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Cross-country agricultural TFP convergence and capital deepening: evidence for induced innovation from 17 OECD countries

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Abstract
Using a newly constructed panel dataset for agriculture in 17 OECD countries over the 1973–2011 period, we investigate the role of capital deepening in affecting agricultural TFP growth and the convergence of relative TFP levels across countries with different relative factor endowments. Our results show that capital deepening contributes positively to agricultural productivity growth among countries with similar levels of land relative to labor as reflected in relative prices. Depending on the relative endowments of land to labor, countries with relatively more abundant land are more likely to achieve technological gains through capital deepening than countries with relatively more labor. This finding is consistent with Hayami and Ruttan (1970a) and provides supportive evidence for the induced innovation hypothesis.

Keywords Agricultural TFP · Cross-country productivity convergence · Capital deepening · Induced innovation hypothesis

Jel code D24 · O13 · O33

1 Introduction

Cross-country differences in agricultural productivity are one of the key factors affecting global food security and rural development. This has important implications for the design of agricultural policy. In 2019, more than half the global production of cereals was by countries whose yields (or land productivity) are around three tons per hectare, less than half of the world best practice (FAO 2020). This implies that there are opportunities for laggard countries to catch up in agricultural productivity. Narrowing the yield gap across countries will significantly increase global food supplies without requiring more use of land. Reducing cross-country differences in agricultural productivity will also help to promote rural development in developing countries. For example, many developing countries have achieved rapid rural development partly because they have achieved more rapid growth of agricultural productivity than the rest of the world (IFAD 2015).

While much of the theoretical and empirical literature attempts to explain cross-country differences in agricultural productivity, puzzles still remain. On the one hand, significant differences in relative levels of agricultural productivity are widely observed between developed and developing countries, when cross-country differences in agro-ecological and climatic conditions, as well as measurement errors, are properly taken into account (Coelli and Rao 2005; Ludina et al. 2007; McMillan and Rodrik 2011; Gollin et al. 2014a, 2014b; Gong 2018). On the other hand, the agricultural productivity gap persists even across developed countries, which have advantages over developing countries in removing institutional barriers and market distortions (Alston et al. 2010, 2015; Sheng et al. 2015; Restuccia and Rogerson 2017). This is despite the fact that globalization has

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contributed to diffusion of technical knowledge across countries more quickly with the digital technology revolution. This highlights the need to better understand how technical progress and capital accumulation affect cross-country differences in agricultural productivity.

Differences in capital per unit of labor have contributed to productivity divergence across countries (Baumol 1986; Barro and Sala-i-Martin 1995; Kumar and Russell 2002; Badunenko et al. 2010, 2013). For example, both Kumar and Russell (2002) and Acemoglu (2010) find that technological progress is usually non-neutral toward saving labor and thus the international divergence could be driven by an increase in the capital-labor ratio (or capital deepening).[1] Moreover, Whelan (2007) and Ball et al. (2001, 2004, 2010, 2014) provide evidence for the embodiment hypothesis by suggesting that innovations embodied in capital inputs are also an important channel for technology adoption. This helps explain the cross-country productivity differences among developed countries. Nonetheless, few studies have examined whether this explanation applies to measured differences in cross-country total factor productivity (TFP) in agriculture. Nor does it explain whether such productivity convergence based on capital deepening is related to the country's initial factor endowments.

This paper investigates the role of capital deepening in affecting agricultural productivity convergence across countries with different relative factor endowments. We start by constructing cross-country consistent production accounts for agriculture in 17 OECD countries including 14 EU countries (Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the United Kingdom, and Australia, Canada, and the United States over the period 1973–2011. The purpose is to develop more robust measures of relative levels of agricultural output, input and TFP. This problem is widely observed in existing cross-country agricultural productivity comparison studies (Gollin et al. 2014a).

Our empirical study takes two steps. The first step is to examine whether capital deepening contributes positively to agricultural productivity growth, while controlling for other potential determinants of productivity differences across countries. We consider capital deepening as a vehicle to facilitate cross-country technology catch-up in agriculture of developed countries. The second step is to use the conditional quantile regression technique to investigate whether productivity convergence driven by capital deepening will differ across countries with different initial factor endowments (measured by using land per unit of labor).

A key finding of our study is that capital deepening will contribute positively to agricultural TFP growth across the 17 OECD countries, but may contribute to the rising cross-country differences in relative TFP levels. This implies that capital deepening may not necessarily facilitate technology catch-up of the laggard countries, which violates conventional wisdom. However, when we group countries by the relative factor endowments (measured by using the relative price of land to labor), we show that capital deepening is likely to facilitate productivity convergence among those countries where we observe a relatively lower price of land to labor. This implies that differences in relative factor endowments affect cross-country productivity differences. Our findings provide supporting evidence for the induced innovation hypothesis, which implies that differences in initial factor endowments matter for the path toward technological progress (Hayami and Ruttan 1970a).

We contribute to the literature in several ways. First, our study constructs a new cross-country consistent system of production accounts for the farm sector in 17 OECD countries, which adjusts inputs for changes in input quality. The production accounts allow us to compare the relative levels of agricultural output, input and productivity, based on internationally peer-reviewed methodology. Second, our study explores whether capital deepening affects the rate of agricultural productivity growth across developed countries. We show that capital deepening may cause productivity divergence across countries, depending on initial factor endowments. This provides a complementary explanation for the observed differences in agricultural productivity across the OECD countries. Third, we show that capital deepening fosters productivity convergence among countries with similar relative factor endowments and is more likely to promote agricultural TFP growth in relatively land-abundant countries. Finally, we also consider the contributions of openness to trade, human capital spillovers, and agricultural output structure to productivity growth in agriculture.

The rest of the paper is organized as follows. Section *Production Accounts for Agriculture in 17 OECD Countries* discusses methods and data used to construct the production accounts that underpin our empirical analysis. Section *Examining Uneven Agricultural TFP Growth across OECD Countries* briefly discusses agricultural TFP differences across OECD countries, and reviews the related literature. Section *Estimation Strategy: The Conditional Convergence Analysis* provides the empirical specifications used to investigate the impact of capital deepening on cross-country agricultural productivity differences and their linkages to the convergence process. Section *Cross-country Convergence of Agricultural TFP and Capital Deepening* discusses the empirical results followed by a series of sensitivity analyses in Section *Robustness check*. Section *Conclusions* concludes.

[1] By "capital deepening" we mean an increase in capital input per unit of labor.

2 Production accounts for agriculture in 17 OECD countries

We construct the production accounts for each of the 17 OECD countries following Ball et al. (2008, 2010, 2016). Data on production patterns for each country are generated by a gross output model of production. Output is defined as gross production leaving the farm, as opposed to real value added. Inputs are not limited to labor and capital but include intermediate inputs as well. The text in this section provides an overview of methods and data.

We construct translog price indices and implicit quantities of output and capital, land, labor, and intermediate inputs for each of the 17 OECD countries over the period 1973–2011. In order to compare relative levels of output and factor inputs across countries, we construct multilateral translog price indices. A price index which converts the nominal value ratio between two countries into an index of real values is referred to in the international comparison literature as a purchasing power parity. 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, labor, 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.[2]

We calculate 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.

2.1 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 non-agricultural 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.[3]

2.2 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.[4] 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

$$S(\tau) = (L-\tau)/(L-\beta\tau),\ (0 \leq \tau \leq \mathrm{L}) \tag{2}$$

$$S(\tau) = 0 \quad (\tau < L)$$

[2] Since our dataset did not cover Japan and Korea which have quite different land-labor endowments, the finding from this work may not necessarily apply to those Asian developed countries.

[3] 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.

[4] 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.

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. Utilizing 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 behavior. They found that the concave depreciation pattern better reflects actual investment decisions. Beutel (1997), Baldwin 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 equipment.

The other variable in the efficiency function is the asset life 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.[5] 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 of investment demand (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 maximize net worth, firms will add to capital stock until Eq. (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 denote 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 $m(\tau)=-[S(\tau)-S(\tau-1)]$, $(\tau=1,2,\ldots,L)$. 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 $c=\frac{rW_K}{1-F}$.

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.[6] An ex ante rate is obtained by expressing observed real rates as an ARIMA process.[7] 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

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

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

[7] 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.

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 1999, 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.

2.3 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 (Rosen 1974). 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

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

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

2.4 Labor input

Data on labor input in agriculture consist of hours worked disaggregated by hired and self-employed and unpaid family workers (European Statistics (Eurostat) 2000; Ball et al. 2010; Sheng et al. 2015). 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 labor 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, labor, 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. These data are reported in Appendix A.

2.5 Other control variables

Other control variables include the human capital index, openness to trade index and agricultural output structure.

