Technological Change, Capital Deepening and Cross-country Agricultural Labor Productivity Growth: Evidence from 17 OECD Countries[1]

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[Abstract]

This paper uses the KR framework to investigate how recent technological (GMO/ICT) revolution could affect the way of technology progress in agriculture. By applying deterministic production-frontier analysis (DEA) to the newly developed production account data for agriculture of 17 OECD countries over the 1973-2011 period, we analyse ALP growth and its components before and after revolution periods. We show that ALP growth among the OECD countries is determined by technology progress other than capital deepening, especially among developed countries. Although technology progress in the very capital-intensive countries continues to grow when new wave of technology revolution arrives after 1998, it does slowdown in most relative labor-intensive countries which caused a decline in both average growth rates of TFP and ALP. Our finding implies that the new wave of technology revolution is causing technology progress in agriculture to shift from Hick-neutral towards the labor augmented direction, causing the concern of increased inequality that could arise from new technology revolution.

[Key Words]

Productivity slowdown in agriculture, Technological progress, DEA, Capital deepening

[JEL Code]

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Introduction

Increasing agricultural labor productivity (ALP) has long been chronicled as the single most important way to maintain rural sustainable development throughout the world. However, relatively poor performance of ALP growth is not only widely observed in developing and transitional economies but also in many industrialized countries that have succeeded to achieve rural transformation by industrializing agricultural production and urbanizing majority rural population. Labor productivity growth in agriculture of many OECD countries is still much slower than in the non-farm economy. According to national account statistics, labor productivity growth in agriculture of 17 OECD countries (defined as real value-added per hour) has grown at the rate of 3.4% a year between 1973 and 2011, less than half the corresponding rate of the non-farm economy (e.g. 6.86%). The uneven growth of labor productivity between agricultural and non-agricultural sectors leads to disparity in labor productivity levels, contributing to misallocation of labor across sectors and making agriculture left-behind the rest of economy (Caselli and Coleman 2001; Herrendorf and Schoellman 2011; Gorlin et al. 2014).

Research over the past 20 years has considerably improved our understanding of divers underlying ALP growth, and summarizes them into four types: endowment conditions, institutional/policy arrangements, physical and human capital accumulation and technology progress. Although their methods differ in important ways, major sectoral productivity studies have reached consensus on that technology progress should rank on the top among the four types of drivers determining long-term ALP growth in developed countries (Kendrick and Grossman 1980; Jorgenson, Gollop and Fraumeni 1987; Jorgenson and Gollop 1992).[2] For example, in the US, total factor productivity growth (TFP)—an widely used indicator for technology progress—in agriculture (1.39%) contributing to more than 90% of agricultural output growth (or the main extensive source of ALP growth) between 1950 and 2015, which was nearly three times the corresponding contribution of TFP in the non-farm economy (0.5%) (Ball et al. 2018). A similar role of TFP growth in affecting output growth between in agriculture and non-agricultural sectors has also been found in other

[2] Around the post-World War II period, most OECD countries have achieved the transformation from animal power to mechanical power and the adaptation of chemistry to agricultural production, reflecting the substation between various inputs (Rasmussen 1962).

OECD countries such as Australia, Canada and the EU countries (Alston and Pardey 2014; Pardey and Alston 2019; Sheng et al. 2020).

It is widely believed that a new wave of technological revolution in the fields of life science, information and communication technology, and artificial intelligence etc. has substantially promoted technology progress in agriculture and changed the way of agricultural production since the mid-1990s (Gordon 2000, 2016; Pardey and Alston 2019). The technological revolution was expected contributing to a sustained burst of faster-than-normal agricultural productivity growth adding to the benefits from the "Green Revolution" back to the 1960s, in particular for the developed countries which have largely removed institutional barriers and market distortions through the 1980-reforms. Yet, recent statistics show that agricultural TFP growth has been slowing down in major OECD countries after 2000 (Alston et al. 2010; Sheng et al. 2015; Ball et al. 2018; Pardey and Alston 2019; Chambers et al. 2020). As is reported in Ball et al. (2018), average agricultural TFP for 17 OECD countries (including 14 EU countries and Australia, Canada and the United States) has grown at a sluggish rate of 0.5 percent a year after 2000, approximately one-third of its long-term average since 1973. The counter-intuitive observation of slowdown agricultural productivity growth stimulated a renewed interest in questions about how new technological revolution may affect agricultural productivity growth.

This paper aims at using the deterministic production-frontier analysis (DEA) to investigate how recent technological (GMO/ICT) revolution changes technology progress in agriculture and agricultural productivity growth. Based on the newly developed production account data for agriculture of 17 OECD countries over the 1973-2011 period, we construct a semi-experiment by examine technology progress in agriculture (for OECD countries) for three 13-year sub-periods: namely, the baseline period (1973-1985), the pre-revolution period (1986-1998) and the post-revolution period (1999-2011). Applying the Kumar and Russell (2002) framework to each of the three periods, we decompose measured ALP (in value-added model) into three components (including technological progress, efficiency improvement and capital accumulation) and analyze how those components between the pre-revolution period (1986-1998) and the post-revolution period (1999-2011). Our analysis is distinguished by adopting nonparametric productivity decomposition analysis and nonparametric statistical techniques to ensure our analysis does not reply on assumption of Hick-neutral technological change and the absence of market imperfection. Under this treatment, exogenous factor accumulation (e.g. capital deepening) is allowed to interact with endogenous technology progress, jointly determining agricultural productivity growth. In addition, we also distinguish between labor-intensive and capital-intensive in the analysis, enabling us to understand how the distribution of agricultural productivity (or technology) shift among the OECD countries will contribute to productivity slowdown over time.

The results show that agricultural productivity growth in the 17 OECD countries has been growing over time but with a slowing rate in the most recent decade when technological (GMO/ICT) revolution took place. This is partly because that technological progress in agriculture changed from Hick-neutral to decidedly non-neutral, causing relatively labor-abundant countries to fall behind not only in technological progress but also in efficiency improvement. In this sense, capital deepening not only affects agricultural labor productivity growth through improving factor intensity but also through affecting the way of technology progress. This highlights the importance of endogenous technology progress (caused by capital deepening) in facilitating ALP growth among the OECD countries, suggesting that increasing capital investment is still the most essential way to gain from the recent technological revolution.

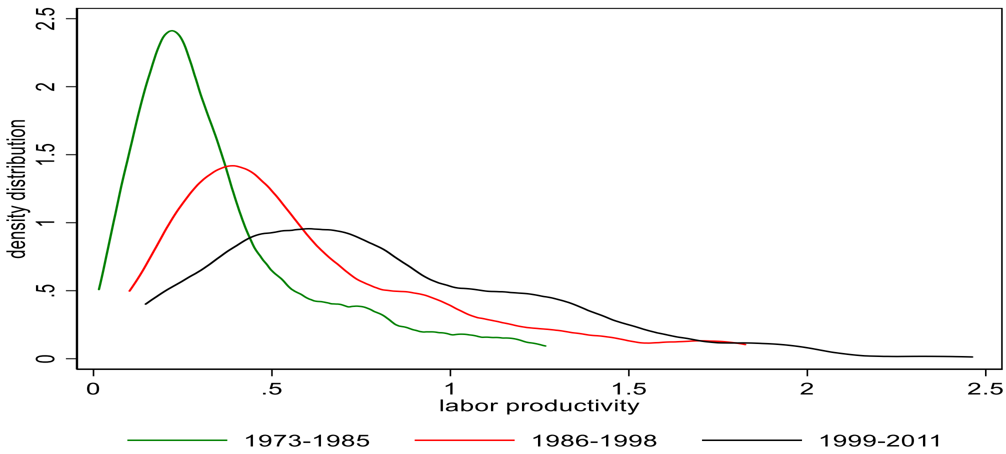
Our study contributes to the literature in two ways. First, we conduct the continuous estimation of agricultural production frontiers (rather than focusing on the cross-sectional comparison). This allows us to monitor the dynamics of technological progress and its components over time, and thus can trace the impact of technological revolution on the way of agricultural technology progress. Second, we are the first to apply the KR framework (Kumar and Russell 2002) to analysing labor productivity growth in agriculture, where both labor-intensive and capital-intensive technology progress are effective choice of particular countries depending on the availability of natural endowments. But, our findings shows evidence for labor augmented technology progress becomes dominant and gives more role to capital deepening in technology progress.

