland, Greece, Germany and Sweden exceeded that for the years preceding the financial crisis. Italy, Denmark and the United States achieved rates of productivity growth below the EU average in the postcrisis period, but above the average of the 17 OECD countries. Finally, several countries experienced rates of TFP growth below the historical trend, namely Canada, Spain, Finland, France, the United States and Australia.

The differences in the postcrisis expansion/contraction (Figure 4) explain the changes in the ranking from the pre-crisis TFP growth (Figure 5) versus the whole period (Figure 3). Notably, Australia and the United States fall below the average growth of the EU and the 17 OECD countries because of a slowdown in productivity growth after the financial crisis (Ball et al., 2013). Ireland exceeded the average in the ranking, and Portugal achieved the highest rate of growth (Figures 3 and 5) due to the postcrisis boost in TFP growth. The Portuguese case

[8]We normalise the relative TFP level of other countries using the US TFP as the numeraire. The values of each country represent the relative level of productivity each year to visualise if the gap with the leader is closing or widening. For instance, Australia was closing the gap until reach −0.03 or a gap of 3% with the US level of productivity in 1999. Moreover, after the drought of the century, the productivity gap between Australia and the US widened until −0.39 or a gap of 39% with the leader.

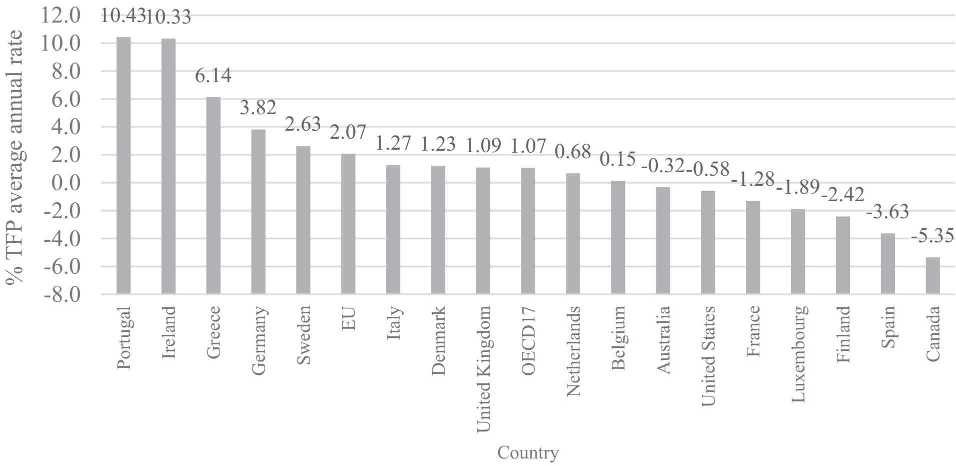

FIGURE 4 Ranking agricultural TFP growth across countries: contraction (%). *Source*: Authors' own estimation.

is probably related to the fact that the agricultural land was nationalised after the 'Carnation Revolution', and since 1975 the rent of agricultural land has been administratively fixed at low levels. Additionally, farmers had access to the European Structural and Investments Funds, which focusses on less developed regions of the EU, and to the Common Agricultural Policy (CAP) subsidies from 1986. From 1974 to 2011, the rate of growth of capital per unit of labour was 1.5% for Portugal while Spain was only 0.6%. The main difference was during the 5 years preceding the financial crisis, Portugal sharply increased the capital intensity whereas Spain saw a decrease. After the financial crisis, both experienced a credit crunch and saw a reduction in capital input. This may explain the gains in productivity in Portugal relative to those in Spain during the postcrisis period (Figure 2).