The human capital index is defined as the average years of schooling at the economy level using the Barro-Lee approach (Barro and Lee 2013). The openness to trade index is defined as the ratio of total export and import value to total GDP. Both human capital and openness to trade indexes are calculated at the economy level. We measure agricultural output structure by using the proportion of cropping output value to total agricultural output value.

3 Examining uneven agricultural TFP growth across OECD countries

Agricultural total factor productivity (TFP) in OECD countries has exhibited a relatively high growth rate over the past four decades, contributing to agricultural development throughout the world. Figure 1 shows the relative levels of agricultural TFP for 17 OECD countries over the 1973–2011 period, using the data that we have constructed. Over this period, agricultural TFP for the 17 OECD countries has grown at an average rate of 2 percent a year, which is about twice the global average for agriculture for the same time period and comparable to manufacturing and service sectors in the same OECD countries (FAO 2018). Agricultural TFP levels in OECD countries are relatively higher than those in their developing country counterparts. The diffusion of technical knowledge promotes productivity growth in many developing countries (IFAD 2015; Pardey and Alston 2021).

Despite the rapid growth in the average rate of agricultural TFP, significant disparities remain in the rates of growth across countries. This contributes to differences in relative levels of TFP across countries (Fig. 1a). As is shown in Fig. 1b, the cross-sectional coefficient of variation of agricultural TFP declines rapidly in the 1970s, but held constant in the 1980s and the 1990s. The variance declined again in the 2000s, but at a decreasing rate. This suggests that cross-country differences in agricultural TFP levels remained large since the early 1980s. This result is contrary to the intuition that globalization is making technological innovation more accessible to these OECD countries which are in similar economic development stages (Gardner 1996) and suffer less from institutional barriers and market distortions relative to their developing country counterparts (Gollin et al. 2014b). It is even more puzzling that the remaining large gap in relative agricultural TFP levels in recent years also coincides with slowdowns in growth of agricultural productivity (Ball et al. 2013; Alston et al. 2015).[8]

It is widely believed that agricultural technology is not readily transferrable across regions with different agro-ecological and climatic conditions. Thus, cross-country differences in agro-ecological and climatic conditions determine cross-country differences in agricultural productivity (McMillan and Rodrik 2011; Gollin et al. 2014a, 2014b; Sheng et al. 2015). However, the revolution in "biological", "mechanical", "chemical" and "information" technologies for the past three decades has facilitated technology transfer. For example, crop varieties and husbandry practices suitable for rainy regions were unsuitable for drought regions. Gene-modified or gene-editing technologies are changing the breeding technology, and drought-resistant crop varieties and husbandry practices are being created for drought regions. Meanwhile, tropical fruits can now be transplanted in nursery houses in most regions of the world. In both examples, capital accumulation plays an important role in supporting cross-country productivity growth.

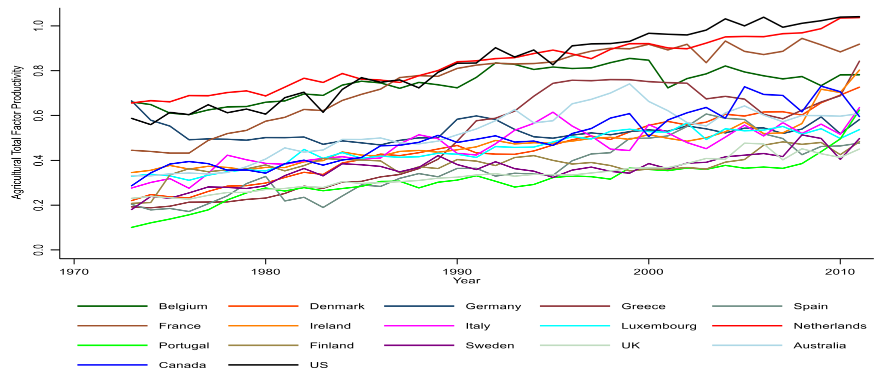
For decades, many studies have examined the role of capital deepening in affecting productivity growth across countries but they do not agree that it will facilitate cross-country productivity convergence. For example, at the economy level, Baumol (1986), Barro and Sala-i-Martin (1995), Quah (1996, 1997) and Temple (1999) found that capital accumulation will foster the convergence of labor productivity across countries. But Kumar and Russell (2002), followed by Henderson and Russell (2005) and Badunenko et al. (2010, 2013), found that capital deepening can drive non-neutral technological progress and cause international productivity divergence. Applying the exercise to agriculture, Ball et al. (2001) examined the role of capital deepening in explaining cross-country agricultural productivity growth patterns in the US and 10 EU countries between 1973 and 1993. The results showed that capital deepening facilitated agricultural TFP convergence for the 11 OECD countries before the 1980s, providing support for the embodiment hypothesis (Solow 1956; Solow 1957; Jorgenson 1966). However, they also showed that the role of capital deepening in facilitating agricultural TFP convergence across developed countries disappeared in the 1980s when net investment became negative.

After accounting for quality changes in capital and labor inputs,[9] we show that relative capital intensities for the 17 OECD countries and changes in agricultural TFP levels

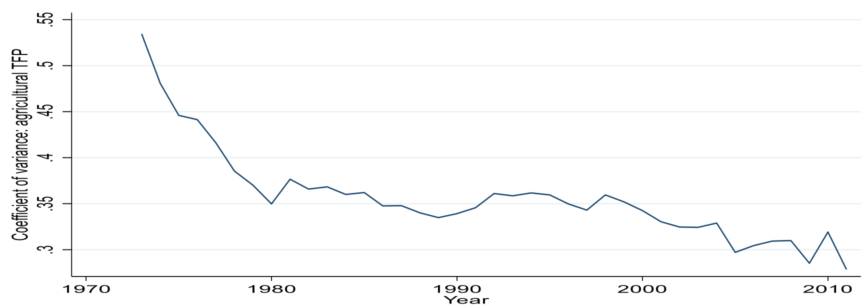
[8] A similar phenomenon is also observed by Ludina et al. (2007), Coelli and Rao (2005) and Fuglie and Rada (2018), although they have used different methodologies, data and indicators to measure agricultural productivity.

[9] Using a common methodology that allows comparisons across countries, Butzer et al. (2010) compiled a data series on fixed capital in agriculture based on national accounts data. The fixed capital measure differs remarkably from the Food and Agriculture Organization's data on tractors, which has been widely used as a proxy for agricultural fixed capital. This highlights the importance of using accurate measures to better understand the cross-country differences in agricultural productivity (Gollin et al. 2004; Gollin et al. 2014a, 2014b).

Fig. 1 Comparing agricultural TFP levels and coefficients of variance across 17 OECD countries. Source: Authors' own estimates



(a) Relative agricultural TFP levels



(b) Coefficient of variation of agricultural TFP across countries

exhibit similar patterns. For example, as most OECD countries have faced increasing farm labor shortages since the 1970s, substitution of capital input for labor input closed the gap in cross-country capital intensities before the 1980s. However, capital intensities grew at a slower rate throughout the 1980s and the 1990s, when high real interest rates choked off new investment. This, combined with the spike in world energy prices resulted in obsolescence of the capital stock (Ball et al. 2001; 2010). This trend persisted through the 2000s. As seen in Figs. 1 and 2, the relationship between convergence of capital intensities and convergence of cross-country agricultural TFP still requires a thorough empirical examination.

4 Estimation strategy: the conditional convergence analysis

To analyze the impact of capital deepening on agricultural TFP growth across countries, we derive the determinants of agricultural TFP growth from a standard growth accounting model. Specifically, we assume that the agricultural sector of our sample countries shares the same general multi-input and multi-output production technology, which takes the following transformation form

$$f(Y_1, \ldots, Y_M, X_1, \ldots, X_J; t) = \exp(v) \tag{8}$$

where $Y_1,\ldots,Y_M$ denote outputs and $X_1,\ldots,X_J$ denote inputs. The variable t indicates time trend and v reflects exogenous production shocks including but not restricted to technology progress, weather shocks, etc.