The rest of paper is organized as below. Section 2 briefly discusses labor productivity, total factor productivity and capital-labor ratio and their change among 17 OECD countries throughout the period of 1973-2011. Section 3 provides the theoretical model and empirical specification that are employed to decompose agricultural productivity. Section 4 describes the constructed production accounts for agriculture comparable across countries, followed by the discussion on the results in Section 5. Section 6 makes some robustness checks and Section 7 makes the conclusion.

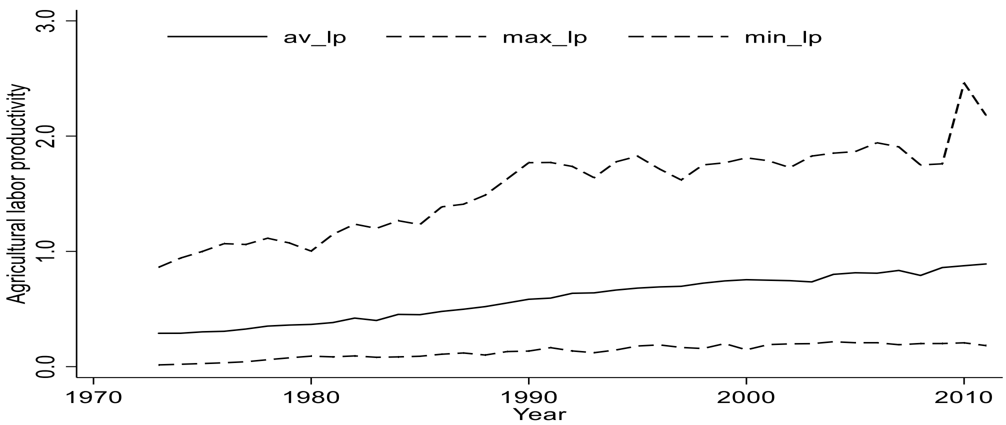
2. Technology Progress and Agricultural Labor Productivity Growth

ALP in developed countries has experienced a rapid growth over the past four decades, but its growth rate declined in recent years. As is shown in Figure 1(a), the kernel density distribution of ALP (defined as real agricultural value added per unit of labor input) for 17 OECD countries shift to the right between 1973 and 2011, with average ALP growing at the rate of 3.4 percent a year. The rapid growth of average ALP was mainly coming from the more rapid growth of ALP among the frontier countries, as the mass on the right-hand tails of the kernel density distribution of ALP shifted more quickly to the right than that on the left-hand tails. The uneven growth of ALP between the frontier and laggard countries also enlarges the gap in relative ALP levels across countries. Between 1973 and 2011, the coefficient of variance for ALP across countries for each year continued to increase from 1.22 to 1.77. However, the growth rate of average ALP declined in recent years. Although the frontier countries continued to move forward, the average growth rate of ALP for the 17 OECD countries decreased to 1.5 percent a year after 1999, which is less than half of its long-term growth rate since 1973 (Figure 1(b)).

Figure 1. ALP and Its density distribution for 17 OECD countries: 1973-2011



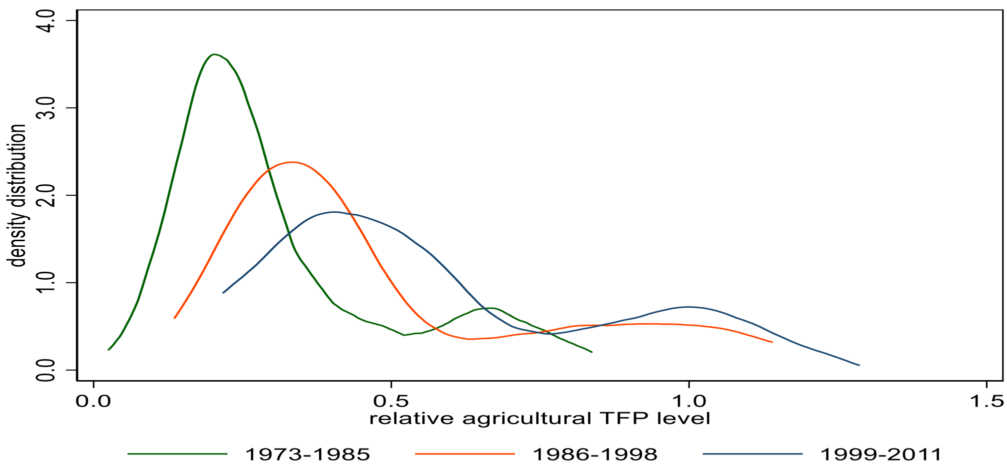
(a) Density distribution of ALP for three sub-periods: 1973-1985, 1986-1998 and 1999-2011



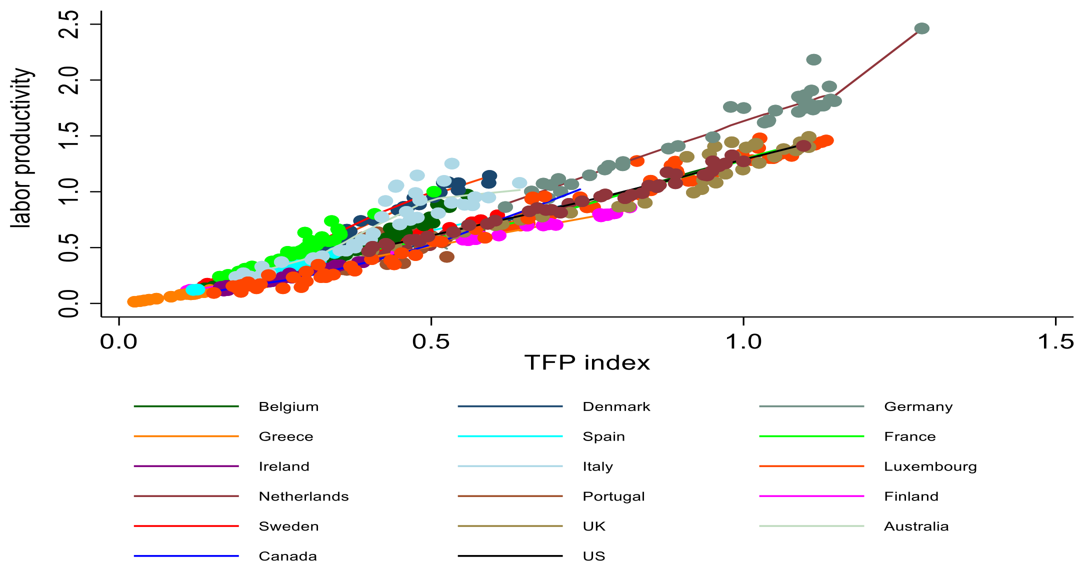
(b) Change in mean and variance of ALP: 1973-2011

Underlying the growing pattern of ALP, technology progress and on-farm innovation (measured by using the total factor productivity, or TFP) is believed to be another important driver (other than capital accumulation). Figure 2(a) compares the kernel density distribution of agricultural TFP for 17 OECD countries among three sub-periods: 1973-1985, 1986-1998 and 1999-2011. The bimodality in the kernel density distribution of agricultural TFP for each period implies a particular characteristics of technology progress in agriculture: there are always two pathways for technology progress (i.e. labor-intensive and capital-intensive technologies) depending on countries' relative factor endowments. Consistent with the change in the kernel density distribution of ALP over time, the mean of TFP also shifted to the right with the right-hand tails moved more quickly than the left-hand tails. Also, the cross-country difference in agricultural TFP was also enlarged over time. This phenomenon, to some extent, reflect how agricultural technologies (i.e. mechanization, biology technology, fertilizer and chemicals usage etc.) were invented, progressed and diffused among the OECD countries throughout the third quarter of the century (Gordon 2000; 2016; Alston and Pardey 2019). The strong positive correlation between ALP and TFP is further confirmed, when we plot the two variables by country for the 1973-2011 period in Figure 2(b).