Figure 6 compares the historical trend in TFP growth (1973–2011) versus the postcrisis expansion/contraction. Specifically, Figure 6 compares the average annual per cent TFP growth rate from 1973 to 2011, minus the per cent TFP growth rate from 2008 to 2011 (orange bars) versus the average annual TFP growth rate from 1973 to 2011 (the blue bars). This represents the postcrisis expansion/contraction. Among the 17 OECD countries, Canada, Spain, France and Finland achieved negative differences in rates during the contraction period compared with the historical trend. However, Ireland, Portugal, Germany, Greece and Denmark show expansions in economic activity boosts, with an average annual rate of growth in TFP in 2008 to 2011 exceeding the historical trend growth rate (Figure 6). Australia and the United States show a smaller pattern of (or slowdown in bust) productivity growth during the postcrisis period.

The ranking by country of the TFP average rate of growth during the postcrisis (or contraction) period shows that the EU average growth rate exceeds the growth rate of the 17 OECD countries. In the postcrisis period, countries with a high level of TFP (the United States and the Netherlands) achieved a rate of growth below the average of the 17 OECD countries. The changes in the relative levels of productivity can be appreciated if we normalise the productivity level relative to the leader (TFPUS =1). Having developed this unique panel dataset on agricultural TFP from 1973 to 2011, we can thus examine whether there is a process of convergence.

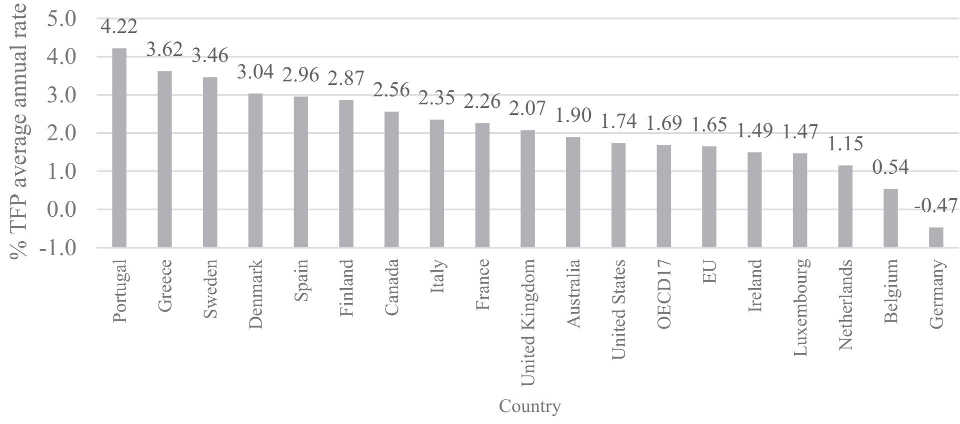

FIGURE 5 Ranking agricultural TFP growth across countries: expansion (%). *Source*: Authors' own estimation.

TABLE 1 Summary statistics on key variables

	Mean	Std. dev.	Min	Max
Agricultural TFP (US 2005 = 1.00)	0.461	0.190	0.071	1.041
Capital–labour ratio	0.581	0.639	0.005	3.165
Capital–land ratio	4.323	3.966	0.021	36.022
Barro–Lee index	9.1888	2.097	2.784	13.478
Openness to trade index (%)	2.844	1.961	0.512	13.473
Output structure (%)	42.292	13.372	18.549	71.422
OTG dummy	0.480	0.500	0.000	1.000

Note: The total number of observations is 663.

5 | AGRICULTURAL TFP CATCH-UP, EMBODIMENT AND THE BUSINESS CYCLE

5.1 | Empirical model specification

Following Escribano and Stucchi (2014), and Ball et al. (2014), our baseline model to examine the (conditional) convergence of productivity and the embodiment hypothesis takes the form of

$$\log\left(\frac{TFP_{it}}{TFP_{it-1}}\right) = \beta_0 + \beta_1 \log\left(TFP_{it-1}\right) + \beta_2 \log\left(KLA_{it}\right) + \beta_3 X_{it} + u_i + \tau_t + \varepsilon_{it} \quad (8)$$

where TFP_{it} and TFP_{it-1} are relative levels of agricultural TFP and its lag, respectively. KLA_{it} represents capital intensities. We measure them using two indicators: one is the capital-labour ratio and the other is the capital-land ratio. X_{it} is a vector of control variables, which includes years of schooling (HC) reflecting possible technology spillovers from investment in human capital (Parman, 2012), and the level of the countries' productivity at the national level (Feenstra et al., 2015). Other control variables also include the measure of openness to trade and output structure. u_i is country-specific fixed effect, τ_t is a time dummy, and ε_{it} is the residual.