Taking the logarithm on both sides of Eq. (8) and making the total derivative, we get

$$\sum_m \frac{\partial lnf(X,Y,t)}{\partial lnY_m}\frac{dlnY_m}{dt} + \sum_j \frac{\partial lnf(X,Y,t)}{\partial lnX_j}\frac{dlnX_j}{dt} + \frac{\partial lnf(X,Y,t)}{dt} = \frac{dv}{dt} \tag{9}$$

where $\partial lnf(X, Y, t)\partial t \equiv \lambda_t$ captures technology progress, weather shocks and/or other exogenous factors that may affect agricultural productivity. Defining $\frac{\partial lnf(X,Y,t)}{\partial lnY_m} \equiv \lambda_{Y_m}$ and $\frac{\partial lnf(X,Y,t)}{\partial lnX_j} \equiv \lambda_{X_j}$, we re-arrange Eq. (9) as follows: $\sum_m \lambda_{Y_m}\dot{Y}_m + \sum_j \lambda_{X_j}\dot{X}_j + \lambda_t = \frac{dv}{dt}$, where the dot over a variable indicates its rate of change. Agricultural TFP

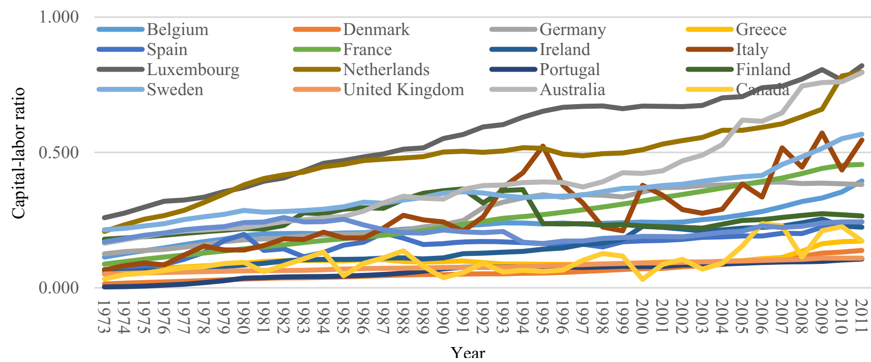


Fig. 2 Comparing relative capital intensities across 17 OECD countries: 1973–2011. Source: Authors' own estimates

growth (defined as $\dot{TFP} = \sum_m R_m \dot{Y}_m - \sum_j S_j \dot{X}_j$ where $R_m = P_m Y_m / \sum_m P_m Y_m$ and $S_j = w_j X_j / \sum_j w_j X_j)$ can thus be written as

$$\dot{TFP} = (RTS - 1)\sum_j S_j \dot{X}_j - \left(\frac{\lambda_t}{\lambda_Y}\right) + \sum_m Q_m \dot{Y}_m + \sum_j D_j \dot{X}_j + \frac{dv}{dt}/\lambda_Y \tag{10}$$

where RTS denote returns to scale, $Q_m = [\left(\frac{\lambda_{Y_m}}{\lambda_Y}\right) - R_m]$ and $D_j = [\left(\frac{\lambda_{X_j}}{\lambda_Y}\right) - \frac{\lambda_X}{\lambda_Y} S_j]$. When producers are assumed to maximize profit subject to Eq. (8), we have $Q_m = 0$ and $D_j = 0$, and thus Eq. (10) is reduced to

$$\dot{TFP} = (RTS - 1)\sum_j S_j \dot{X}_j - \left(\frac{\lambda_t}{\lambda_Y}\right) + \frac{dv}{dt}/\lambda_Y \tag{11}$$

Equation (11) decomposes industry-level TFP growth into four components, including scale effects, changes in input mix (or capital-labor ratio) and output structure, and other external shocks. If the production technology is strongly labor saving and has externalities of production and all inputs are categorized into two groups: labor and capital, we can re-write Eq. (11) into

$$\dot{TFP} = (RTS - 1) S_j (\dot{K} - \dot{L}) - \left(\frac{\lambda_t}{\lambda_Y}\right) + \frac{dv}{dt}/\lambda_Y \tag{12}$$

Equation (12) shows that agricultural TFP change can be decomposed into four components, which include increasing returns to scale, capital deepening, output structural change, and technological progress and other external shocks. Moreover, if we further impose the condition of constant return to scale and assume the factors affecting agricultural TFP growth but not related to capital deepening are held constant, we can take the integral of Eq. (13) such that

$$\ln TFP = \emptyset \ln\left(\frac{K}{L}\right) + \mathrm{C} \tag{13}$$

which implies that capital deepening tends to facilitate agricultural TFP growth.

To put the theoretical framework into empirical practice, we use conditional convergence analysis to investigate how capital deepening affects the convergence of agricultural TFP—an indicator of technological progress and innovation. The conditional convergence analysis, initially used by Baumol (1986) and standardized by Barro and Sala-i-Martin (1995), has long been regarded as an important empirical tool used to examine sources of productivity growth across countries (Jones 1997; Temple 1999; Quah 1996). For decades, many studies have used this approach to explore the role of capital-deepening in affecting cross-country differences in productivity growth either at the economy-wide or the sectoral level. But most focus on labor productivity while neglecting that capital-deepening could also cause productivity convergence through affecting technological change (Kumar and Russell 2002). As Bernard and Jones (1996, p. 1043) pointed out, "…future work on convergence should focus much more carefully on technology."

Applying the conditional convergence framework to analyze the role of capital deepening in affecting agricultural TFP convergence across countries, the basic model is assumed to take the form of :[10]

$$\widehat{lnTFP}_{i,t} = \beta_0 + \beta_1 lnTFP_{i,t-1} + \beta_2 ln\widehat{\left(\frac{K_{it}}{L_{it}}\right)} + \beta_3 ln\left(\frac{\widehat{M_{it}}}{L_{it}}\right)/ln\left(\frac{\widehat{K_{it}}}{L_{it}}\right) + \beta_4 \widehat{H}_{it} + \beta_5 X_{it} + u_i + v_t + \varepsilon_{it} \tag{14a}$$

$$\widehat{lnTFP}_{i,t} = \beta_0 + \beta_1' lnTFP_{i,t-1} + \beta_3' ln\left(\frac{\widehat{M_{it}}}{L_{it}}\right)/ln\left(\frac{\widehat{K_{it}}}{L_{it}}\right) + \beta_4' \widehat{H}_{it} + \beta_5' X_{it} + u_i + v_t + \varepsilon_{it} \tag{14b}$$

[10] The theoretical relationship has also been derived following Acemoglu (2010) and shown in Appendix B. In addition, a similar model specification has been used in Ball et al. (2001) for the United States and nine European countries over the period of 1973–1993 and Ball et al. (2004; 2014) for cross-state analysis in the US over the period of 1960–2004. Meanwhile, for simplicity, we exclude material-intensity from the baseline model (while leaving it to be controlled in the full model), since we believe that material-deepening may play a similar role as capital deepening in affecting agricultural productivity convergence across countries.

where $lnTFP_t$ is the logarithm of the TFP level of country i at time t. $\frac{K_{it}}{L_{it}}$ is the ratio of capital input to labor input which is used to capture the effects of relative capital intensities, $\frac{M_{it}}{L_{it}}$ is material-labor ratio and H_{it} is the Barro-Lee human capital index. The circumflexes (^) denote time derivatives or relative rates of change. X_{it} is a vector of other control variables including openness-to-trade and output structure measured as the value share of crop products in total agricultural outputs. Country fixed effects (u_i) are included to deal with the time invariant omitted variable problem and year-dummies (v_t) are included to account for year-to-year technology shocks. It is to be noted that we use a relative measure between material-intensity and capital-intensity (namely, $\widehat{\left(\frac{M_{it}}{L_{it}}\right)} / \widehat{\left(\frac{K_{it}}{L_{it}}\right)}$) to capture the impact of materials and capital intensities on technology convergence across countries in our model. This is because capital intensity and material intensity are highly correlated. Their correlation coefficient in our sample is 0.752. Directly incorporating material intensity into our model would introduce the multi-collinearity problem.

Comparing the estimated coefficients obtained from Eq. (14a) with those obtained from Eq. (14b) that excludes $\frac{K_{it}}{L_{it}}$, the null hypothesis is: if capital deepening contributes to technology (or TFP) convergence across OECD countries, two conditions should hold. The first condition is that the estimated coefficient β_1 should be more negative than the estimated coefficient β'_1, implying that agricultural TFP of the laggard countries will grow more rapidly to catch up with the frontier when capital intensities are accounted for. The second condition is the estimated coefficient β_2 should be positive and significant, indicating capital deepening contributes positively to cross-country TFP growth through embodied technical change.

The estimation of Eqs. (14a) and (14b) could suffer from the omitted variable problem, mainly caused by unobserved time variant factors such as technological breakthroughs independent of capital deepening and human capital accumulation. For example, recent developments in bio-technology and the widely used custom machine services have greatly impacted agricultural production practices, which are embodied in intermediate input (Ball et al. 2010; Andersen et al. 2018). Similarly, capital accumulation is also widely believed to affect the convergence in levels of total factor productivity (TFP) (Henderson and Russell 2005). To deal with this problem, we adopt the general method of moments (GMM) estimator), in addition to controlling for country fixed effects.[11] Meanwhile, we also conduct panel unit root tests proposed by Levin-Lin-Chu (2002), Im-Pesaran-Shin (2003) and Breitung (2000), respectively, to minimize the potential for spurious regression results.[12] All of the test statistics are less than the critical value of −2.59 at the 1% level. Thus, we reject the null hypothesis of a unit root and proceed to estimate Eqs. (14a) and (14b) assuming stationarity.

