International Jthenal of Food and Agricultural Economics
ISSN 2147-8988, E-ISSN: 2149-3766
Vol. 5, No. 4 2017, pp. 11-24

THE IMPACT OF EDUCATION ON AGRICULTURAL PRODUCTIVITY: EVIDENCE FROM EAST ASIAN ECONOMIES

Yir-Hueih Luh
National Taiwan University, Department of Agricultural Economics, No. 1, Section 4, Roosevelt Road, Taipei, Taiwan, E-mail: yirhueihluh@ntu.edu.tw

Abstract

This study presents an efficient version of test for the hypothesis that education plays a key role in influencing agricultural productivity based on a switching regression model. In the present setting, farmers' ability to deal with disequilibria is allowed to change with education, which thereby provides a concrete evidence of the effect of education on selected East Asian production agriculture. The results suggest that there exists a threshold for education to be influential to agricultural productivity change when the selected East-Asian economies are categoried by their degree of economic development. Moreover, for the group of economies where education constitutes a major determinant of productivity growth in both the technological progression and/or stagnation/recession regimes, the effect of education is found to vary from economy to economy and from regime to regime. Generally speaking, however, those East-Asian economies tend to reach their turning point in short time despite of the mentioned differences. This result therefore leads to important policy implications concerning giving an impetus to human capital investment in the agriculture sector.
Keywords: *Human capital, Education, Productivity growth, East Asian agriculture, Switching regression.*
JEL Codes: *O13, O15, Q11, Q18*

1. Introduction

Inter-country comparison of patterns of productivity growth in agriculture has been extensively discussed in the literature. According to Alauddin, Heady and Rao (2005), international study of agricultural productivity was originated from Clark's (1940) work. Because Clark (1940) only focused on partial productivity indices of labor and land which are restrained in the way that only one factor is allowed to vary in the production process, most recent studies investigated the sources of inter-country productivity differences through the estimation of cross-country production functions and multifactor productivity indices.

The present study aims at inter-country comparison of the growth patterns of agricultural productivity, with a special emphasis on methodological refinement to the measurement of the effect of education on agricultural productivity. The main streams of research this paper extends from can be addressed as the following. First of all, regardless of its significance in the theory of human capital, in a rapidly changing technological environment, education becomes even more important because farmers' ability to deal with disequilibria induced by technological change depends largely on education (Schultz, 1975). Although a couple of studies did find better educated farmers to adjust more successfully than their less educated counterparts (e.g., Schultz, 1975; Ali & Byerlee, 1991; Appleton & Balihuta, 1996), most empirical work on education and agricultural productivity are based on a temporal equilibrium framework. In the present setting, farmers' ability to deal with disequilibria is allowed to change with education, a concrete evidence of the key role of education can thus be inferred from the empirical analysis undertaken in this paper.

On the other hand, for the developing countries, it is well documented that agriculture has undergone considerable technological progress following the innovation of high-yielding crop varieties and massive use of chemical fertilizers. However, cross country comparison of agricultural productivity assuming homogenous technology may obscure the true contribution of education to the growth of agricultural productivity (Alene & Manyong, 2007). Therefore, this study proposes to examine the effect of education on agricultural productivity through the switching regression. The switching regression model relies on the mechanism which signals a change in the state of technology from the stagnation or recession regime into the progression regime or vice versa. By separating the entire time span into two separate regimes—the progression and stagnation/reession regimes—the differential productivity effects of education in different technology state can thus be examined.

The empirical analysis in this study involves examining the effect of education on total factor productivity (TFP) change in the agriculture sector for eight East Asian economies – China, Indonesia, Japan, Malaysia, the Philippines, South Korea, Thailand and Taiwan. Part of the East Asian growth in the agricultural sector appears to have been the result of remarkable gains in educational attainment (Jamison & Lau, 1982; Bosworth & Collins, 2007). However, limited attention has been paid to investigating the association of human capital investment, in the form of education, and agricultural productivity growth for the East Asian economies. In order to provide a significant complement to the existing body of research, the present study presents an efficient version of test for the hypothesis that education plays a key role in influencing East-Asian agricultural productivity. This study therefore adds to the existing body of research on East-Asian agriculture by providing a methodological refinement to quantify the effect of education on agricultural productivity.

The remainder of the paper is organized as follows. In the next section, a brief literature review is provided. The following section gives a detailed delineation of the model and the empirical specifications. Description of the data is then provided, followed by presenting the empirical estimates and discussion of the results in the following section. Finally, some concluding remarks are offered in the last section.