Figure 2. Density distribution of agricultural TFP and its correlation with ALP for 17 OECD countries: 1973-2011



(a) Density distribution of TFP for three sub-periods: 1973-1985, 1986-1998 and 1999-2011

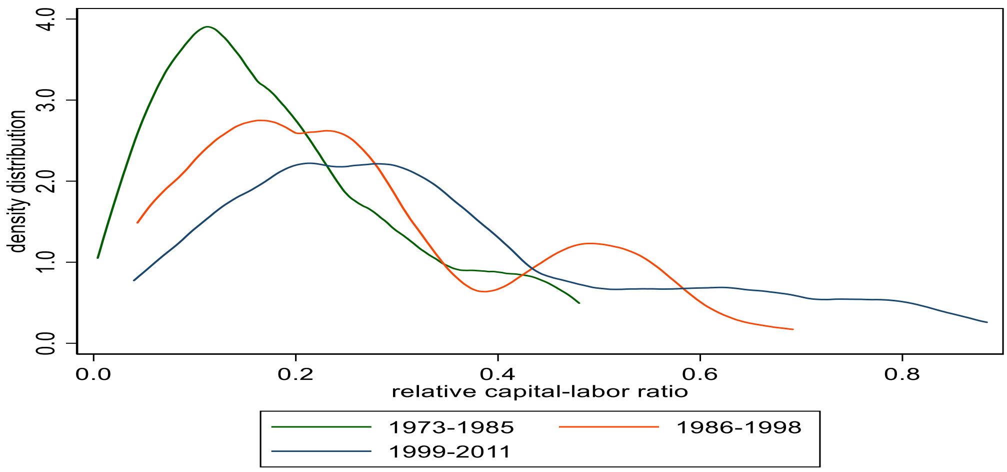


(b) Correlation between ALP and TFP by country: 1973-2011

Some recent statistics provides some compelling evidence for a slowing pattern of agricultural TFP growth in the OECD countries over the recent two decades, providing an explanation on the recent slowdown in ALP growth. For example, Andersen et al. (2018), Pardey and Alston (2019) among others provided evidence of a slowdown in productivity growth in the US agricultural sector since 1990s. They showed that agricultural TFP in the US grew by 1.18% a year since 1990, which is less than the average rate of growth of 1.52% a year for 1910-2007, and substantially less than the rate for several preceding decades. Similar pattern has also been found around the world especially in the developed world such as Australia, Canada and EU countries (Sheng et al. 2017a, 2017b; Ball et al. 2018; Ball et al. 2020), which shows that the agricultural TFP has on average grown at the rate of 0.6% a year for the period of 199-2011—around half of its long-term growth rate (say, 1.3% a year) since 1973. However, this is a puzzling issue because technology progress under the new wave of industrialization (e.g. GMO, ICT and IoT) should have accelerated the globalization process and helped facilitating the technology diffusion especially in agriculture of developed countries.

Many studies have attempted to explain the puzzle phenomenon that agricultural productivity growth slowed in the face of new wave of technology revolution among the OECD countries, but no consensus has been reached. By applying regression analysis to either time-series or cross-regional data, some studies found that this recent productivity slowdown could be related to reduced public investments in agricultural science or on-farm innovations back to the 1970s (Pardey and Alston 2019). Other studies attempted to explain the puzzle by attributing the slowdown of agricultural productivity growth to climate change, adverse climatic shocks and their induced technology adoption behaviours (Liang et al. 2019; Chambers and Pierrali 2020; Chambers et al. 2020). In addition, there are still arguments supporting that slowdown in ALP may come from the stagnation of capital accumulation (as is shown in Figure 3). While these studies helped to improve our understanding of agricultural productivity growth and its determinants, little is known on how the new wave of technology revolution may change the way of agricultural production and technology progress. If technological (GMO/ICT) revolution change the way of technology progress in agriculture while majority countries could not adapt to the situation, technology progress on average may slowdown but this is not caused by lack of innovation. Although the idea was initially raised by Kumar and Russel (2002) and Henderson and Russel (2005) which showed that recent technology progress is more likely to be decidedly non-neutral benefiting more for rich countries at the economy wide, but little evidence has been found for agriculture.

Figure 3. Density distribution of capital intensity in agriculture of 17 OECD countries: 1973-2011



Our analysis aims at focusing on the change of density distribution of ALP over time and its two potential determinants: technology progress and capital accumulation, based on the Kumar and Russel (2002) framework. By applying the tripartite decomposition approach based on the determined DEA approach to the newly developed agricultural production account data for 17 OECD countries, we will decompose the growth of ALP into three components: technological progress, technical efficiency change and capital deepening. The purpose is to examine whether the gradually enlarging "agricultural productivity gap" around the world in particular among the OECD countries (Figure 4, and as described by Gollin et al. 2014), are related to the changing way of production caused by new wave of technological progress, or something else (e.g. industrial structural transformation).

3. Nonparametric Construction of Technologies and ALP Decomposition

This section provides the theoretical model used to estimate agricultural production frontier and decompose ALP into its components, followed by a brief discussion on the empirical estimation procedure. The data in use for the 17 OECD countries over the 1973-2011 period is then summarized.

3.1 Baseline Model

We assume that there is a general production technology for agricultural value-added output production across all the OECD countries. Agricultural production function for each country based on the value-added model takes the non-parametric form $f(.)$ which uses two types of inputs, labor (L_t) and capital (K_t), for output (Y_t). Intermediate inputs are excluded from both the output and input sides. For simplicity, we define $k_t = K_t/L_t$ as a vector of two input variables, where capital include both land and depreciable capital.

$$y_t = f_t(k_t) \tag{1}$$

where $k_t > 0$ and both capital and labor inputs are experiencing the quality adjustment.

The labor productivity measure equals to the real value-added divided by the aggregate labor input. We measure productivity changes to create indexes relative to a base period. If there are two period t and 0, the labor productivity index ($y_{t,0}$) in period t relative to that in period 0 is given by

$$y_{t,0} = (\frac{Y_t}{L_t})/(\frac{Y_0}{L_0}) \tag{2}$$

where subscripted variables and functions correspond to values in period t and 0.

Following Chambers and Pieralli (2019) and Chambers, Pieralli and Sheng (2020), we define efficiency of production at time t as $E_t(y_t, k_t) = y_t/f_t(k_t)$. Using this definition, the productivity index decompose into two components as

$$y_{t,0} = \frac{E_t(y_t,k_t)}{E_0(y_0,k_0)} \frac{f_t(k_t)/k_t}{f_0(k_0)/k_0} \tag{3}$$

where the first component measures the efficiency with which the technology available has been applied in practice, and the second measures the average yield for particular amount of inputs in use.

We further decompose the second term, $\frac{f_t(k_t)/k_t}{f_0(k_0)/k_0}$, into three components which include technology change, efficiency improvement and the impact of capital deepening.

$$\frac{f_t(k_t)/k_t}{f_0(k_0)/k_0} = T_{t,0}K_{t,0}$$

where

$$T_{t,0} = [\frac{f_t(k_0)}{f_0(k_0)}\frac{f_t(k_t)}{f_0(k_t)}]^{1/2}$$
$$K_{t,0} = [\frac{f_t(k_t)}{f_t(k_0)}\frac{f_0(k_t)}{f_0(k_0)}]^{1/2}\frac{k_0}{k_t}$$

Since the total factor productivity (TFP) index is $TFP_{t,0} = T_{t,0}\frac{E_t(y_t,k_t)}{E_0(y_0,k_0)}$, we have

$$y_{t,0} = TFP_{t,0}K_{t,0} \quad (4)$$

From (4), we have the difference between ALP and TFP is determined by capital accumulation, or the substitute of labor with capital (whose marginal impact is decreasing with the increase of capital intensity).

3.2 Empirical Specification

The empirical approach that we use to approximate the frontier technology is nonparametric productivity analysis or data envelopment analysis (DEA). As applied by numerous authors in a variety of different contexts (for example, Charnes, Cooper, Golany, Seiford, and Stutz 1985; Byrnes, Färe, Grosskopf, and Level 1988; Fawson and Shumway 1988, Färe, Grosskopf, and Lee 1990, Färe et al. 1993; Chambers and Lichtenberg 1996; Kumar and Russell 2002; Henderson and Russell 2005; Murty et al. 2012; Chambers et al. 2014), DEA builds upon methods originally developed by Afriat (1972) and traceable through Farrell (1957) to Koopmans' (1951) fundamental activity-analysis model. The essential idea is to use observed data to develop an approximation to the "best attainable technology" by enveloping it and then imposing sufficient structure to ensure that it is consistent with non-increasing returns to scale. Formally, this is done by taking an observed set of data on observed inputs and outputs, constructing the convex hull of the observed data, and then imposing "free disposability properties" on that convex hull associated with the traditional notions of non-negative marginal returns, positive marginal costs, and non-increasing returns.