Although Eqs. (14a) and (14b) can be used to examine whether capital deepening contributes to convergence in relative levels of agricultural TFP, they do not explain whether capital deepening affects technology catch-up of laggard countries with different initial factor endowments. In the literature, differences in relative endowments of land to labor will affect the ability of a country to adopt capital-intensive technology, which is termed the "induced innovation hypothesis". As in Hayami and Ruttan (1970b, 1985), a country with relatively more abundant land is more likely to adopt capital-intensive technology while a country with relatively more abundant labor is more likely to adopt material-intensive technology. To further examine the impact of initial factor endowment on the TFP convergence across countries, we need to determine how capital deepening affects agricultural TFP convergence among countries with different initial factor endowments. However, the conventional linear regression technique assumes their marginal returns to investment are the same (Koenker and Hallock 2001; Ma et al. 2020).

To resolve this problem, we further adopt the conditional quantile regression technique to decompose the average impact of capital deepening on agricultural TFP convergence into the marginal impacts by clustering countries with similar initial endowments of land relative to labor. Compared to linear regression, the conditional quantile regression technique provides a convenient approach to implement the decomposition procedure. Instead of assuming the means fall on a line or some linear surface, conditional quantile regression allows us to group observations into homogeneous cells according to the relative land-labor price where relative prices are intended to proxy relative input levels. When we define the quantiles by using the relative land-labor price, the marginal impacts of capital deepening on cross-country TFP convergence can be measured for the countries facing similar land-labor prices (Tomohiro and Bai, 2015; 2020; Ma et al. 2020; Cai et al. 2022).

In this paper, we assume that the marginal impacts of capital deepening on cross-country TFP convergence depend on a country's relative endowment of land to labor, and they are unknown functions of the relative prices of

[11] The instruments used in the IV-GMM estimation are two-period lagged input usages, and performed in STATA. We conduct the post-Sargan test to examine whether the econometric model is valid and whether the instruments included are exogenous.

[12] Compared with individual unit root tests, such as the Augmented Dickey-Fuller test or the Phillips and Perron (1988) test, all of these have common advantages when dealing with small samples. However, they also have their own limitations, which suggest that a joint interpretation of the test results would be preferred. The panel data unit root test results are reported in Appendix Table A15.

land to labor. Thus, Eq. (9) can be transformed into

$$\widehat{lnTFP_{i,t}} = \beta_0 + \beta_1^T(U_{it})lnTFP_{i,t-1} + \beta_2^T(U_{it})ln\widehat{\left(\frac{K_{it}}{L_{it}}\right)} + \beta_3 ln\left(\frac{\widehat{M_{it}}}{L_{it}}\right)/ln\left(\frac{\widehat{K_{it}}}{L_{it}}\right) + \beta_4\widehat{H_{it}} + \beta_5 X_{it} + u_i + v_t + \varepsilon_{it} \tag{15}$$

where $\beta_1^T(.)$ and $\beta_2^T(.)$ are two vectors of smoothed functions defined on G, which have continuous second derivatives and may take a flexible functional form for different individuals, U_{it} denotes the relative labor supply for each country (proxied by the relative price of land to labor). $\varepsilon_{it} = \gamma_2^T f_{2t} + e_{it}$ where f_{2t} is a vector of unobserved common factors and e_{it} is the idiosyncratic error. We use the relative price of land to labor as a measure of relative factor endowments for three reasons. First, changes in the relative prices of land and labor may reflect initial factor endowments, under which capital deepening may play different roles in affecting productivity convergence. Second, the relative price between land and labor input is exogenous to agriculture, since agriculture is such a relatively small share of the total economy in most developed countries. Third, capital investment in agriculture is more likely to be induced by market price signals than by relative factor scarcities. Finally, in order to reduce the potential impact of agricultural production on the relative price of land to labor input, we adopt the 5-year lags of these price as the measure in practice.

Equation (15) can be treated as a non-parametric decomposition of Eq. (14a) while accounting for the dependence condition (or particular initial endowments of labor and land for a country). It can be used to make inferences on the quantile co-movement of technology adoption in response to the relative labor supply (Tomohiro and Bai, 2015; 2020; Ma et al. 2020; Cai et al. 2022). In order to estimate Eq. (10), we need not only to resolve the conventional endogeneity problem, but also to resolve the problem arising from the potential correlation between the unobserved factors f_{2t} and our main independent variables including lagged TFP level $lnTFP_{i,t-1}$ and the percentage change in capital intensity $\widehat{\left(\frac{K_{it}}{L_{it}}\right)}$.

Following Cai et al. (2022), we address this problem by using a locally common correlated effect pooled technique (LCCEP) to estimate $\beta_1^i(.)$ and $\beta_2^i(.)$ and apply a two-step procedure in the estimation process. Specifically, in the first step, we use Eq. (14a) to exclude the impact of control variables such as material intensity and human capital spillovers on the change in agricultural TFP after properly accounting for country fixed effects and time dummies. In the second step, we use the one-step LCCEP approach developed by Cai et al. (2022) to estimate the marginal impact of capital deepening on agricultural TFP growth and the convergence of relative productivity levels as the relative prices of land to labor vary across the sample (which is split into ten quantiles).[13]

Finally, a nonparametric goodness-of-fit statistic is proposed for testing the constancy of functional coefficients. Specifically, for the τth conditional quantile function (where $u_\tau \in U$), we have

$$\widehat{lnTFP_{it}^{\tau}} = \beta_0 + \beta_1^\tau(U_{it})lnTFP_{i,t-1} + \beta_2^\tau(U_{it})ln\widehat{\left(\frac{K_{it}}{L_{it}}\right)} + \beta_3 ln\left(\frac{\widehat{M_{it}}}{L_{it}}\right)/ln\left(\frac{\widehat{K_{it}}}{L_{it}}\right) + \beta_4\widehat{H_{it}} + \beta_4 X_{it} + u_i + v_t + \varepsilon_{it} \tag{16}$$

and the estimated coefficients $\widehat{\beta_j^*}(.)$ (where $j = 1,2$) could be written as

$$\widehat{\beta_j^*}(u_\tau) = \begin{pmatrix} \widehat{a} \\ \widehat{b} \end{pmatrix} = arg\max_{a,b} \sum_{t=1}^{T} \left[\widehat{lnTFP_{it}} - Z_{it}\left(a + \frac{b(U_{it} - u_\tau)}{h}\right) - \vartheta_i q_t\right]^2 k_h(U_{it} - u_\tau/h) \tag{17}$$

where $k(.)$ is a kernel function and $k_h(.) = k(./h)/h$, and a and b represent the lower and upper bound of u_τ. Please see appendix C for a more detailed discussion of the conditional quantile regression approach. Using the estimated coefficients from (16), we are expecting that $\widehat{\beta_1^*}(u_\tau)$ is positively correlated with u_τ while $\widehat{\beta_2^*}(u_\tau)$ is negatively correlated with u_τ, if the labor shortage induces the adoption of capital-intensive technology.

5 Cross-country convergence of agricultural TFP and capital deepening

In this section, we first describe the relationship between agricultural TFP growth and the initial level of TFP for the 17 OECD countries for the period 1973–2011. Next, we examine the effect of capital deepening in fostering TFP growth across countries and whether this will facilitate technology catch-up of the laggard countries. Finally, we investigate how differences in relative factor endowments will affect the role of capital deepening in productivity convergence. We do this by clustering our sample according to their initial endowments of land relative to labor, proxied by the price of land relative to the price of labor.

We find that (1) agricultural TFP grows faster in the laggard countries than in the frontier countries; (2)

[13] For more a detailed discussion on the conditional quantile regression approach, please refer to Appendix C.

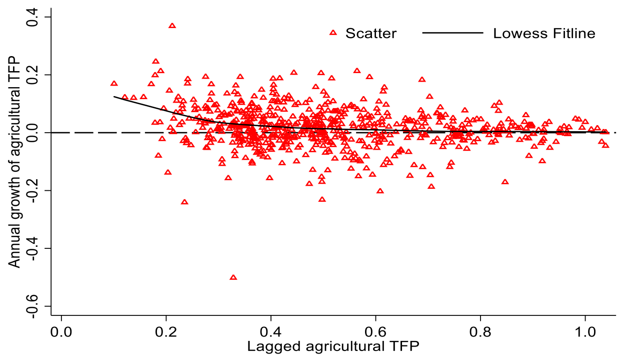


Fig. 3 The relationship between annual TFP growth and the lagged TFP level. Note: the dotted line is a horizontal reference line. The "lowess" function has been used to generate the non-linear fit-line from the "scatters" between lagged agricultural TFP and annual growth of agricultural TFP (Cleveland 1979). Source: Authors' own estimates

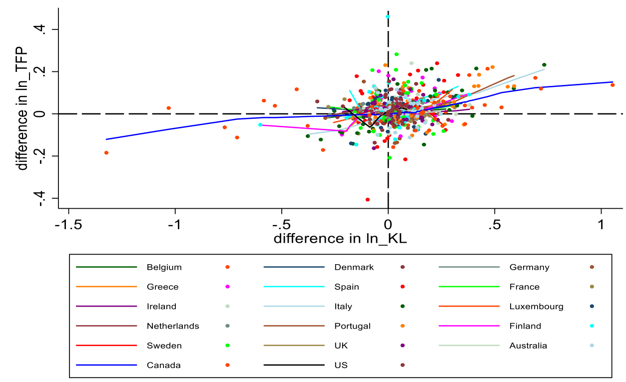


Fig. 4 The relationship between TFP and capital intensities. Source: Authors own estimates

agricultural TFP converges among the 17 OECD countries over the 1973–2011 period; (3) the rate of technology catch-up will differ among countries, that club convergence of agricultural TFP is more likely to be achieved than is global convergence, and that capital deepening can facilitate technology catch-up among country groups with similar initial factor endowments.