2. Literature Review

The emphasis of education as a driving force for the growth of agricultural productivity can be dated back to the early 1960s in Griliches (1963) which "focused on minimizing the unexplained portion of growth in U.S. agriculture by adjusting labour for quality, using education." (Zepeda, 2001, p. 10) One of the reasons that education may affect agricultural productivity stems from the general-skill building up perspective of education. For instance, literacy improved through education might enable farmers' capability of following written instructions for applying fertilizer or pesticide, whereas numeracy may assist their calculation of correct dosages in the practice of fertilizer or pesticide applications (Appleton & Balihuta, 1996). In addition to accumulation of human capital, Schultz (1975) posited that well-educated farmers are more capable of collecting and processing useful information, which therefore suggests education is one of the important determinants of agricultural productivity.

Within the context of technology adoption, past literature documented that education not only will positively impact farmers' adoption of new technology, it will also affect their innovative ability and technical efficiency (e.g., Fuglie & Kascak, 2001; Daberkow, Fernandez-Cornejo, & James, 2003; Daberkow & McBride, 2003; Knight, Weir, & Tassew, 2003; Asadullah & Rahman, 2009; Pierpaoli, Carli, Pignatti, & Canavari, 2013; Luh, Chang,

& Huang, 2014). In particular, Knight et al. (2003) found that through the influence of schooling upon attitudes towards risk and thus potential risk undertaking, education is positively associated with the rate of innovation adoption. Taking a different perspective, Asadullah and Rahman (2009) pointed out that "in addition to raising rice productivity and boosting potential output, household education significantly reduces production inefficiencies." (Asadullah & Rahman, 2009, p.17)

Based on macro-level data, education as one of the determinants of cross-country differences in agricultural productivity has been subject to substantial scrutiny in the past. The early efforts of Hayami (1969) and Hayami and Ruttan (1970), followed by the work of Kawagoe and Hayami (1985) and others, suggested the key role of education and human capital on agricultural productivity growth (Chavas, 2001). Most of these past empirical work investigated the association of education and agricultural productivity through the estimation of the aggregate production functions, and thus did not take into account the differential impact of education under different state of the production technology.

3. The Empirical Design

3.1 Malmquist Productivity-Change Indexes

Before assessing the differential impacts of education on agricultural productivity for the eight East Asian economies, the Malmquist productivity index is calculated using the mathematical programming procedure outlined in Färe, Grosskopf, Norris and Zhang (1994). Productivity can be measured with reference to either the period-*t* or *t*+1 technology, therefore, the Malmquist index of productivity change is defined as the geometric mean,

$$\mathrm{M}_0(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\left(\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}\right)\left(\frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)}\right)\right]^{1/2} \tag{1}$$

The terms in the first parentheses in (1) is a distance-function-based multi-factor productivity index. The reference technology of this productivity index is the period-*t* technology. With reference to the period-*t* technology, the distance function in the numerator, $D_0^t(x^{t+1}, y^{t+1})$, measures the maximal output change necessary to make it feasible to observe the input-output combination (x^{t+1}, y^{t+1}) in period *t*+1. The distance function in the denominator, $D_0^t(x^t, y^t)$, instead measures the reciprocal of the maximum proportional expansion of the output vector y^t given x^t (Luh et al., 2008). The second parentheses is similarly defined as the Malmquist productivity index with technology in period $t+1$ as the reference technology.

Following Färe, Grosskopf, Lindgren and Roos (1989), the Malmquist productivity-change index can be calculated through the linear-programming approach. The basic idea in this nonparametric technique is to construct a best-practice frontier from the data of the decision-making units which are the eight East-Asian economies in this study. Comparing individual economy with the grand or world frontier yields the the Malmquist productivity indexes for the sample economy. The annual percentage measures of total factor productivity change can thus be calculated using this method for each economy in each pair or adjacent years.

To delineate the pattern of growth, the smoothed measure is usually reported in the form of cumulative percentage change measures (e.g., Coelli, Prasada Rao, O'Donnell, & Battese, 2005; Luh et al., 2008). Therefore, to examine the differential productivity effects of education in different regimes, the cumulative measure of TFP change is regressed on the core variable in the present study—the percentage of secondary-school enrollment—controlling for economy characteristic measured by the ratio of arable land to total agriculture population.