The data that we use to construct the empirical approximation to the technology consist of observations on agricultural labor productivity (measured by using the real value-added output per unit of labor) and capital-labor ratio (measured by using capital input per unit of labor) for 17 OECD countries over the period of 1973-2011. Letting (y_{it}, l_{it}) denote the observed values of labor productivity and capital-labor ratio for region i at period t, the DEA approximation to the aggregate production function at period t for input bundle l_{it} is

$$f_t(x) = \max\{\sum_t \sum_i \lambda_{it} y_{it} : \mathrm{k} \geq \sum_t \sum_i \lambda_{ti} k_{ti},\ 1 \geq \sum_t \sum_i \lambda_{it},\ \lambda_{it} \geq 0, t = 1, \dots, T\} \tag{5}$$

where $y_t = f_t(\mathrm{k}_t)$ is the aggregate output and k is the aggregate capital-labor ratio.

This DEA approximation to the production function for a given input vector l_{it} is calculated as a linear program that chooses mixture terms $(\lambda_{it}, i = 1, \dots, 17; t = 1973, \dots, 2011)$ to ensure that the aggregate output associated with l_{it} lies on the frontier of the "best attainable" technology. The task of the mixture terms is to select the combination of observed input and output variates that form the empirical approximation to the empirical frontier at l_{it}. We construct the year-to-year production frontier so as to capture the nature of technology progress over time is path-dependent. This specification satisfies Diewert's (1980) "sequential production set formulation" that ensures that technical know-how for a given set of inputs does not degrade.

3.3 Data Construction

We assume that data on production patterns of the 14 European countries and the United States, Canada and Australia are generated by a gross output model of production. Output is defined as production leaving the farm plus additions to producer-owned inventory and consumption by farm households, minus intermediate inputs. Inputs are not limited to labor and capital but also include land. Differing from other existing cross-country datasets which can only be used for the comparison of productivity growth rates (e.g. FAO data or ERS data), our dataset allows the comparison of relative levels of agricultural inputs and outputs, as well as agricultural TFP, across countries (comparable to the Penn World Table). The text in this section provides an overview of the sources and methods used to construct the product and factor accounts for agricultural production of the 17 OECD countries for the 1973-2011 period.[3]

Agricultural ALP and TFP are measured as the ratio of valued-added output to labor input and all primary inputs in real terms. The methodology used to estimate agricultural ALP and TFP was initially proposed by Jorgenson and Nishimizu (1978) at the economy level and Jorgenson and Nishimizu (1981) at the industry level for two countries (i.e. the US and Japan). Ball et al. (2001; 2010) extended this framework to measure and compare the relative levels of agricultural TFP for 11 OECD countries over the period of 1973-2002. In this study, we adopt the approach of Ball et al. (2010) to measure relative agricultural TFP levels for 17 OECD countries and extend the time-series to 2011.[4] Measures of total output and total input are constructed as Tornqvist-Theil indices. Then, we then construct measures of relative levels of output and input following Caves-Chistensen-Diewert (1982). Total output is defined as gross output leaving the farm as opposed to value added. Inputs are not limited to primary factors but include intermediate inputs as well.

The capital input include both land and depreciable capital inputs, which refers to capital services derived from land and depreciable assets (including non-dwelling building and structure, plant and machinery, and transportation vehicles). Methodologically, we adopt the constant efficiency model to derive capital services from capital stocks and construct the purchasing power parity between countries for cross-country comparison.[5] Specifically, we first construct the capital stock for each asset type by using the perpetual inventory method (PIM) from data on investment in constant prices.

[3] The accounting framework is that proposed in Manual on the Economic Accounts for Agriculture and Forestry (Eurostat, 2000). This approach ensures consistency of the accounts across countries and, hence, facilitates international comparisons.

[4] For a more detailed discussion on the methodology, please refer to Appendix D or Ball et al. (2010).

[5] Please refer to Ball et al. (2016) and Sheng et al. (2020) for more detailed estimation procedure for land and depreciable capital.

Capital stock at each point in time is a weighted sum of past investments with the weights corresponding to the relative efficiencies of capital goods of different ages, so that the weighted components of capital stock have the same efficiency. In this process, we adopt a set of assumptions that allow us to model variations in service lives and the rate of capacity depreciation in efficiency of capital stock (rather than assuming fixed asset lives) to capture the actual service lives of assets. The estimates of capital stock are converted into capital service flows by means of capital rental prices. Implicit rental prices for each asset type are based on the correspondence between the purchase price of the asset and the discounted value of future service flows derived from that asset. Finally, cross-country comparisons of relative levels of capital input are estimated by using relative investment goods prices, taking into account the flow of capital services per unit of capital stock in each country. The treatment ensures that the comparison of levels of capital input accounts for efficiency differences across countries. It is to be noted, for the estimates of land services, we construct indexes of relative price for land in each country by using the hedonic method to eliminate the impact of spatial differences in land characteristics or quality (that prevent the direct comparison of observed prices).

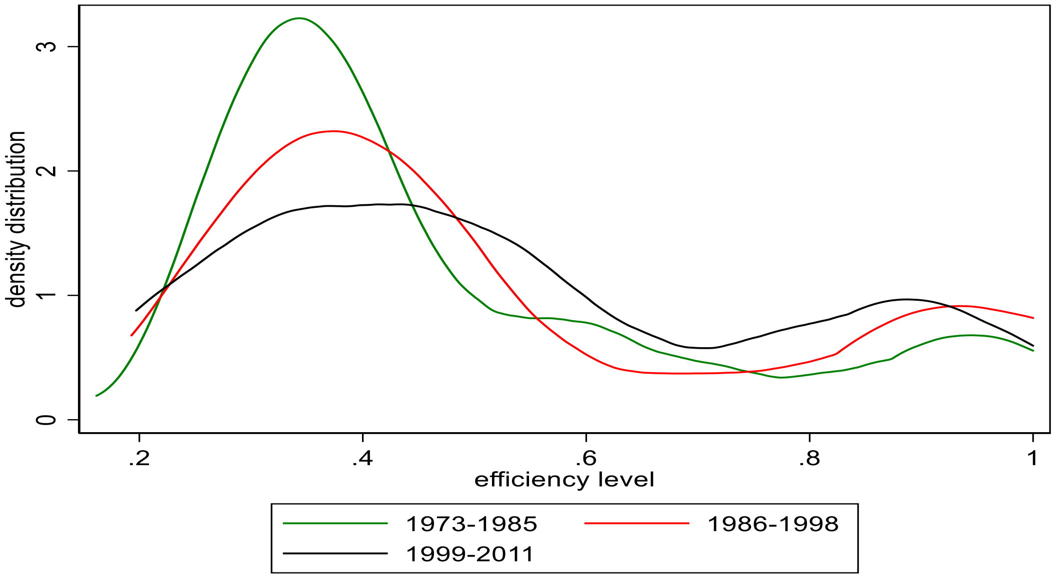
The labor input is defined as hours worked by hired, self-employed and unpaid family workers (Eurostat, 2006; Ball et al., 2010). Our aggregation procedure, based on the index approach, captures a substitution of hours with higher marginal productivity for hours with lower marginal productivity, as it uses the compensation for labor as the weights for aggregation. Compensation for 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 identify where the value of total output value is equal to total factor outlay. The characteristics of the agricultural labor force, such as age, education level and working experience, have been included to adjust for labor input quality.

4. Technological Catch-up across OECD Countries

Technical efficiency is a good measure of technology adoption, which affects agricultural productivity growth and its cross-country difference. Applying the deterministic non-parametric DEA approach to the production account data for agriculture, we first measure the efficiency levels of our sample countries for the three sub-periods: 1973-1985, 1986-1997 and 1998-2011 (Table 1). Among all the 17 OECD countries, Netherlands has efficiency scores of 1.0 in 21 out of 38 years ranking on the top through all three sub-periods with its average efficiency score being 0.98, 0.98 and 0.97 respectively. Also, Belgium and Greece located on the frontier for 10 years (including 1973, 1984, 1985, 1988-1992, 1998-2000) and for 8 years (including 1991-1998), and the US located on the frontier in 2004.