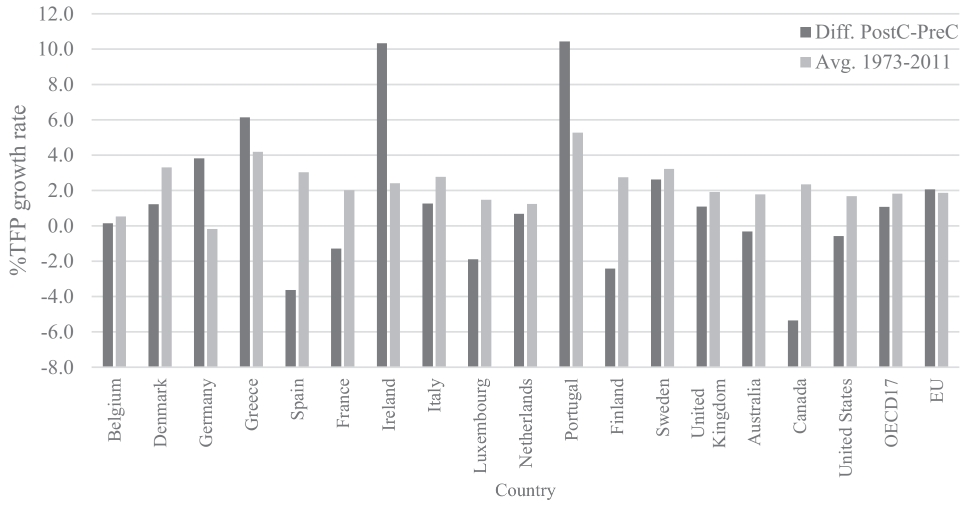

FIGURE 6 Historic trend versus the postcrisis TFP growth. *Source*: Authors' own estimation.

When we use the panel data regression with fixed effects to reduce the potential endogeneity problem (related to country fixed effects), Equation (8) can be estimated.[9] We examine the convergence of agricultural productivity across countries at the aggregate level and test whether the embodiment hypothesis holds.

We test two null hypotheses. Under the first hypothesis (convergence), if H_0: $\beta_1 < 0$, there is conditional convergence of agricultural TFP across countries. The larger the magnitude of β_1 in absolute value, the higher the speed of productivity convergence. If H_0: $\beta_2 > 0$, an increase in capital intensity will facilitate technology catch-up among countries, supporting the embodiment hypothesis. Under the second hypothesis (embodiment), if our measure of capital input fully reflects changes in input quality, then β_2 would equal zero (i.e. no embodiment).

Moreover, we examine whether the pattern of agricultural TFP convergence will change with fluctuations in economic activity (i.e. the business cycle). We introduce a new dummy variable (based on the concept of 'output gap') into Equation (8). This is to capture changes in the speed of productivity convergence and its potential determinants (i.e. capital intensities) in different phases of the business cycle. Thus, we can rewrite Equation (1) as

$$\begin{aligned}\log\left(\frac{TFP_{it}}{TFP_{it-1}}\right) &= \beta_0 + \gamma_0 OTG_{it} + \beta_1 \log\left(TFP_{it-1}\right) + \beta_2 \log\left(KLA_{it}\right) \\ &+ \beta_3 X_{it} + \beta_1' OTG_{it} * \log\left(TFP_{it-1}\right) + \beta\prime_2 OTG_{it} * \log\left(KLA_{it}\right) + u_i + \tau_t + \varepsilon_{it}\end{aligned} \tag{9}$$

where OTG_{it} is the dummy for business cycle which equals 1 if the economy is in a contraction phase, and the other variables are defined as in Equation (8). The output gap is defined as the difference between the actual and the potential levels of output of an economy, expressed as a percentage of the potential output. Potential output is commonly defined as the level of output that can be achieved when the factors of production are utilised at noninflationary levels. In the literature, the output gap summarises the overall amount of slack present in the economy. It is used by the US Federal Reserve and the European Central Bank (see ECB, 2005). To define cycles, we use

[9]The model is estimated using the general method of moments (GMM) approach. The results are reported in Appendix S1.