3.2 The Identification Strategy

The identification strategy starts out with the definition of the regime separation index which is the technical change component (TCC) and is measured as the following as in Färe et al. (1989):

$$TCC = \left[\left(\frac{D_0^t(x^{t+1},y^{t+1})}{D_0^{t+1}(x^{t+1},y^{t+1})}\right)\left(\frac{D_0^t(x^t,y^t)}{D_0^{t+1}(x^t,y^t)}\right)\right]^{1/2} \tag{2}$$

According to Färe et al. (1994), the improvements in the technical-change component of the Malmquist productivity-change index can be interpreted as an indicator of technical change in multilateral analysis. That is, this variable measures how much the world frontier shifts given each economy's observed input mix over time. Accordingly, when the technical change component is greater than one, the production technology is characterized as in the progression state. Nonetheless, a less-than-one value of the technical change component in turn indicates the state of technology is in stagnation or recession.

The switching mechanism on which the switching regression model relies on signals a change in the state of technology from the stagnation or recession regime into the progression regime when the value of the technical change component is greater than unity. The technical change component, therefore, is used in the present study to separate the entire time span into two separate regimes, the technological progression regime and the stagnation/recession regime. Based on the switching mechanism, the differential productivity effects of education in different technology state can thus be explicitly examined.

The switching mechanism is summarized in what follows,

$$gTFP_{it} = \begin{cases} gTFP_{it}^* \ (Regime\ 1) & if\ TCC > 1 \\ gTFP_{it}^* \ (Regime\ 2) & if\ TCC \le 1 \end{cases}$$

In the switching regression model, $gTFP_{it}$, represents the observed proportional growth rate of total factor productivity, whereas $gTFP_{it}^*$ (Regime 1) and $gTFP_{it}^*$ (Regime 2) are, respectively, the TFP growth rate at the two different regimes. The population regression functions, respectively, for the technological progression regime, Regime 1, and the technological stagnation/recession regime, Regime 2, are specified as

$$\begin{aligned} gTFP_{it}^*(\text{Regime 1}) = \alpha_0 + \alpha_{HK} Education_{it} + \alpha_{HK2} Education_{it}^2 \\ + \alpha_{SC} Scale_{it} + \alpha_{SC2} Scale_{it}^2 + \varepsilon_{it} \end{aligned} \tag{4a}$$

$$\begin{aligned} gTFP_{it}^*(\text{Regime 2}) = \beta_0 + \beta_{HK} Education_{it} + \beta_{HK2} Education_{it}^2 \\ + \beta_{SC} Scale_{it} + \beta_{SC2} Scale_{it}^2 + \varepsilon_{it} \end{aligned} \tag{4b}$$

In (4a)-(4b), the key variable is $Education_{it}$ which is used to quantify the direct influence of education through the proxy variable—the proportion of population with a secondary-school enrollment. The disembodied technological change rate in the two regimes are measured by the two constants, α_0 and β_0, in the regime-specific equations. The variable $Scale_{it}$, the land-labor ratio, is used to capture one of the major economy-specific characteristics of the agricultural sector in East Asian production agriculture. The land-labor ratio is calculated by dividing the areas of arable land by the total number of labor used in the agriculture sector.

4. Data Description

The data used in the present study includes agricultural production data for eight East Asian economies over a forty years of time span. Except for Taiwan, data for the other seven economies including China, Indonesia, Japan, South Korea, Malaysia, Philippines, and

Thailand is taken from the Food and Agriculture Organization (FAO) of the United Nations' statistical database. Data of the seven economies are accessed through the internet website: http://www.fao.org. The data provided in the Agricultural Yearbook published by the Council of Agriculture, Executive Yuan is the major data source for Taiwan's production agriculture.

The DEA model is composed of one single output and three inputs. The data for the output variable is drawn from the "crop primary" in the FAO database. The three input variables are land, labor, and fertilizer. Agricultural land is measured by the areas harvested. Agricultural population, which is defined as all workers whose livelihood depend on agriculture, hunting, fishing or forestry, is used as a proxy variable for agricultural labor. The third input, fertilizer, is the quantity of chemical fertilizer consumed by the sample economy. More detailed description of the data used in this study can be found in Luh et al. (2008).

To quantify the effect of education on agricultural productivity, the proportion of secondary school enrollment in total population is used as a proxy variable for the agriculture sector. The growth of output can be easily derived as a function of changes in the stock of education in a neoclassical growth model (Mankiw, Romer, & Weil, 1992), whereas output growth is modeled as a function of the level of human capital in an endogenous growth framework (Lucas, 1988; Romer, 1990). This study follows Mankiw et al. (1992) to specify productivity growth as a function of growth of human capital which is proxied by the secondary school enrollment rate.