Although the four countries were on the frontier, the nature of their agricultural production (focused on different enterprises and determined by different natural endowment) are different which could be characterized by different capital-labor ratios. Specifically, Netherlands and Belgium specialized in producing high-valued horticulture products and used the most capital-intensive technology. Greece had advantage in traditional cropping and livestock products and relied on using the labor-intensive technology. In between, the US produced both high-valued horticulture products (as in California) and industrialized cropping and livestock products (e.g. in the corn and maize belt), and the technology in use is characterized by capital intensity lower than Netherlands and Belgium but higher than Greece. Thus, the change in the density distribution over time may not only reflect technology catch up across countries but also the diffusion of different types of technology characterized by capital-labor ratio (when we categorize them by groups).

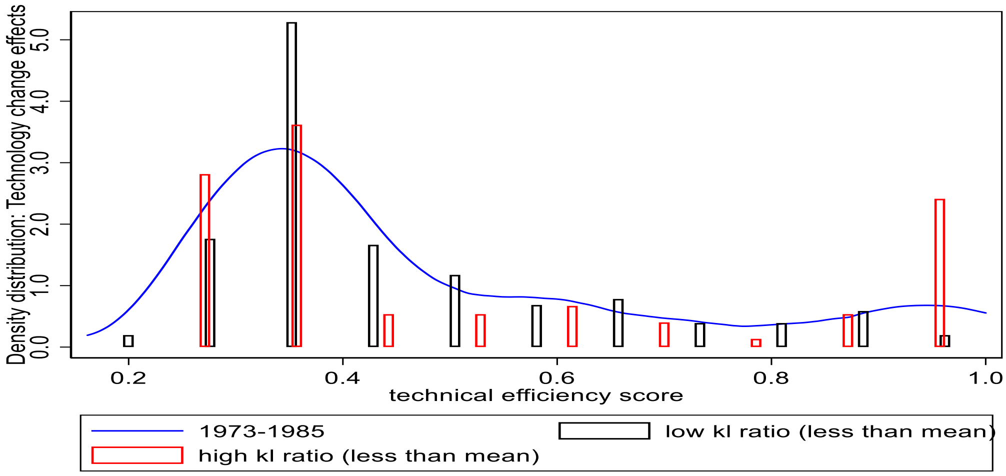
Figure 4. Comparing the density distribution of efficiency level for 17 OECD countries: 1973-1985, 1986-1998 and 1999-2011



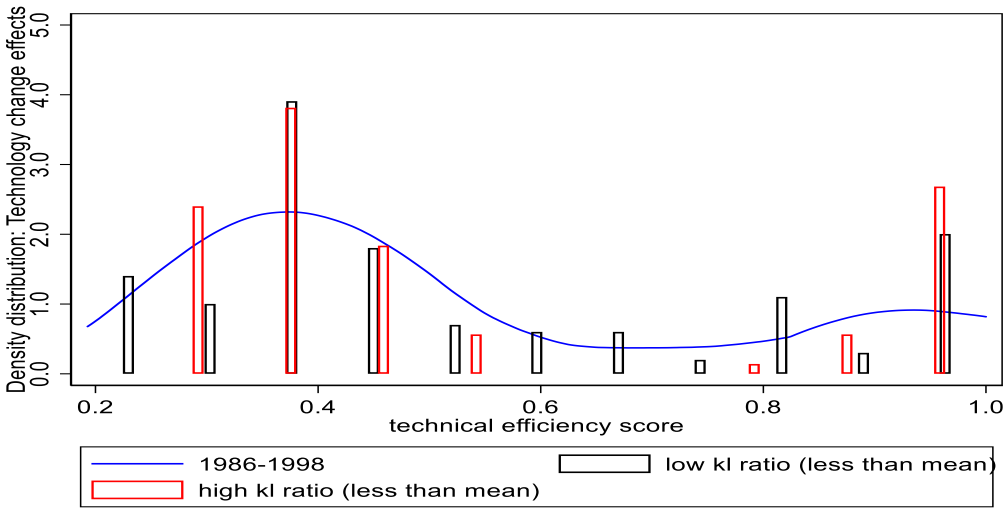
Across the three sub-periods, aggregate technical efficiency level of all sample countries continue to increase. On the one hand, the mean of technical efficiency level shifts to the right with average efficiency score (of our sample) increased from 0.48 in 1973 to 0.54 in 2011. On the other hand, more sample (points) countries move towards the frontier. Figure 4 compares the density distributions of technical efficiency level for the three sub-periods of 1973-1985, 1986-1997 and 1998-2011, obtained under the assumption of non-increasing returns to scale. As is shown, there is a prominent shift in the probability mass towards 1.0 across the three sub-periods: 1973-1985, 1986-1997 and 1998-2011, which suggests that technology adoption of all types is strengthened over time. However, our result is different from Kumar and Russel (2002) in technology catch-up. Kernel density regressions of the change in efficiency on the 13-year lagged level of efficiency show positive and significant coefficients, which implies that less efficient countries were unlikely to benefit more from efficiency improvements than have the more efficient countries.

To explain this phenomenon, we further decompose the distribution of technical efficiency levels by countries using different technologies characterised by capital-intensity. Figure 5 compares the histogram density of technology efficiency levels of the countries using relatively more capital-intensive technology with those using more labour-intensive technology for each of the three sub-periods: 1973-1985, 1986-1997 and 1998-2011. Relative to the countries using capital-intensive technology, the histogram of technology efficiency levels for the countries using labour-intensive technology were shifting to the left over time. This implies that the countries using relatively more labour-intensive technology becomes relatively less efficient compared to the counterparts using relatively more capital-intensive technology.

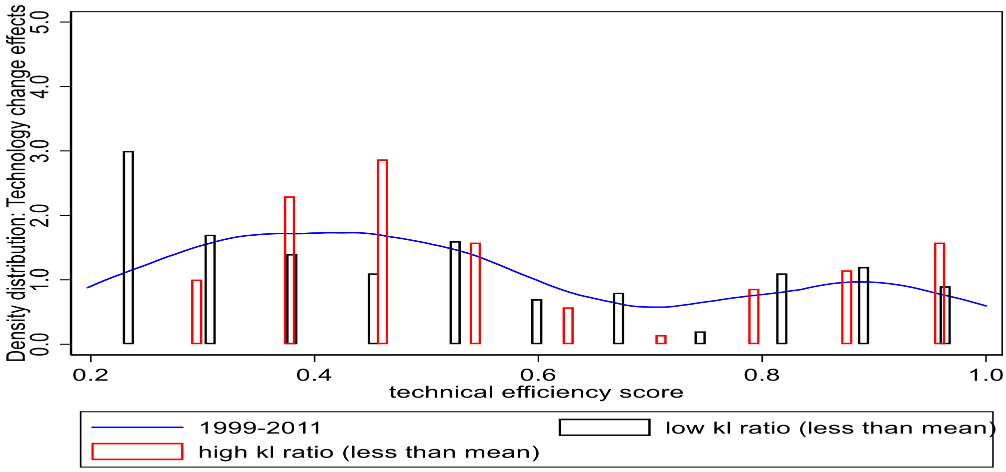
Figure 5. Comparing the density distribution of efficiency level by capital intensities: 1973-1985, 1986-1998 and 1999-2011



(a) the density distribution of efficiency level and histogram of countries by capital intensities: 1973-1985



(b) the density distribution of efficiency level and histogram of countries by capital intensities: 1986-1998



(c) the density distribution of efficiency level and histogram of countries by capital intensities: 1999-2011

The above two findings (though informative) do not necessarily imply that we can explain the slowdown pattern of productivity growth with the enlarging gap across countries. This is because that the impact of efficiency change depends on technology frontier movement. Only when technology progress holds constant, the comparison of efficiency change can be useful. Hence, we need to make a thorough decomposition of labour productivity into technology progress, efficiency change and scale effects.