TABLE 2 Conditional convergence analysis and embodiment hypothesis: FE model

	1-year	3-year	5-year
	(1)	(2)	(3)
Dependent variable: TFP growth (log)			
TFP lag (log)	−0.052***	−0.172***	−0.285***
	(0.015)	(0.023)	(0.025)
Capital–labour ratio (log)	0.200**	0.190**	0.154***
	(0.078)	(0.072)	(0.046)
Capital–land ratio (log)	0.013	−0.015	−0.034
	(0.020)	(0.033)	(0.042)
Barro–Lee Human Capital Index (log)	0.278	0.191	0.224
	(0.253)	(0.311)	(0.288)
Openness to trade	−0.022	−0.022	−0.012
	(0.051)	(0.056)	(0.070)
Output structure	0.285***	0.213***	0.219***
	(0.036)	(0.052)	(0.071)
Constant	−0.037**	−0.123***	−0.206***
	(0.014)	(0.025)	(0.029)
Number of observations	646	612	578
R-squared	0.317	0.333	0.445
Number of countries	17	17	17

Note: Robust standard errors in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

the IMF output-gap data (International Monetary Fund, 2019). Therefore, a year with a negative output gap means that the economy is performing below full economic capacity, as the output-gap definition is *(GDP – PGDP) / GDP*, where GDP is the gross domestic product, and PGDP is the potential GDP. Thus, a negative output gap means a contraction phase.

Based on Equation (9), we investigate the impacts of the business cycle on the convergence process. Specifically, if β_1 captures the convergence rate for the expansion phase, $\beta_1 + \beta\prime_1$ will capture the convergence rate for the contraction phrase. Similarly, $\beta_2 + \beta\prime_2$ will capture the role of capital intensity in the convergence analysis (or the embodiment hypothesis) for the contraction phrase, relative to the expansion phrase. Thus, we can check how the convergence rate β_1 and the embodiment hypothesis β_2 change across different phases of the business cycle by examining the signs and significance of $\beta\prime_1$ and $\beta\prime_2$.

5.2 | Empirical results and the related discussion

Tables 2–4 summarise the empirical results based on the panel data regressions, controlling for country fixed effects. First, the estimate of the coefficient on the initial level of TFP β_1 is negative and statistically significant. This indicates conditional productivity convergence in agriculture in 17 OECD countries during the 1973 to 2011 period. These results are robust to the model specification. Our empirical results with the different models for the 17 countries always show negative and significant estimates of β_1 (Tables 1 and 2). The longer the time lag, the larger the magnitude of β_1 in absolute value. This implies that the speed of productivity convergence is likely to be higher in the long run.

TABLE 3 Productivity convergence and the business cycle: FE model

	1-year	3-year	5-year
	(1)	(2)	(3)
Dependent variable: TFP growth (log)			
ln_TFP_lag	−0.054***	−0.183***	−0.312***
	(0.017)	(0.021)	(0.026)
ln_TFP_lag*DTG	0.011	0.019	0.042
	(0.007)	(0.017)	(0.036)
Capital–labour ratio (log)	0.150***	0.129**	0.095**
	(0.049)	(0.045)	(0.040)
Capital–labour ratio*DTG (log)	0.144**	0.126*	0.122*
	(0.064)	(0.070)	(0.060)
Capital–land ratio (log)	0.009	−0.052	−0.101
	(0.017)	(0.059)	(0.068)
Capital–land ratio*DTG (log)	0.011	0.077	0.116*
	(0.024)	(0.059)	(0.058)
Barro–Lee Human Capital Index (log)	0.371	0.229	0.267
	(0.278)	(0.326)	(0.299)
Openness to Trade Index	−0.009	−0.003	0.002
	(0.050)	(0.055)	(0.062)
Output structure	0.282***	0.205***	0.216***
	(0.036)	(0.051)	(0.063)
DTG	0.005	0.003	0.005
	(0.009)	(0.014)	(0.021)
Constant	−0.038**	−0.128***	−0.216***
	(0.014)	(0.023)	(0.026)
Number of observations	646	612	578
R-squared	0.333	0.353	0.476
Number of countries	17	17	17