The data for secondary-school enrollment rates are taken from the United Nation's Statistical Yearbook for Asia and the Pacific. As for Taiwan, the data for the secondary-school enrollment rate is taken from Taiwan Statistical Data Book published by the Council for Economic Planning and Development of Republic of China. Sample means of the dependent and explanatory variables are reported in Table 1.

Table 1. Sample Means of Eight East-Asian Economies

Economies	Regime 1			Regime 2		
	cumTFP	*Education*	*Scale*	*cumTFP*	*Education*	*Scale*
Group-1 Economies China	0.164	0.050	0.149	0.195	0.054	0.153
Thailand	0.538	0.038	0.527	0.523	0.033	0.520
Philippines	0.844	0.050	0.219	0.705	0.057	0.208
Indonesia	0.663	0.037	0.226	0.692	0.036	0.226
Group-2 Economies Japan	1.805	[1.761]	0.467	1.446	[1.493]	0.345
Malaysia	2.345	0.073	0.279	1.788	0.065	0.214
Group-3 Economies Taiwan	1.036	0.084	0.185	0.986	0.081	0.186
Korea	1.289	0.093	0.228	1.217	0.081	0.199

Notes: The definition of variables *cumTFP, Education and Scale* are as described in the empirical specification. For Japan, *Education* is replaced by the stock of human capital constructed in Luh et al. (2008).

5. Results and Discussion

The scatter diagrams in Figures 1-3 demonstrate three different growth patterns revealed by the time trend of the cumulative proportional changes of the productivity-change index. The first group exhibiting similar growth patterns, as depicted by Figure 1, is composed of Thailand, Philippines, Indonesia and China. Since improvements in productivity are associated with the Malmquist productivity-change index greater than one whereas $TFP \leq 1$ indicates stagnation or deterioration of productivity performance (Färe et al., 1994), the time trend of cumulative $gTFP$ suggests a deteriration of agricultural productivity for this group of economies in the early periods. The trend then reveals a gradual leveling-off in the later periods for the same group of economies.

Figure 2 demonstrates a different pattern of agricultural productivity growth for Malaysia and Japan. From Figure 2, obvious improvements in agricultural productivity over the entire time span for the two economies are observed. Moreover, Figure 2 indicates that cumulative productivity growth of Malaysia exceeded that of Japan in the 1970s and continued to maintain a sizable growth rate afterwards. As for Japan, a comparatively steady and mild growth also started to kick in since the early 1970s.

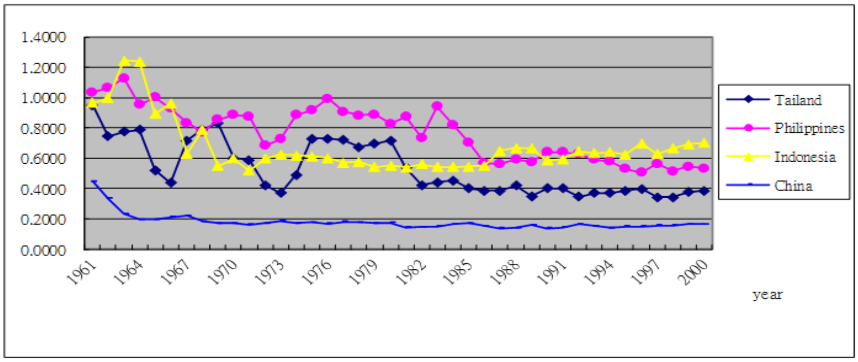

Figure 1. Growth Patterns of Thailand, Philippines, Indonesia, and China

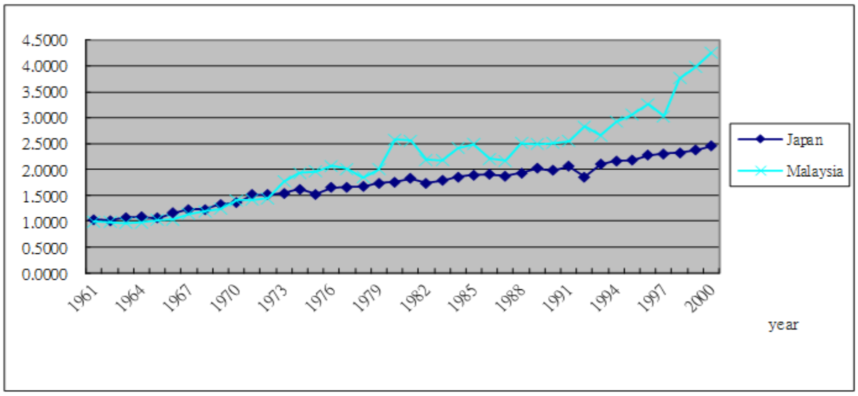

Figure 2. Growth Pattern of Malaysia and Japan

As portrayed in Figure 3, the remaining two economies, South Korea and Taiwan, exhibited a quite different pattern of agricultural productivity change over the sample period. Although the agricultural productivity in Taiwan exhibited a short period of growth during 1980-1983, it dropped to around the average rate of the entire time span shortly. As for South Korea, the agricultural productivity-change index did not exhibit either an upward or a downward trend as that revealled by the other two groups of economies.