5. Labor Productivity Growth, Technological Progress and Capital Deepening

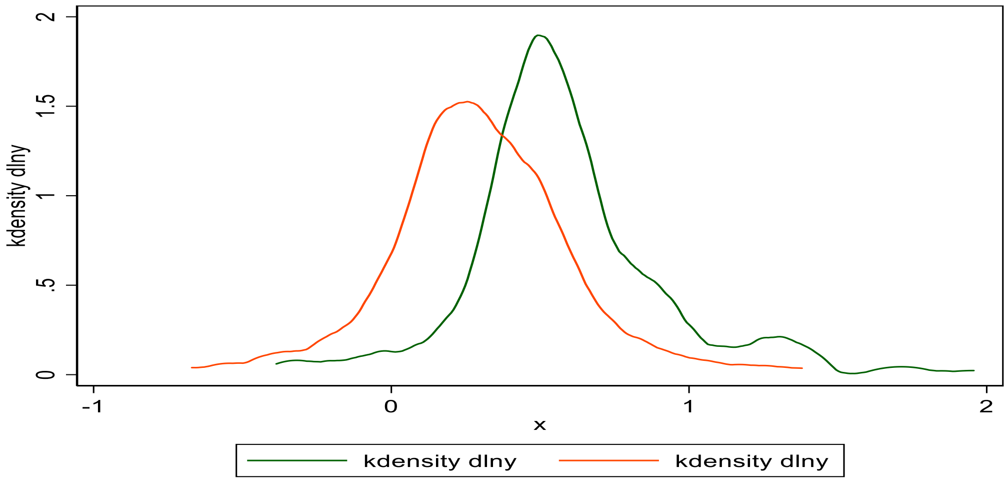
Technology progress and capital deepening are two most important factors determining labor productivity growth, in addition to efficiency improvement. To examine their relative roles in contributing to the recent trend change in ALP, we apply the KR framework to further decompose ALP growth between 1973-1986 and 1986-1998 and between 1986-1998 and 1999-2011 into technology progress, efficiency improvement and capital deepening.

5.1 Tripartite Decomposition of Labor Productivity

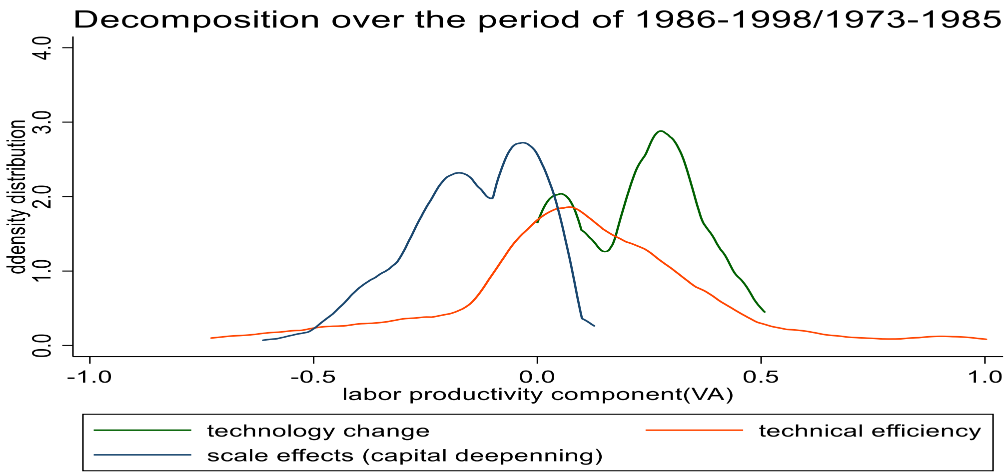
Using the proposed approach in Section 3, we carry out the decomposition analysis on labor productivity for each 13-year interval, with the aim to analyse the change of agricultural productivity and its components for the 17 OECD countries throughout the whole period of 1973-2011. The agricultural labor productivity growth is decomposed into three components: efficiency change, technological progress and scale effect (caused by capital deepening). Overall, ALP for the 17 OECD countries continue to grow throughout the whole period with the growth rate of 3.40% a year and it is mainly driven by technological progress and efficiency improvement. The average contribution of both technology progress and efficiency improvement to labor productivity growth are 1.44% and 0.39% respectively, which add up to account for 54% of overall labor productivity growth. In contrast, capital deepening on average negatively contributed to labor productivity growth with its average impact being -1.15% a year.

We now split the calculation for the 1986-1998 period (relative to the 1973-1985 period) from that for the 1999-2011 period (relative to the 1986-1998 period). As is shown in Figure 6, ALP growth has slowed down in the most recent decade. The average annual growth rate of labor productivity decreased from 4.48% a year for the period of 1986-1998 down to 2.99% a year for the period of 1999-2011. Underlying this change, both technological progress efficiency improvement slowdown substantially. Average contribution of technology progress to labor productivity growth declined from 1.69% a year for the 1986-1998 period to 1.18% a year for the 1999-2011 period, down by more than 30%. At the same time, average contribution of efficiency improvement to labor productivity growth also declined from 0.7% a year to 0.1% a year (down by around 80%), although the impact of efficiency improvement on labor productivity growth is relatively small compared to technology progress. This is a puzzling phenomenon because the wide spread of biology and telecommunication technologies has gradually change the way of agricultural production since the mid-1990s, which is expected to promote outward shift of technology frontier for developed countries compared to the past.

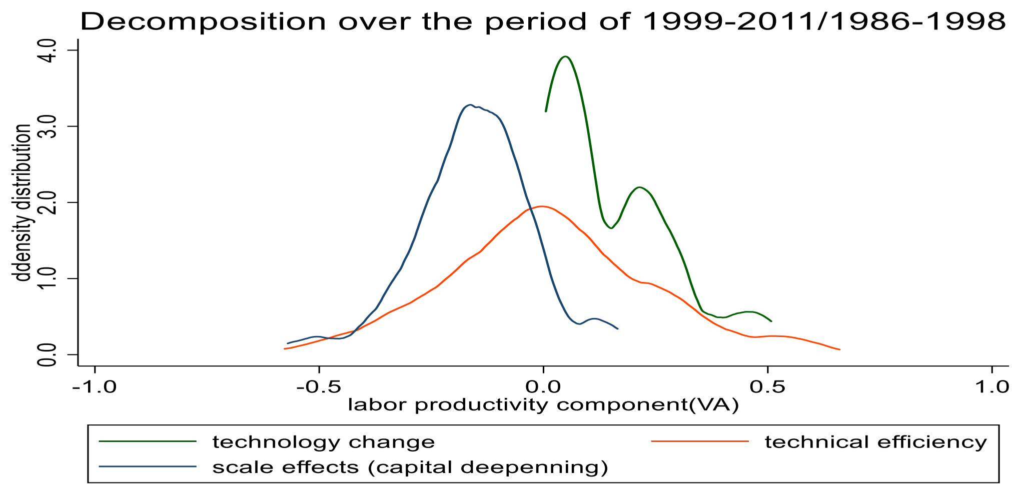
Figure 6. Tripartite Decomposition of Labor Productivity: 1986-1998/1973-1985 vs. 1999-2011/1986-1998



(a) ALP change between 1973-1985 and 1986-1998 vs. that between 1986-1998 and 1999-2011



(b) Decomposition of ALP change into technology change, efficiency improvement and capital deepening between 1973-1985 and 1986-1998

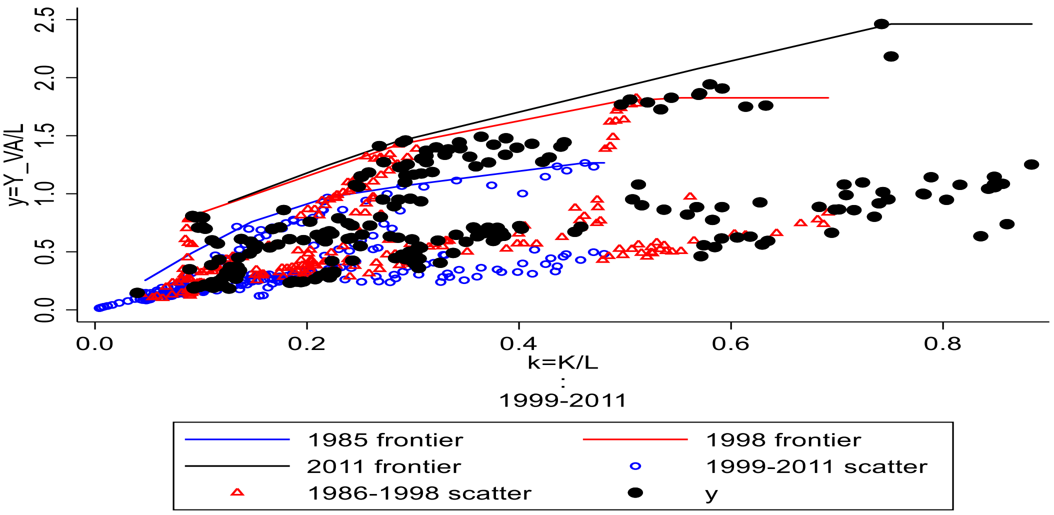


(c) Decomposition of ALP change into technology change, efficiency improvement and capital deepening between 1986-1998 and 1999-2011