5.1 Agricultural TFP growth across OECD countries

Based on the descriptive statistics, we observe that agricultural TFP growth is inversely related to the initial level of TFP. Figure 3 confirms that annual agricultural TFP growth and the lagged TFP level are inversely related. This implies that agricultural TFP grows faster in the laggard countries than in the frontier countries, suggesting diffusion of technical knowledge and productivity catch-up (or convergence) among the 17 OECD countries over the sample period.

Capital deepening is positively correlated with agricultural TFP growth. Figure 4 illustrates the relationship between annual TFP growth rates and changes in capital intensity for each of the 17 OECD countries (to be used as the dependent and independent variables, respectively). Over the entire sample period, annual agricultural TFP growth rates are positively correlated with changes in capital intensities for all countries. This strong positive relationship between relative TFP growth rates and changes in relative capital intensities suggests that a substitution of capital for labor has contributed to agricultural productivity growth. While capital deepening is a fundamental driver (Gardner 1996; Haniotis 2018) of agricultural TFP growth, it is not clear whether it will lead to the convergence of relative TFP levels across countries. If capital deepening occurs more rapidly in the frontier (or the laggard) countries, it is expected to enlarge (or reduce) the gap in relative TFP levels across countries.

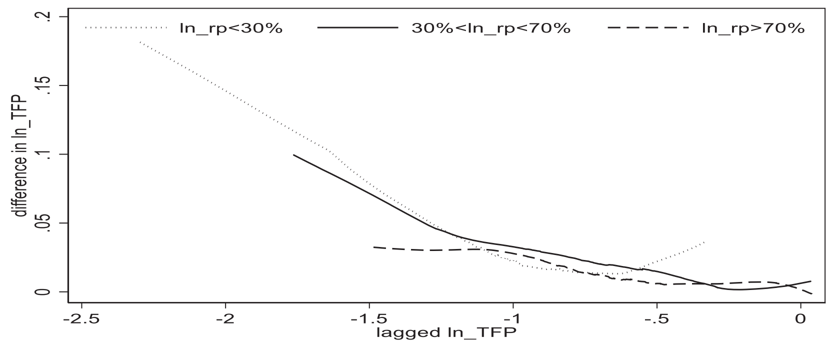
It is widely believed that initial factor endowments of land (measured as land per unit of labor) affect investments in physical capital which in turn influence technology adoption (Hayami and Ruttan 1970a). Therefore, differences in relative factor endowments may drive agricultural TFP growth through capital deepening, leading to a widening gap in relative levels of TFP in agriculture. To illustrate this point, we split our sample into three groups according to the relative price of land to labor: <30, 30–70 and >70%. The relative prices of land and labor are used as a proxy for the relative factor endowments.

Figure 5 compares the relationships between TFP growth and lagged TFP levels for the three groups (<30, 30–70 and >70%) (Fig. 5a), as well as the relationship between TFP growth and capital intensities grouped by the relative prices of land to labor (Fig. 5b). We observe an inverse relationship between agricultural TFP growth and the lagged TFP level for the three groups. With capital deepening contributing positively to agricultural TFP growth, the inverse relationship between agricultural TFP growth and the lagged TFP level decreases when the relative price of land to labor increases. This suggests that capital deepening is likely to facilitate technology catch-up among countries with a larger land endowment relative to labor.

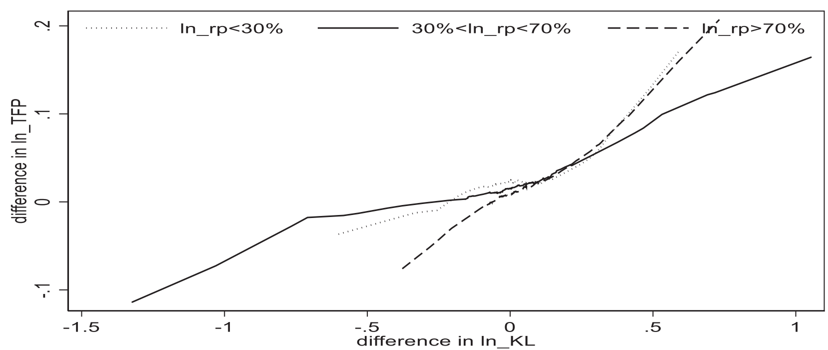
5.2 The convergence analysis: testing the embodiment hypothesis

Using Eqs. (14a) and (14b), we examine how capital deepening affects agricultural TFP convergence across the 17 OECD countries. Growth in TFP is regressed on the lagged TFP level, with and without controlling for changes in capital intensities (representing capital deepening). In addition, we have also controlled for the impact of changing material intensities, human capital spillovers, openness to trade of the economies, changes in output structure, and included dummy variables to capture year-to-year productivity shocks. The results are reported in Table 1, with

Fig. 5 Relationship among relative price of land to labor, change in capital intensity and agricultural TFP growth. Source: Authors' own estimates



(a) the relationship between TFP growth and lagged TFP level under different relative prices of land to labor



(b) the relationship between capital intensities and TFP growth under different relative prices of land to labor

columns 1 through 4 representing different models such as panel data regression controlling for country fixed effects (FE) and the general method of moments with lagged variables as instruments (GMM) based on Eqs. (14a) and (14b) respectively.

Our estimation results confirm the convergence of agricultural TFP among the 17 OECD countries over the 1973–2011 period. Controlling for country-specific effects (e.g., commitment to freedom of trade and government policies to support agriculture), year-to-year productivity shocks and other potential endogeneity problems caused by time variant omitted variables (by using the GMM regression), we estimate the proposed models and compare their results. The estimated coefficients on lagged TFP levels are −0.16 and −0.14 and significant at the 1% level, obtained from the models with and without controlling for differences in capital intensity. The negative and significant coefficients on lagged TFP levels imply that agricultural TFP in the laggard countries is growing faster as a result of diffusion of technical knowledge. This finding is consistent with Ball et al. (2001) which used the data for 11 OECD countries over the period of 1973–1993, and is robust when different model specifications and estimation techniques are employed.

Moreover, capital deepening contributes positively to agricultural TFP growth. This suggests that capital accumulation will foster technological progress either through embodiment or through labor-saving technology innovation. In the convergence model controlling for capital intensity, the change in the logarithm of capital intensity has a coefficient of 0.13, which is significant at the 1% level (Column 4 in Table 1). This implies that a one percent increase in capital intensity contributes to TFP growth of 0.13%. However, when comparing the models without controlling for capital intensity, the estimated coefficients on the lagged TFP level increased from −0.16 to −0.14 and the goodness of fit of the model measured by using the R-squared increased from 0.14 to 0.32. This indicates that the speed of productivity convergence decreased. As an

Table 1 The conditional convergence analysis: capital deepening and its impacts

	Model I: Without K/L ratio		Model II: With K/L ratio	
	FE	GMM	FE	GMM
Dependent variable: TFP growth (log)				
Lagged agricultural TFP (log)	−0.139*** (0.044)	−0.164*** (0.041)	−0.119*** (0.0403)	−0.140*** (0.037)
Change in K/L ratio (log)	–	–	0.135*** (0.0444)	0.130*** (0.037)
Change in M/L ratio (log)	–	–	−0.000 (0.000)	−0.000 (0.000)
Change in human capital index (log)	0.684*** (0.242)	0.066 (0.490)	0.438 (0.324)	0.087 (0.468)
Change in openness to trade index (log)	−0.016 (0.067)	0.038 (0.075)	−0.110 (0.0731)	−0.067 (0.076)
Change in crop share (%)	0.516*** (0.151)	0.620*** (0.178)	0.539*** (0.150)	0.640*** (0.183)
Constant	0.012 (0.037)	0013 (0.037)	0.034 (0.037)	0.011 (0.036)
Year dummies	Yes	Yes	Yes	Yes
Heteroskedasticity	Yes	Yes	Yes	Yes
Number of observations	646	646	646	646
R-squared	0.143	–	0.315	–
Wald Test: Chi2-statistics		507.43		770.37
Number of countries	17	17	17	17

The numbers in parentheses below the coefficients are robust standard errors. "*" indicates statistical significance at the 10% level, "**" indicates statistical significance at the 5% level, and "***" indicates statistical significance at the 1% level. The chi-square statistics for the post-Sargan test of two GMM models are 484.2 and 484.5 respectively, which suggests that the model specification is valid and instrumental variables are correctly specified

Source: Authors' own estimation

increase in capital intensity will contribute positively to agricultural TFP growth, this also implies that capital deepening tends to enlarge the cross-country productivity gap by increasing technological progress of the frontier countries more rapidly than in the laggard countries.