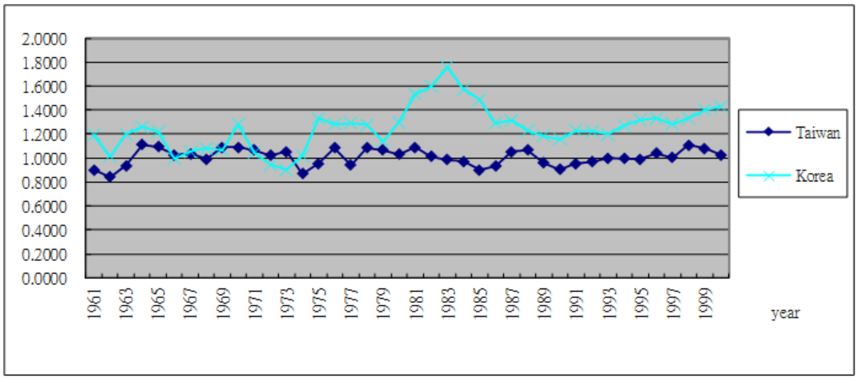

Figure 3. Growth Pattern of Korea and Taiwan

Results from switching regression are reported in Tables 2 and 3. The results in Table 2 indicate that, for the first group of economies composed of Thailand, Philippines, Indonesia and China, variations in the education ratio does not seem to constitute a plausible explanation for the observed pattern of growth. Nonetheless, it is interesting to note that, for this group of economies whose degree of economic development is on the lower tier of the eight East Asian economies, the size of the farm land appears to be a crucial factor in explaining the growth of agricultural productivity. Figures reported in Table 3, however, demonstrate that education is an important determinant in both the technical progression and stagnation/recession regimes for Malaysia and Japan.

According to the specifications in (4a)-(4b), the marginal effects of education for the progression and stagnation/recession regimes in country *i*, respectively, is measured according to the following formula,

$$\frac{\partial \mathrm{E}[\mathrm{gTFP}_i^*(\text{Regime 1})]}{\partial Education_i} = \hat{\alpha}_{HK} + 2\hat{\alpha}_{HK2}\overline{Education_i}$$

$$\frac{\partial \mathrm{E}[\mathrm{gTFP}_i^*(\text{Regime 2})]}{\partial Education_i} = \hat{\beta}_{HK} + 2\hat{\beta}_{HK2}\overline{Education_i}$$

In the above calculation, the estimate of the marginal effects of education for each country is based on the average value of the proportion of secondary school enrollment in total population, i.e., $\overline{Education_i}$. The estimates of the marginal effects of education for Malaysia, Japan, South Korea and Taiwan are also reported in Table 3.

Two insightful observations can be summarized from the marginal effect estimates in Table 3. Firstly, a cross-country comparison of the marginal effect estimates of Malaysia and Japan indicate that the marginal effect of education is much greater for Malaysia than for Japan. This suggests that relative to Japan, general human capital investment may well serve as the major determinant for the sizable growth of Malaysian agricultural productivity since the 1970s.

Table 2. Results of Switching Regression for China, Thailand, Philippines, Indonesia

Variable	Coefficient (b/St.Er.)			
	China	Thailand	Philippines	Indonesia
Regime 1				
Intercept	2.595*** (3.241)	-8.277 (-0.944)	12.773*** (8.715)	7.182** (1.683)
Education	-0.292 (-0.149)	-13.380 (-0.790)	2.049 (0.837)	-16.671 (-0.496)
Education^2	0.292 (0.149)	73.244 (0.377)	-201.065*** (-3.505)	226.628 (0.532)
Scale	-33.432*** (-3.253)	35.341 (1.029)	-85.140*** (-7.701)	-60.350 (-1.368)
Scale^2	116.098*** (3.446)	-33.521 (-1.010)	155.381*** (7.584)	144.475 (1.380)
Regime 2				
Intercept	2.970*** (3.355)	-9.693* (-1.752)	11.241 (0.767)	18.228*** (3.491)
Education	0.084 (0.053)	-6.250 (-0.632)	3.376 (0.03)	14.974 (0.798)
Education^2	-0.084 (-0.053)	-24.744 (-.0181)	-200.951 (-0.199)	-144.177 (-0.608)
Scale	-38.087*** (-3.448)	41.676* (1.903)	-80.032 (-0.533)	-169.808*** (-3.566)
Scale^2	128.991*** (3.634)	-40.806* (-1.894)	157.407 (0.461)	399.772*** (3.705)
Sigma (1)	0.031 (4.935)	0.164 (4.556)	0.146 (1.058)	0.127 (4.16)
Sigma (0)	0.034 (4.220)	0.110 (5.791)	0.168 (4.377)	0.098 (5.168)
Log likelihood statistics	61.296	4.232	68.197	13.802