5.2 Bimodal Technological Progress and Capital Deepening

What happens to technology progress among the OECD countries in recent years when biology and telecommunication technology is introduced to agriculture? To answer this question, we construct the empirically production frontiers for 1985, 1998 and 2011, along with scatterplots of labor productivity and the capital-labor ratio. Each colour represents a particular year and each kink is an actual observation on these ratios for a sample point with a full efficiency for that year. Comparing the empirically constructed production frontiers for 1985 with that for 1998, we show that the frontier shift in the $k - y$ space vertically used to be by same proportional amount at all capital-labor ratio, which is consistent with the assumption of Hicks-neutral technological progress. For the decade thereafter (say, the 1999-2011 period), technology progress has continued but mainly for the high-end countries in terms of capital intensities. While the outward shift of the frontier for high capital-labor ratios for the 1999-2011 period remains same as that for the 1986-1998 period, very little change in the frontier for the medium and low parts of the distribution of capital-labor ratios (shown in Figure 8). In other words, technology progress in agriculture of developed countries has gradually become decidedly non-neutral with rapid expansion only at high capital-labor ratios, when biology and telecommunication technologies are widely applied in practice. This finding is consistent with Kumar and Russel (2002), which has shown that technological progress of the whole economy is more relying on capital deepening since the 1990s.

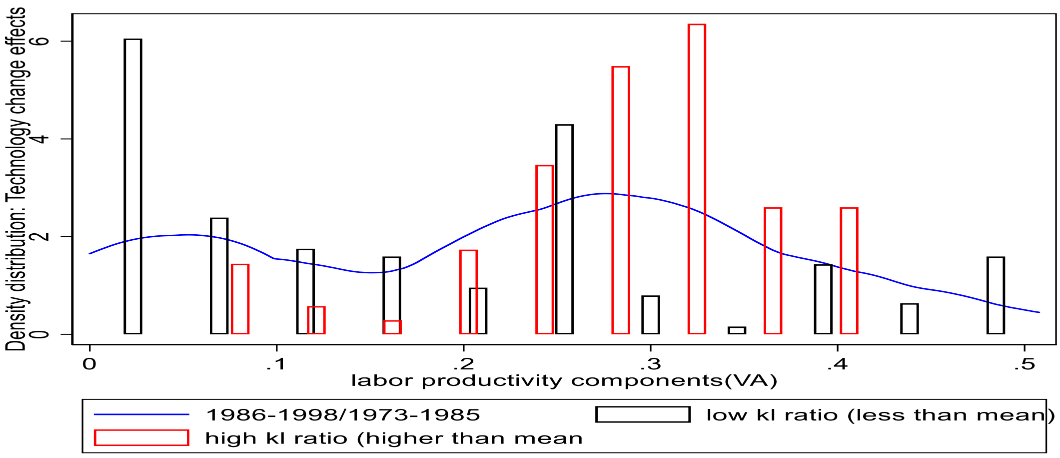
Figure 7. Comparing the empirically constructed production frontiers for 18 OECD countries using the DEA approach: 1985, 1998 and 2011



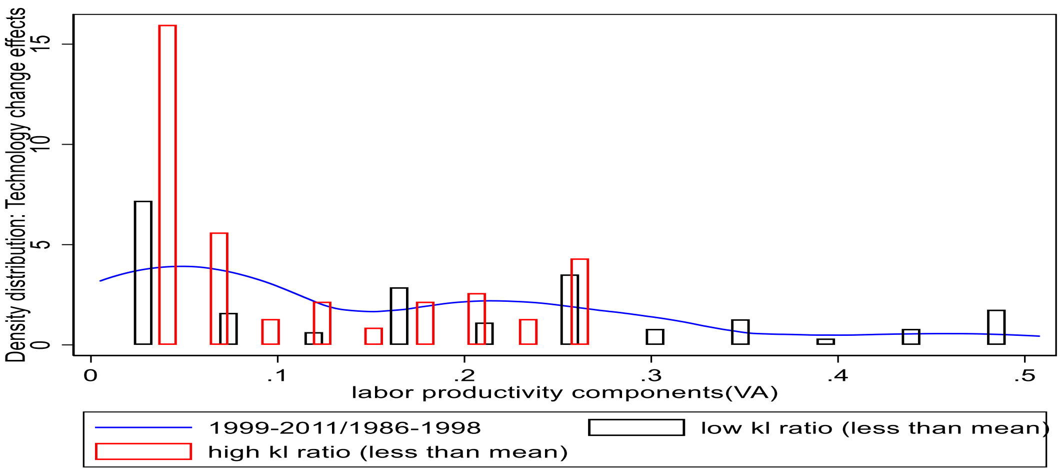
To further examine how biology and telecommunication technologies affect technology progress in agriculture over time, we compare the density distribution of technological progress components for the 1986-1998 period with the 1999-2011 period, and pair the density distribution of technology change with the histogram of capital-labor ratios for each period. As is shown in Figure 9, the distribution of technological progress has taken the form of bimodality for both periods. This implies that there are always been two types of technological progress (partly determined by their endowment conditions) contributing to the frontier movement of agricultural production in OECD countries. One is the relatively labor-saving technology (or the right hump) and the other is the relatively capital-saving technology (or the left hump).

Figure 8. Comparing the density distribution of technology progress between 1986-1998/1973-1985 and 1999-2011/1986-1998

(a) the density distribution of technology progress between 1986-1998/1973-1985 and 1999-2011/1986-1998



(b) the density distribution of technology progress and histogram of countries by capital intensity for 1986-1998/1973-1985

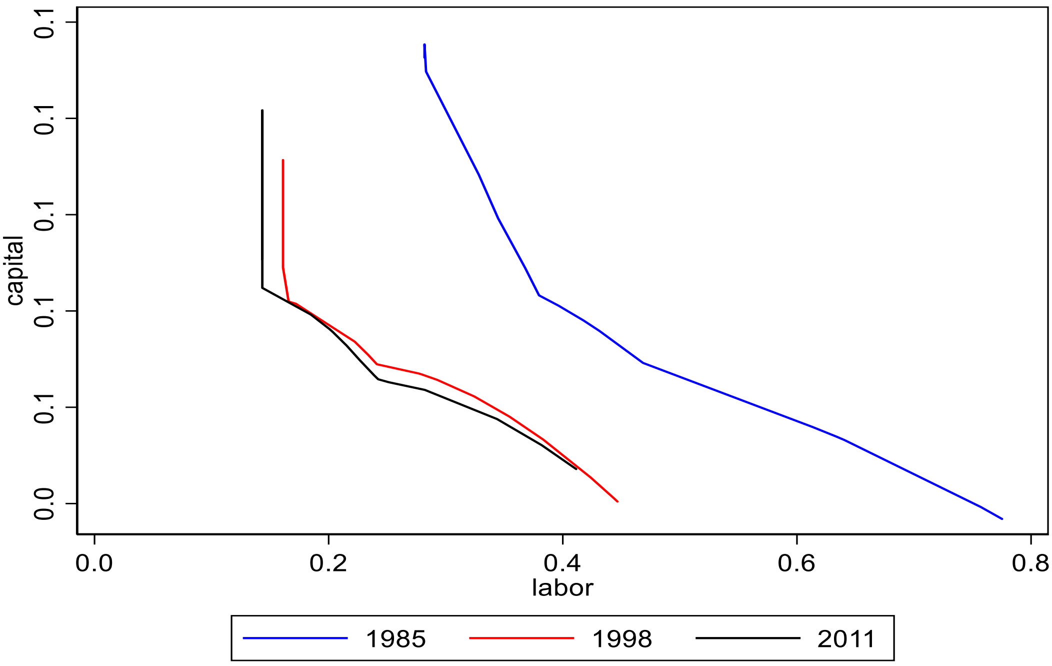


(c) the density distribution of technology progress and histogram of countries by capital intensity for 1999-2011/1986-1998

For the 1986-1998 period, technology progress are evenly distributed across countries, with the relatively labor-abundant countries specializing more in capital-saving technology progress (and vice versa). As is shown in Figure 9B, the density distribution of technological progress components for the 1986-1998 period shows a twin-peak shape, with the left-hand peak overlapping with the histogram of low capital intensive countries and the right-hand peak with the histogram of high capital intensive countries. However, for the 1999-2011 period when biology and telecommunication technologies are introduced, the density distribution of technological progress components shifted to the left with more mass clustering around the left-hand peak (representing capital-saving technology progress). Since technological progress is more relying on capital deepening, such a shift from labour-saving technology progress towards capital-saving technology progress will cause slowdown in technology progress.