Finally, we use agricultural TFP rather than labor productivity measures in the analysis. Thus, the impact of capital deepening on productivity convergence is likely due to its impact on technological progress rather than from decreasing marginal return on investment. Our results corroborate the finding of Kumar and Russell (2002) which show that capital deepening is more likely to cause international productivity divergence through accelerating technological progress among the frontier countries.

Other factors such as material intensities and human capital spillovers may also affect productivity growth and cross-country productivity convergence. As a control variable, changes in material intensities also increase agricultural TFP growth. The estimated coefficient on the relative change between materials and capital-intensities is not significant, suggesting that materials deepening has played a similar role as capital deepening. In addition, the coefficient on the human capital index (measured by using the Barro-Lee human capital index) is positive but insignificant. A possible explanation for this is that we have quality-adjusted the measures of labor input, which in turn weakens the impacts of human capital accumulation and its spillover effects. Finally, the change in the share of crops in total output is found to contribute positively to productivity growth.

5.3 Club convergence: impact of initial factor endowments

The convergence analysis provides a measure of the average impact of capital deepening on agricultural TFP growth and cross-country differences in relative TFP levels. However, questions remain. Why does capital deepening promote productivity growth but cause productivity divergence in relative levels across countries? Is capital deepening driving the TFP divergence consistently across countries? Or, is it possible that capital deepening is causing the TFP convergence among some country groups while driving the TFP divergence among other groups? What is the role of initial factor endowment in affecting capital deepening and cross-country TFP convergence?

Since countries with different initial factor endowments will have different production technologies, the rate of technology catch-up will differ among countries. As noted by Hayami and Ruttan (1970a), technological innovation in agriculture is usually induced by market price signals, which

Table 2 Marginal contributions of capital deepening to productivity convergence

	β_1	β_2
Dependent variable: Agricultural TFP growth (log)		
1%	−0.606	0.169
5%	−0.437	0.134
10%	−0.416	0.159
25%	−0.405	0.065
50%	−0.371	0.045
75%	−0.286	0.033
90%	−0.261	0.006
95%	−0.231	−0.022
99%	−0.152	−0.127
Other control variables	Yes	Yes
Constant	Yes	Yes
Year dummies	Yes	Yes
Heteroskedasticity	Yes	Yes
Number of observations	561	561

The numbers in parentheses below the coefficients are robust standard errors. "*" indicates statistical significance at the 10% level, "**" indicates statistical significance at the 5% level, and "***" indicates statistical significance at the 1% level

Source: Authors' own estimation

loosen growth constraints imposed by relative factor scarcities. Thus, one may expect that capital deepening—an important vehicle for embodied technologies—is more likely to facilitate technology catch-up among countries with similar factor endowments. To test this hypothesis, we cluster the sample into 10 quantile groups (namely, 1, 5, 10, 25, 50, 75, 90, and 99%) according to the relative factor endowments between land and labor, proxied by their relative prices. The conditional quantile regression technique is applied to re-examine the impact of capital deepening on agricultural TFP growth, $\beta_2(U_{it})$, and the convergence of relative TFP levels, $\beta_1(U_{it})$ for each quantile group. The results are compared with the estimated β_1 and β_2 obtained from the convergence analysis, which is shown in Table 2. For robustness, we also cut off the tails at the top and bottom 1% level, and the estimation results are illustrated in Figs. 6 and 7.[14] Three interesting findings are discussed below.

First, the speed of TFP convergence across countries increases substantially when we cluster the 17 OECD countries by their relative factor endowments. As is shown in Fig. 6, the estimated coefficients on the lagged TFP levels for all 10 quantiles ranged from −0.23 to −0.62, which are far less than that (e.g., −0.14) obtained from Eq. (9).[15] This implies that technology catch-up is more likely to be achieved among countries with similar factor endowments. In other words, the club convergence of agricultural TFP is more likely to be achieved than is global convergence, a result that is consistent with the recent literature such as Quah (1996) and Gong (2018). But, we show the club convergence will occur among countries with similar factor endowments.

Second, capital deepening has played different roles in affecting agricultural TFP growth for the countries facing different relative prices of land to labor. As is shown in Fig. 7, the marginal contribution of capital deepening to agricultural TFP growth is positive and large for the countries with relatively lower prices of land to labor, but declines when the relative price of land to labor increases.[16] In particular, for the very labor abundant countries, the marginal contribution of capital deepening to agricultural TFP growth becomes negative. This implies that capital deepening is more likely to promote agricultural TFP growth among land abundant countries. (See Hayami and Ruttan 1970a).

Third, capital deepening can facilitate technology catch-up among country groups with similar initial factor endowments. Figure 8 plots the relationship between the marginal impact of capital deepening on TFP growth and the speed of TFP convergence, obtained from the conditional quantile regression. As is shown, the estimated coefficients on lagged TFP level by quantile groups are negatively correlated with the marginal contribution of capital deepening to productivity growth, when we control for the impact of their different initial factor endowments. This indicates that for countries with similar initial factor endowments, the convergence speed increases with capital deepening.

6 Robustness check

In this section we conduct four robustness checks: (1) we check whether our findings are robust to the way that we measure differences in factor endowments across countries; (2) we examine whether capital deepening is the channel through which differences in relative factor endowments affect cross-country technology catch-up; (3) we explore whether the marginal impacts of capital deepening across different quantile groups are robust to the estimation method; (4) we examine the role of adding public R&D knowledge stock in our results. Finally, we also test whether

[14] At the tails, the sample size is really small and thus the impact becomes unstable.

[15] The statistical test (reported in Appendix C) shows that the conditional quantile regression model fit the data better than the baseline model.

[16] We noticed that there is an inconsistent change in marginal impacts from 1 to 5%, and believed that this is more likely to be caused by the small sample issue.

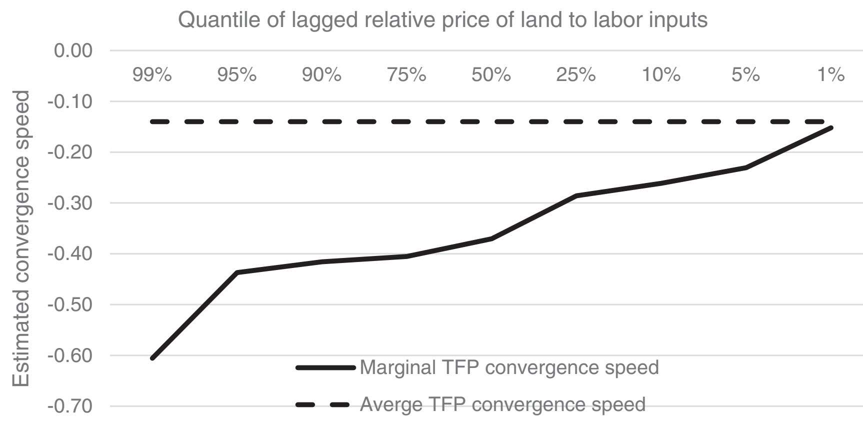


Fig. 6 Change in TFP convergence speed among countries facing different relative input prices. Source: Authors' own estimation

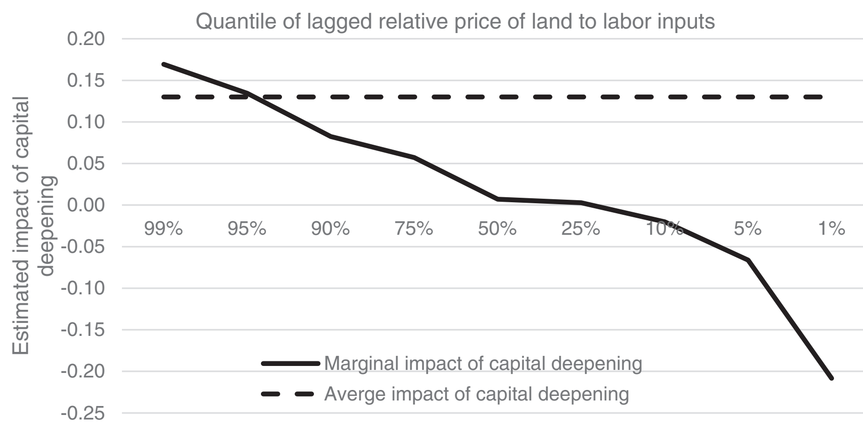


Fig. 7 Marginal contribution of capital deepening to TFP growth among countries facing different relative input prices. Source: Authors' own estimation

year-to-year fluctuations in agricultural TFP growth could negatively affect the robustness of our empirical results.[17]

First, we use the lagged relative price of land to labor to measure cross-country differences in factor endowments. However, there are concerns that the lagged relative price could be affected by other factors than the relative endowments of land and labor. As a robustness check, we directly use the level of lagged land input per unit of labor to group the countries into 10 quantiles, and re-conduct the conditional quantile analysis. Generally, the change in the marginal impact of capital deepening on agricultural TFP growth and cross-country differences in relative TFP levels for each quantile are consistent with our results shown in Section *Club Convergence: Impact of Initial Factor Endowments*.