Note: Robust standard errors in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Second, we examine how changes in capital intensity contribute to productivity convergence among OECD countries, but find mixed evidence for the embodiment hypothesis. Although our capital measure incorporates efficiency differences in capital input across countries and over time, we still find that new investment affects productivity convergence. Specifically, when we use the capital–labour ratio to measure capital intensity, we find that an increase in the capital–labour ratio results in a positive and significant effect on productivity convergence. That is, new investment facilitates productivity catch-up of laggard countries. However, when we use the capital–land ratio to measure capital intensity, an increase in the capital–land ratio does not affect productivity convergence (coefficient is not significant) (see Table 2). The comparison of different effects between capital–labour ratio and capital–land ratio suggests that the embodiment hypothesis could be highly related to the capacity usage of capital assets (as land and labour could move in different directions over the business cycle). This result also corroborates the finding from Ball et al. (2001). They found that capital intensity plays different roles in affecting productivity convergence over different periods of time. That is, capital intensity has a positive and significant effect on productivity convergence before 1981, but not

TABLE 4 Productivity convergence and the business cycle for the EU countries: FE model

	1-year	3-year	5-year
	(1)	(2)	(3)
Dependent variable: TFP growth (log)			
ln_TFP_lag	−0.040*	−0.165***	−0.307***
	(0.020)	(0.024)	(0.030)
ln_TFP_lag*DTG	0.038***	0.024**	0.015***
	(0.068)	(0.096)	(0.040)
Capital–labour ratio (log)	0.011	−0.044	−0.092
	(0.018)	(0.063)	(0.072)
Capital–labour ratio*DTG (log)	0.351	0.272	0.274
	(0.363)	(0.376)	(0.316)
Capital–land ratio (log)	−0.006	0.026	0.038
	(0.046)	(0.048)	(0.067)
Capital–land ratio*DTG (log)	0.277***	0.231***	0.255***
	(0.035)	(0.047)	(0.058)
Barro–Lee Human Capital Index (log)	0.022*	0.003	0.002
	(0.011)	(0.021)	(0.032)
Openness to trade	0.021**	0.019	0.043
	(0.007)	(0.020)	(0.044)
Output structure	0.101	0.102	0.119
	(0.070)	(0.117)	(0.072)
DTG	−0.002	0.066	0.111*
	(0.024)	(0.060)	(0.062)
Constant	−0.039*	−0.139***	−0.249***
	(0.020)	(0.031)	(0.033)
Number of observations	532	504	476
R-squared	0.386	0.398	0.516
Number of countries	14	14	14

Note: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

after that. We note, however, that net investment was negative during much of the 1980s and 1990s. Ball et al. (2001) conclude that the failure to replace the existing capital stock resulted in obsolescence of a significant portion of that stock. They have examined the dynamic impact of capital intensity on productivity catch-up across countries over the business cycle. They found a highly significant inverse relation between the rate of productivity convergence and the initial level of productivity consistent with the 'catch-up' hypothesis. Also, their results generally support the existence of a positive interaction between capital accumulation and productivity growth, suggesting embodiment.