The nature of technological change among 1985, 1998 and 2011 can be further illustrated by referring to "unit isoquants" for the three years. As is shown in Figure 10, the shift in the unit isoquant reflects technological progress in those regions of capital-labor space where the unit isoquant has shifted inwards. Also, isoquants in each year are simply radial contraction of these "unit" isoquants under the assumption of non-increasing return to scale. For the 1986-1998 period, the unit isoquant shifts quickly inwards across countries with different capital-labor ratios, where the radio contraction is on the relatively higher order for the relative more capital-intensive countries. This implies that technological progress takes place to in both directions to save capital and labor which are substantive to each other. However, for the 1999-2011 period, technology progress becomes more polarized and takes place only two diversification cones. One is locating at the region where the slope the isoquant becomes less steep representing the labor-intensive technology, while the other is locating at the region where the slope the isoquant becomes very steep representing the capital-intensive technology. Moreover, comparing between the two types of technology progress, we show that technological progress in capital-intensive technology affects the shift of "unit" isoquant more heavily than labour-intensive technology. The findings here corroborate what we obtained from Figure 8, where we attribute slowdown in technology progress for the recent decade partly to lack of strong capital deepening in the new era (when technology progress relies more heavily on capital intensities).

Figure 9. Comparing the isoquant curves between 1985, 1998 and 2011



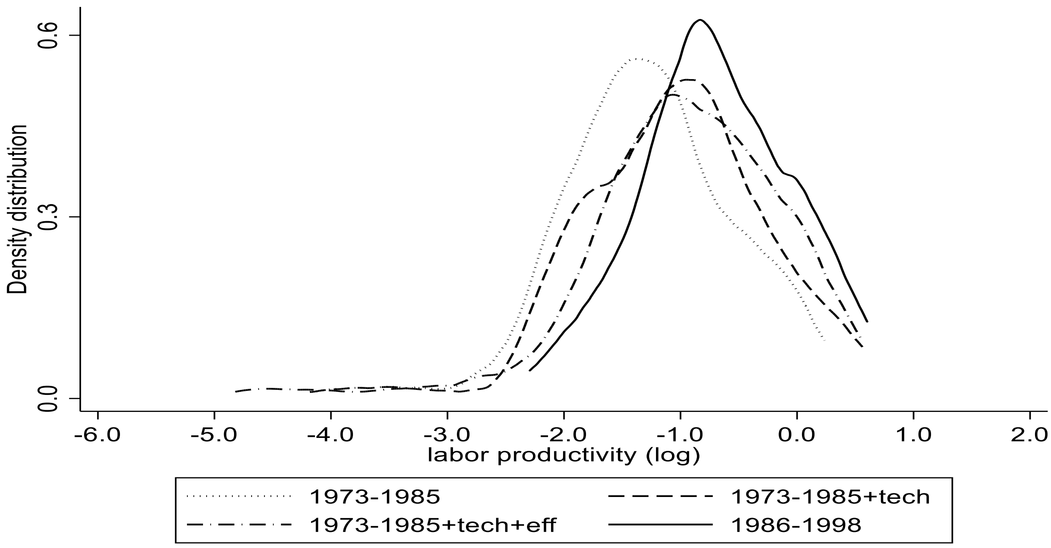
5.3 Counterfactual Analysis

How much technology progress and efficiency improvement affect labor productivity growths in agriculture of the OECD countries and their cross-country difference? To answer the question, we construct the counterfactual distributions of labor productivity growth between 1973 and 1998 and between 1999 and 2011, caused by technological progress and efficiency improvement respectively.

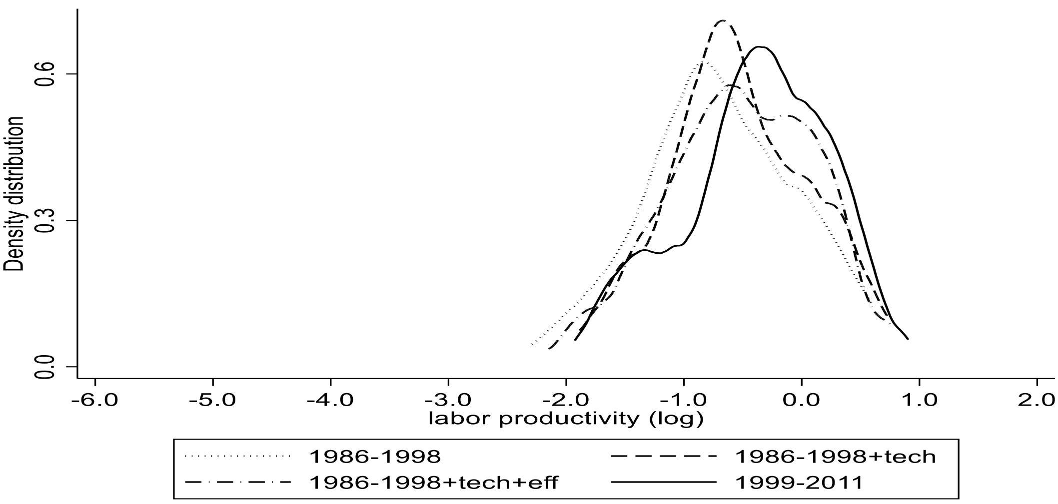
As is shown in Figure 10, labor productivity continues to growth over time with enlarging gap across countries. Technological progress and efficiency improvement add up together have on average accounted for more than half change of labor productivity growth for both the 1986-1998 period and the 1999-2011 period. This result is different from the finding from Kumar and Russel (2002) which shows that labor productivity growth at the economy level comes mainly from increased capital intensities. As technology progress slows down more rapidly for the 1999-2011 period, it thus has significantly contributed to the slowdown of labor productivity growth.

Figure 10. Comparing the density distribution of labor productivity (log) among three periods: 1973-1985, 1986-1998 and 1999-2011

Figure 11. Counterfactual analysis for the density distribution of labor productivity (log)



(a) the counterfactual density distribution between 1973-1985 and 1986-1998



(b) the counterfactual density distribution for between 1986-1998 and 1999-2011

Moreover, our non-parametric decomposition also shows that technology progress determines the enlarging gap in agricultural labor productivity across countries (rather than capital deepening). As is shown in Figure 10, the counterfactual distributions of labor productivity growth caused by technology progress share the similar tails with the distributions of labor productivity growth. It is true for both the 1986-1998 period and the 1999-2011 period, when technology progress has significantly slowed down. This implies that the best innovators among the OECD countries have continued to push up the best production frontier when biology and telecommunication technologies are widely applied.

6. Conclusions

This paper uses the KR framework to investigate how recent technological (GMO/ICT) revolution changes technology progress in agriculture and agricultural productivity growth. By applying deterministic production-frontier analysis (DEA) to the newly developed production account data for agriculture of 17 OECD countries over the 1973-2011 period, we examines the production frontier movement in agriculture over time, and split it into three 13-year sub-periods: namely, the baseline period (1973-1985), the pre-revolution period (1986-1998) and the post-revolution period (1999-2011). We then decompose ALP growth for the 17 countries its three components: technology progress, efficiency improvement and capital deepening, and compare their change before and after new wave of technology revolution.

Our results show that labor productivity growth in agriculture is more likely to be influenced by technology progress other than capital deepening, especially among developed countries. For the 17 OECD countries over the 1973-2011 period, more than half of ALP growth come from technology progress and efficiency improvement. Although technology progress in the very capital-intensive countries continues to grow when new wave of technology revolution arrives after 1998, it does slowdown in most relative labor-intensive countries which caused a decline in both average growth rates of TFP and ALP. Our finding implies that the new wave of technology revolution is causing technology progress in agriculture to shift from Hick-neutral towards the labor augmented direction (favouring the production of capital intensive countries). The results confirm the findings from Kumar and Russel (2002) and Henderson and Russel (2005) at the economy wide, causing the concern of increased inequality that could arise from new technology revolution.

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