Notes: The figures reported in the parentheses are t-values. *, ** and *** denote, respectively, significant at the 0.1, 0.05 and 0.01 significance level.

Table 3. Results of Switching Regression for Malaysia, Japan, South Korea, Taiwan

Variable	Coefficient (b/St.Er.)			
	Malaysia	Japan	Taiwan	South Korea
Regime 1				
Intercept	4.003*** (2.930)	0.416** (2.035)	0.526 (0.517)	2.936 (4.133)
Education	-64.399** (-2.040)	[0.307]** (2.577)	23.347 (2.049)	-20.137 (-2.098)
Education^2	812.625*** (2.954)	—	-164.775 (-1.981)	176.053 (2.871)
Scale	-15.801** (-2.348)	2.122*** (8.014)	-2.776 (-0.306)	-12.047 (-2.179)
Scale^2	34.323*** (2.970)	—	7.674 (0.328)	23.907 (2.147)
Regime 2				
Intercept	-0.319 (-0.548)	0.830** (2.218)	0.715 (0.530)	3.162 (4.239)
Education	20.053** (2.583)	[-0.670] (-1.534)	22.453 (2.642)	-31.732 (-2.887)
Education^2	—	[0.302]** (2.469)	-160.393 (-2.617)	234.927 (3.437)
Scale	4.610*** (8.110)	3.186*** (15.819)	-4.243 (-0.305)	-9.212 (-1.843)
Scale^2	—	-1.131*** (-5.191)	11.587 (0.312)	18.333 (1.866)
Sigma (1)	0.165** (2.383)	0.514*** (2.796)	0.081 (5.278)	0.135 (5.312)
Sigma (0)	0.297*** (5.149)	0.027*** (6.915)	0.048 (3.658)	0.135 (5.421)
Log likelihood statistics	-13.582	58.162	34.719	4.332
Average estimates				
Marginal Eff. (Regime 1)	0.542	0.003	-0.004	0.126
Marginal Eff. (Regime 2)	0.201	0.002	-0.003	0.006

Notes: The figures reported in the parentheses are t-values. *, ** and *** denote, respectively, significant at the 0.1, 0.05 and 0.01 significance level.

Moreover, a comparison of the progression and stagnation/recession regimes reveals differential impact of education on agricultural productivity. Compared with that predicted for the technological stagnation or recession regime, the technological progression regime predicts a greater marginal effect estimates for both Malaysia and Japan. The result suggests possible bias in evaluating the effect of education on agricultural productivity once the differential effect of education under different state of technology is not properly accounted for. For the third group of economies where productivity remains rather stable over time, results in Table 3 similarly suggest the importance of education in both the technical progression and stagnation/recession regimes. This result is in accordance with the general expectation that investment in human capital such as education or schooling is necessary for the newly developed technology to be influential to productivity (Antle & Capalbo, 1988; Alene & Manyong, 2007).

A further delineation of the effect of education when categorizing the three groups of economies by their degree of economic development yields some interesting empirical implications. First of all, summarizing from the results in Tables 2-4, the results suggest that there exists a threshold for the effects of education to be influential to agricultural productivity. That is, selected East-Asian economies need to reach certain level of development for education to play an important role in affecting the productivity and thus growth of the agriculture sector.

For the group of economies where education constitutes a major determinant of productivity growth, the effect of education is found to vary from economy to economy. Specifically, Figures A1-A4 in the appendix suggest a nonlinear effect of education on cumulative TFP change in either or both of the two regimes for the last two groups of economies. For Japan and Malaysia, Figures A1 and A2 suggest that before the turning point, the effects of education is negligible. Only when passing the turning point, cumulative TFP starts to increase with education and then gradually level off. Contrast to this pattern, the association of cumulative TFP and education in Taiwan and South Korea as shown in Figures A3-A4 reveal a different pattern. Generally speaking, however, despite of the mentioned differences, economies where education plays a role in influencing agricultural productivity reach their turning point in short time.