Third, we examine the relationship between productivity convergence and the business cycle. Our results show that the contribution of capital intensity to productivity convergence differs depending on the period analysed. During years with a negative output-gap, the estimated coefficients on the interaction term between the dummy for the output gap and the capital–labour ratio are positive although they are not significant at 10% and 5% levels (Table 3). This implies that the speed of convergence was higher during periods of contraction in economic activity than during periods of expansion (as in Ball et al., 2001, 2014) but with large cross-country variation. In addition, we also find the intensity of capital by land is positive and significant at the 10% level when the output gap is negative (column 3 of Table 2). This implies that innovation embodied in working capital is more likely to explain the difference in convergence rates across the 17 OECD countries over the economic downturn period. A possible interpretation of the model results is that capital accumulation in the countries with relatively low TFP levels generates more spillovers that accelerate convergence in levels of TFP during contractions.

Finally, we also examine whether the rate of convergence for the EU countries is slower than when we consider all 17 countries. Results, shown in Table 3, suggest that European policies (i.e. CAP and ESIF) act as a safety net for less productive farms, possibly delaying bankruptcies and exiting of the industry. The fixed-effects results for the EU countries show that the convergence process in Europe is slower during periods of negative output gaps (the impact of lagged TFP is relatively smaller, and the interaction term between lagged TFP and the dummy for output gap is positive and significant), and the impact of capital intensity on convergence is not significant (capital intensities expressed as the capital–labour ratio and as the capital–land ratio are each insignificant at the conventional levels). Besides, when output gaps are negative, the productivity impact of capital intensity is higher in Europe. The level of agricultural productivity of the economy appears to affect TFP convergence more during the EU's negative output-gap years. The coefficients on all other control variables have the expected signs and are significant. Regarding the catching-up process, the convergence is not symmetric. As in Ball et al. (2014), we found results confirming that countries with below average levels of TFP converge at a considerably faster rate than those above the average.

6 | CONCLUSIONS AND POLICY IMPLICATIONS

We use the newly developed production accounts data for 17 OECD countries in this paper to examine the convergence of agricultural TFP. First, we find evidence for conditional convergence in agricultural TFP levels across the 17 OECD countries and that capital deepening will contribute to productivity convergence. Second, capital deepening is likely to play a more important role in facilitating productivity convergence during periods of contraction in economic activity than during periods of expansion.

Our findings are consistent with those from the manufacturing sector (Basu & Fernald, 2001; Geroski & Walters, 1995). The magnitude of the effects of the business cycle appears to be smaller in the agricultural sector than in the manufacturing sector. We attribute this to physical investment over the business cycle and its spillovers from embodied technology adoption. Even if we have accounted for the efficiency differences in capital assets, capital intensity still affects the convergence after the financial crisis. Regarding the EU versus Australia, Canada and the United States, our model results also show that the European Union TFP is catching up in the long run. Finally, there is evidence that countries with below average TFP levels converge to the mean level at a faster rate than nations with high average TFP levels.

Many factors affect technology adoption in agriculture of countries through the capital deepening process. Market distortions caused by impeding institutional arrangements are significant even for the 17 OECD countries. For example, agricultural productivity growth has long been driven by innovation embodied in the capital and material deepening process, as well as by agricultural research and development (R&D). Since there are economic and political pressures for increasing food supply especially during economic downturns, countries may promote the adoption of embodied technology and accelerate TFP growth by reallocating investments in physical capital and land from the less efficient farms to the more efficient ones (Godfray & Garnett, 2014).

The slower convergence rate among the EU countries compared with the US, Canada and Australia over the recent decade could be due to rigid European policies (i.e. CAP and ESIF). These policies act as a safety net for less productive farms, delaying bankruptcies and farm exits. These market distortions have become especially harmful during economic downturns by slowing the reallocation of resources to more productive farms. In this sense, more deregulation in agriculture, especially among the EU countries, could help the diffusion of technology among the OECD countries.

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DATA AVAILABILITY STATEMENT

I hereby confirm that all the data that have been used to generate the empirical results in the manuscript will be shared publically once the work is published at AJARE. The website which is under construction also provided the related data and the data appendix for the work (https://139.196.168.246:1080/).

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