Second, there could be concerns about whether capital deepening is the appropriate channel through which different relative factor endowments may affect technology catch-up across countries. As a robustness check, we examine the marginal impacts of human capital spillovers by using the conditional quantile regression technique. We perform this test because the relative endowment of land is not expected to directly affect human capital accumulation but strongly affects technological progress (Hayami and Ruttan 1970b). Comparing the estimated coefficients on human capital for different quantile groups (proxied by the relative prices between land and labor) in the conditional quantile regression, we find little change in human capital's marginal impact across different quantile groups. This suggests that capital deepening is the channel through which differences in relative factor endowments affect cross-country technology catch-up.

Third, there could be concerns that our findings on the marginal impacts of capital deepening across different quantile groups may not be robust to the estimation approach (e.g., the conditional quantile regression analysis). Therefore, we conduct a two-stage regression to check the robustness of our findings in Section *Club Convergence: Impact of Initial Factor Endowments*. Specifically, we first regress capital intensity on the relative price of land to labor, and calculate the fitted values for capital intensity. Then, we conduct the convergence analysis by using the predicted capital intensity as a conditional variable in the convergence analysis. This two-stage regression approach provides an alternative way to examine the relationship among factor endowment, capital deepening and agricultural productivity convergence. The results show that

[17] The related results for all the five robustness checks are available in Appendix D.

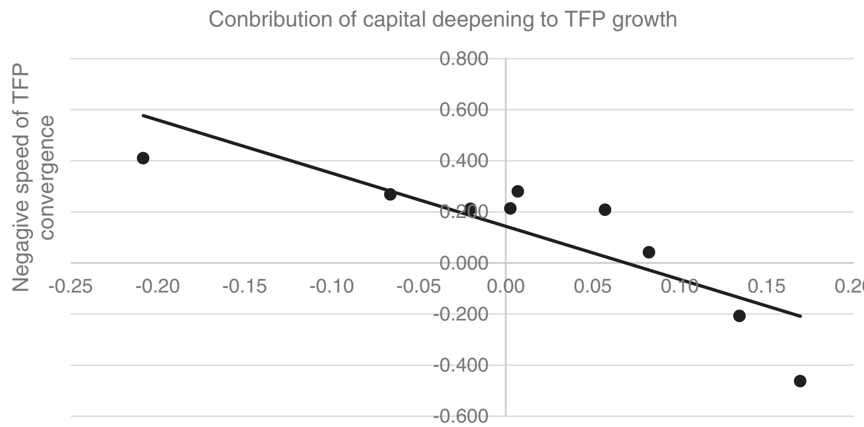


Fig. 8 Correlation between contribution of capital deepening and cross-country TFP convergence speed. Source: Authors' own estimates

relative abundance of land to labor (proxied by using the relative price of land to labor) is positively related to capital deepening. This contributes to agricultural TFP growth and cross-country productivity convergence, which is consistent with our findings in Section *Club Convergence: Impact of Initial Factor Endowments*.

Fourth, it is believed that public R&D investment is a relevant and direct factor that could affect the speed of TFP convergence in the literature. Failure to account for its impact may lead to biased estimates. To examine the robustness of our finding to public R&D investment, we construct the public R&D knowledge stock by applying the 25-year lag profile to the public R&D investment data from Fuglie and Rada (2018) and include the measure as a control variable in our regressions. The estimated results are generally consistent with what we have obtained before.

Finally, year-to-year fluctuations in agricultural TFP growth could negatively affect the robustness of our empirical results. To deal with this concern, we also use 3-year and 5-year averages for the rates of change to reduce random noise in the convergence analysis. The results obtained from these new exercises generally corroborate our earlier finding that capital deepening contributes positively to TFP growth but drives agricultural TFP divergence across countries. When the relative price of land to labor is used to group countries by quantiles, capital deepening contributes to agricultural TFP convergence among each country group. In particular, such an impact is relatively larger among the more land abundant countries than among the relatively labor abundant countries.

7 Conclusions

Relative factor endowments and technological gains embodied in capital are the two most important factors contributing to the convergence in levels of agricultural productivity across developed countries. While capital deepening contributed to convergence in levels of TFP before the 1980s (Ball et al. 2001), differences in levels of TFP persisted since the early 1980s even as capital per unit of labor continued to increase. To better explain the inconsistent role of capital deepening in affecting cross-country productivity convergence, this paper applies the conditional quantile regression technique to a newly constructed panel dataset for 17 OECD countries. We then re-examine cross-country productivity TFP convergence and its potential determinants.

By incorporating differences in relative factor endowments across countries in the convergence analysis, we find that capital deepening may play different roles in affecting technology catch-up among different country clusters. In particular, capital deepening is more likely to promote agricultural TFP growth in relatively land abundant countries than in relatively labor abundant countries. This implies that differences in relative factor endowments across countries may affect endogenous technological progress (through capital deepening) and cause cross-country productivity differences. Our findings provide supportive evidence for the induced innovation hypothesis (Hayami and Ruttan 1970a).

Our findings also provide an alternative explanation for why capital deepening contributes to the convergence of agricultural productivity across OECD countries before the 1980s, but not since then. We conclude that capital deepening would have helped the laggard countries to catch up in agricultural productivity to their frontier counterparts, had those countries shared the same relative factor endowments. However, there are significant differences in relative factor endowments across countries. Capital per unit of labor grew more slowly in relatively labor abundant countries than in relatively land abundant countries. This diminishes the role of capital deepening in facilitating cross-country productivity catch-up, in particular for those countries with relatively abundant labor. Yet, will this finding survive when more data for other countries are available? We can only leave it for future study.

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Compliance with ethical standards

Conflict of interest The authors declare no competing interests.

References

Acemoglu D (2010) When Does Labor Scarcity Encourage Innovation? J Polit Econ 118(6):1037–1078

Alston JM, Babcock BA, Pardey PG (2010) The Shifting Patterns of Agricultural Production and Productivity Worldwide. Center for Agricultural and Rural Development. CARD-MATRIC online volume edition, Ames, IA

Alston JM, Andersen MA, Pardey PG (2015) The Rise and Fall of U.S. Farm Productivity Growth, 1910–2007. Staff Paper Series P15-02, Department of Applied Economics, University of Minnesota, Minnesota. https://ageconsearch.umn.edu/record/200927

Andersen MA, Alston JM, Pardey PG, Aaron S (2018) A Century of U.S. Farm Productivity Growth: A Surge then a Slowdown. Am J Agric Econ 100(4):1072–1090

Australian Bureau of Statistics (ABS) (2018) National Accounts Statistics, Cat. 8650. Canberra, Australia

Badunenko O, Henderson DJ, Russell RR (2010) Productivity Growth and Convergence: Updated Evidence of a Structural Change, mimeo. Available at: https://www.semanticscholar.org/paper/Productivity-Growth-and-Convergence-%3A-Updated-of-a-Badunenko-Henderson/34cd7ce97dfb22774ca730ed6baede8727bbe1a6

Badunenko O, Henderson DJ, Russell RR (2013) Polarization of the worldwide distribution of productivity. J Prod Anal 40(2):153–171

Baldwin JR, Liu H, Tanguay M (2015) An Update on Depreciation Rates for the Canadian Productivity Accounts. Statistics Canada Working Paper Cat. No. 15- 206-X, Statistics Canada

Ball VE, Bureau JC, Butault JP, Nehring R (2001) Levels of farm sector productivity: an international comparison. J. Product. Anal. 15(1):5–29

Ball VE, Bureau JC, Juan CS, Mora R (2010) Productivity and International Competitiveness of Agriculture in the European Union and the United States. Agric Econ 41(6):611–627