Finally, the results suggest that for the same group of economies, the effect of education also exhibit differences from regime to regime. For South Korea, the turning point for the technological progression regime (regime1) is at 5.7% of $Education$, while the turning point for the recession/stagnation regime (regime2) is 6.75%. Similarly, the technological progression regime reaches the turning point earlier than that for the stagnation/recession in the case of Taiwan.

6. Conclusion

Assessing the economic value of education to agricultural productivity for developing economies has been one of the main themes of agricultural development studies lately. However, most previous work on education and agricultural productivity is confined due to the fact that agricultural technology changes over time. By explicitly accounting for the improvement of farmers' ability to deal with disequilibria through the accumulation of general human capital, this study presents an efficient version to test for the hypothesis that education plays a key role in influencing agricultural productivity. It is found that variations in the ratio of educated population does not seem to constitute a plausible explanation for the observed pattern of growth for economies where productivity experienced deterioration in the early periods and then gradually leveled off. However, the results do suggest that, for economies where agricultural productivity exhibits obvious improvements throughout the entire time span, education constitutes a major determinant of the change in productivity.

A comparison of the progression and stagnation/recession regimes reveals differential impact of education on agricultural productivity. The result suggests possible bias in evaluating the effect of education on agricultural productivity once the differential effect of education under different state of technology is not properly accounted for. Moreover, the results suggest that there exists a threshold for education to be influential to agricultural productivity change when the eight East-Asian economies are categoried by their degree of economic development. Generally speaking, however, the group of economies where education constitutes a major determinant of productivity growth in the progression and/or stagnation/recession regimes tend to reach their turning point in short time. Therefore, the results render support to policies aiming at giving an impetus to human capital investment in the agriculture sector.

Acknowledge

An earlier version of this paper was presented by the author and Fung-Mey Huang at the 2009 International Association of Agricultural Economists Conference, Beijing, China, August 16-22. The author thanks Fung-Mey Huang for her valuable efforts devoted to present the work as well as the assistance in the estimation of the econometric model.

References

Alauddin, M., Headey, D. & Rao, D. S. P. (2005). Explaining agricultural productivity levels and growth: an international perspective. Centre for Efficiency and Productivity Analysis Working Paper 02/2005.

Alene, D. A. & Manyong, V. M. (2007). The effects of education on agricultural productivity under traditional and improved technology in northern Nigeria: an endogenous switching regression analysis. *Empirical Economics*, 32, 141-159.

Ali, M. & Byerlee, D. (1991). Economic efficiency of small farmers in a changing world: a survey of recent evidence. *Journal of International Development*, 3, 1-27.

Antle, J. & Capalbo, S. (1988). An introduction to recent developments in production theory and productivity measurement. In S. Capalbo & J. Antle (Eds.), *Agricultural Productivity Measurement and Explanation*. Washington, DC: Research for the Future.

Appleton, S. & Balihuta, A. (1996). Education and agricultural productivity: evidence from Uganda. *Journal of International Development*, 8, 415-444.

Asadullah, M. N. & Rahman, S. (2009). Farm productivity and efficiency in rural Bangladesh: the role of education revisited. *Applied Economics*, 41, 17-33.

Bosworth, B. & Collins, S. M. (2007). Accounting for growth: comparing China and India. National Bureau of Economic Research Working Paper, No. 12943.

Clark, C. (1940). The conditions of economic progress. London: Macmillan.

Chavas, J.-P. (2001). An international analysis of agricultural productivity. Chapter 2 in L. Zepeda (Eds.) Agricultural investment and productivity in developing countries. FAO Economic and Social Development Paper, No. 148.

Coelli, T. J., Prasada Rao, D. S., O'Donnell, C. J. & Battese, G. E. (2005). An introduction to efficiency and productivity analysis. Springer.

Daberkow, S., Fernandez-Cornejo, J. & James, P. (2003). Factors affecting the likelihood of corn rootworm bt seed adoption. *AgBioForum*, 6, 79-86.

Daberkow, S. G. & McBride, W. D. (2003). Farm and operator characteristics affecting the awareness and adoption of precision agriculture technologies in the US. *Precision Agriculture*, 4, 163-77.

Färe, R., Grosskopf, S., Lindgren, B. & Roos, P. (1989). Productivity developments in Swedish hospitals: a Malmquist output index approach. Southern Illinois University, Discussion Paper No. 89-3.

Färe, R., Grosskopf, S., Norris, M. & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *American Economic Review*, 84, 66-83.