Ball VE, Lindamood WA, Nehring R, Juan CS (2008) Capital as a factor of production in OECD agriculture: measurement and data. Appl Econ 40:1253–1277

Ball VE, Hallahan C, Nehring R (2004) Convergence of Productivity: An Analysis of the Catch-up Hypothesis within a Panel of States. Am J Agric Econ 86:1315–1321

Ball VE, Wang SL, Nehring R, Mosheim R (2016) Productivity and economic growth in U.S agriculture: a new look. Appl Econ Perspect Policy 38(1):30–49

Ball VE, San-Juan-Mesonada C, Ulloa CA (2014) State productivity growth in agriculture: catching-up and the business cycle. J Product Anal 42(3):327–338

Ball VE, Cahill S, San-Juan-Mesonada C, Nehring R, Sheng Y (2016) Comparison of capital input in OECD agriculture, 1973-2011. Rev Econ Finance 2016(6):25–48

Ball VE, Schimmelpfennig D, Wang SL (2013) Is Agricultural Productivity Growth Slowing? Appl Econ Perspect Policy 35(2013):435–450

Barro RJ, Lee JW (2013) A New Data Set of Educational Attainment in the World: 1950-2010. J Dev Econ 104(9):184–198

Barro RJ, Sala-i-Martin X (1995) Technological Diffusion, Convergence, and Growth. National Bureau of Economic Research Working Paper No. 5151, National Bureau of Economic Research, Washington DC

Baumol WJ (1986) Productivity Growth, Convergence, and Welfare: What the Long-run Data Show. Am Econ Rev 76(5):1072–1085

Bernard AB, Jones CI (1996) Technology and Convergence. Econ J 106(437):1037–1044

Beutel J (1997) Capital Stock Data for the European Union. Report to the Statistical 30 Office of the European Communities, November 1997

Breitung J (2000) The Local Power of Some Unit Root Tests for Panel Data. Adv Econometrics 15:161–177

Butzer R, Mundlak Y, Larson DF (2010) Measures of Fixed Capital in Agriculture. The World Bank Policy Research Working Paper 5472, The World Bank, Washington, DC

Cai Z, Fang Y, Xu Q (2022) Testing Capital Asset Pricing Models using Functional-Coefficient Panel Data Models with Cross-sectional Dependence. J Econometrics 227(1):114–133

Cleveland WS (1979) Robust locally weighted regression and smoothing scatterplots. J Am Stat Assoc 74:829–836

Coen RM (1975) Investment Behavior in Measurement of Depreciation and Tax Policy. Am Econ Rev 65:59–74

Coelli TJ, Rao DP (2005) Total Factor Productivity Growth in Agriculture: A Malmquist Index Analysis of 93 Countries, 1980-2000. Agric Econ 32:115–134

European Statistics (Eurostat) (2000) Manual on the Economic Accounts for Agriculture and Forestry EAA/EAF 97 (Rev. 1.1). Office for Official Publications of the European Communities, Luxembourg

FAO (2018, 2020) FAO Statistics. www.faostats.org

Fuglie K, Rada N (2018) International Agricultural Productivity Database. ERS-US Department of Agriculture, Washington, DC

Gardner B (1996) European Agriculture: Policies, Production and Trade. Psychology Press, Hove, East Sussex, United Kingdom

Gollin D, Lagakos D, Waugh ME (2014a) Agricultural Productivity Differences across Countries. Am Econ Rev 104(5):165–170

Gollin D, Lagakos D, Waugh ME (2014b) The Agricultural Productivity Gap. Q J Econ 129(2):939–993

Gollin D, Parente SL, Rogerson R (2004) Farm Work, Home Work and International Productivity Differences. Rev Econ Dyn 7(4):827–850

Gong B (2018) Effects of International Trade on World Agricultural Production: Evidence from a Panel of 126 countries 1962–2014. Paper presented at the Annual Meeting of the Agricultural and Applied Economics Association, No. 274284, Washington, DC, August 5–7, 2018

Haniotis T (2018) The Future of Food and Farming: EU and the CAP. Presented at 12th Annual Working Meeting of Ministers of Agriculture from South East Europe. 14-16 November 2018. Republic of Macedonia, Struga

Hayami Y, Ruttan VW (1970a) Factor Prices and Technical Change in Agricultural Development: The United States and Japan, 1880–1960. J Polit Econ 78(5):1115–1141

Hayami Y, Ruttan VW (1970b) Agricultural Productivity Differences among Countries. Am Econ Rev 60(5):895–911

Hayami Y, Ruttan VW (1985) Agricultural Development: An International Perspective. Johns Hopkins University Press, Baltimore

Henderson DJ, Russell RR (2005) Human Capital and Convergence: A Production-Frontier Approach. Int Econ Rev 46(4):1167–1205

International Fund for Agricultural Development (IFAD) (2015) IFAD Annual Report. United Nation

Im KS, Pesaran MH, Shin Y (2003) Testing for Unit Roots in Heterogeneous Panels. J Econom 115(1):53–74

Jones CI (1997) On the Evolution of the World Income Distribution. J Econ Perspect 11(3):19–36

Jorgenson DW (1966) The Embodiment Hypothesis. J Polit Econ 74(1):1–17

Koenker R, Hallock KF (2001) Quantile Regression. J Econ Perspect 15(4):143–156

Kumar S, Russell RR (2002) Technological Change, Technological Catch-up, and Capital Deepening: Relative Contributions to Growth and Convergence. Am Econ Rev 92(3):527–548

Levin A, Lin CF, Chu CSJ (2002) Unit Root Test in Panel Data: Asymptotic and Finite Sample Properties. J Econom 108(1):1–24

Ludina CE, Hertel TW, Preckel PV, Foster K, Nin A (2007) Productivity Growth and Convergence in Crop, Ruminant, and Nonruminant Production: Measurement and Forecasts. Agric Econ 37(1):1–17

Ma S, Linton O, Gao J (2020) Estimation and Inference in Semiparametric Quantile Factor Models. J Econom 222(1):295–323

McMillan MS, Rodrik D (2011) Globalization, Structural Change and Productivity Growth. National Bureau of Economic Research Working Paper No. 17143, National Bureau of Economic Research, Washington DC

OECD (1999) Purchasing power parities and real expenditures-EKS Results. OECD, Paris

Pardey PG, Alston JM (2021) Unpacking the agricultural black box: the rise and fall of american farm productivity growth. J Econ Hist 81(1):114–155

Penson JB, Hughes DW, Nelson GL (1977) Measurement of Capacity Depreciation based on Engineering Data. Am J Agric Econ 59(2):321–329

Phillips PC, Perron P (1988) Testing for Unit Roots in Time Series Regression. Biometrika 75(2):335–346

Quah DT (1996) Convergence Empirics across Economies with Capital Mobility. J Econ Growth 1(1):95–124

Quah DT (1997) Empirics for growth and distribution: Stratification, Polarization, and Convergence Clubs. J Econ Growth 2(1):27–59

Restuccia D, Rogerson R (2017) The Causes and Costs of Misallocation. J Econ Perspect 31(3):151–174

Rosen S (1974) Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. J Polit Econ 82(1):34–55

Romain RF, Penson Jr JB, Lambert RE (1987) Capacity Depreciation, Implicit Rental Price, and Investment Demand for Farm Tractors in Canada. Can J Agric Econ 35(2):373–385

Sanchez PA, Palm CA, Buol SW (2003) Fertility capability soil classification: a tool to help assess soil quality in the tropics. Geoderma 114(3-4):157–185

Sheng Y, Ball VE, Nossal K (2015) Comparing Agricultural Total Factor Productivity between Australia, Canada, and the United States, 1961-2006. Int Product Monitor 38(3):38–59

Shi YJ, Phipps TT, Colyer D (1997) Agricultural land values under urbanizing influences. Land Econ 73(1):90–100

Solow RM (1956) The Theory of Economic Growth. Q J Econ 70(1):65–94

Solow RM (1957) Technical Change and the Aggregate Production Function. Rev Econ Stat 39(3):312–320

Triplett J (1989) Price and Technological Change in a Capital Good: A Survey of Research on Computers. In: Jorgenson DaleW, Landau Ralph eds Technology and Capital Formation. MIT Press, Cambridge, Massachusetts

Temple J (1999) Equipment investment and the Solow model. Oxf Econ Pap 50(1):39–62

Tomohiro A, Bai J (2015) Asset pricing with a general multifactor structure. J Financial Econ 13(3):556–604

Tomohiro A, Bai J (2020) Quantile Co-movement in Financial Markets: A Panel Quantile Model with Unobserved Heterogeneity. J Am Stat Assoc 115(529):266–279

Whelan K (2007) Embodiment, Productivity, and the Age Distribution of Capital. J Macroecon 29(4):724–740