Fuglie, K. O. & Kascak, C. A. (2001). Adoption and diffusion of natural-resthece-conserving agricultural technology. *Review of Agricultural Economics*, 23, 386-403.

Griliches, Z. (1963). The sources of measured productivity growth: United States agriculture, 1940-1960. *Journal of Political Economy*, 71, 331-346.

Hayami, Y. (1969). Sources of agricultural productivity gap among selected countries. *American Journal of Agricultural Economics*, 51, 564-575.
Hayami, Y. & Ruttan, V. W. (1970). Agricultural productivity differences among countries. *American Economic Review*, 60, 895-911.
Jamison, D. & Lau, L. (1982). *Farmer education and farm efficiency*. Washington, DC: World Bank.
Kawagoe, T. & Hayami, Y. (1985). An intercountry comparison of agricultural production efficiency. *American Journal of Agricultural Economics*, 67, 87-92.
Knight, J., Weir, S. & Tassew, W. (2003). The role of education in facilitating risk-taking and innovation in agriculture. *The Journal of Development Studies*, 39, 1-12.
Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, 22, 3-42.
Luh, Y.-H., Chang, C. C. & Huang, F.-M. (2008). Efficiency change and productivity growth in agriculture: a comparative analysis for selected East-Asian economies. *Journal of Asian Economics*, 19, 312-324.
Mankiw, N. G., Romer, D. & Weil, D. N. (1992). A contribution to the empirics of economic growth. *Quarterly Journal of Economics*, 107, 407-437.
Pierpaoli, E., Carli, G., Pignatti, E. & Canavari, M. (2013). Drivers of precision agriculture technologies adoption: a literature review. *Procedia Technology*, 8, 61-69.
Romer, P. (1990). Endogenous technological change. *Journal of Political Economy*, 98, 71-102.
Schultz, T. W. (1975). The value of the ability to deal with disequilibria. *Journal of Economic Literature*, 13, 827-846.
Zepeda, L. (2001). Agricultural investment and productivity in developing countries. FAO Economic and Social Development Paper, No. 148.

Appendix. Figures of Turning Points

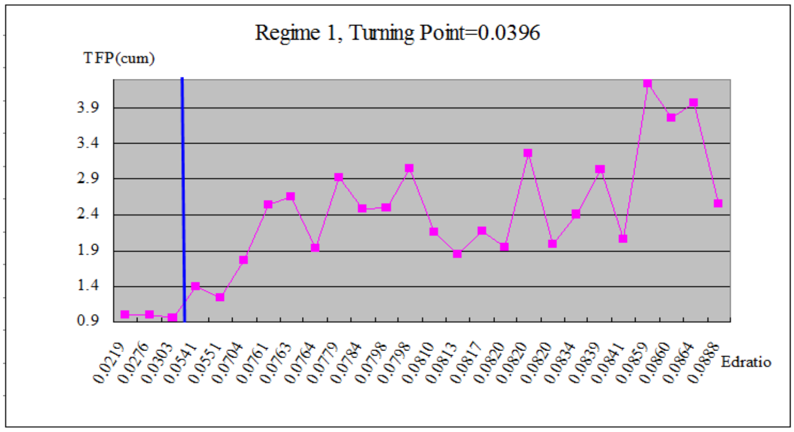

Figure A1. Effects of Education – Malaysia

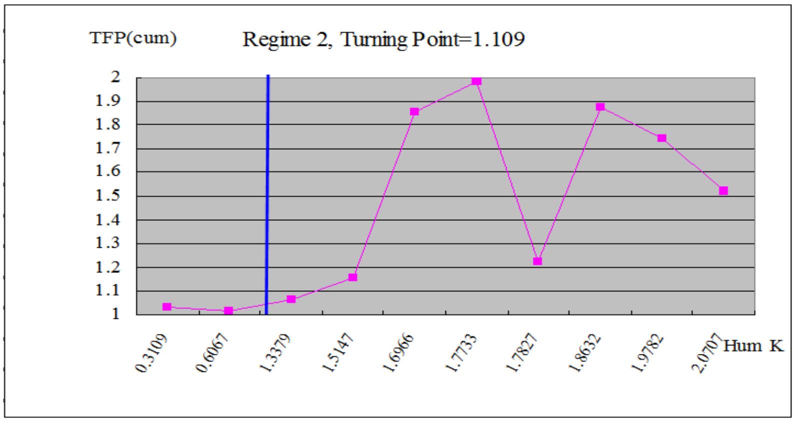

Figure A2. Effects of Education – Japan

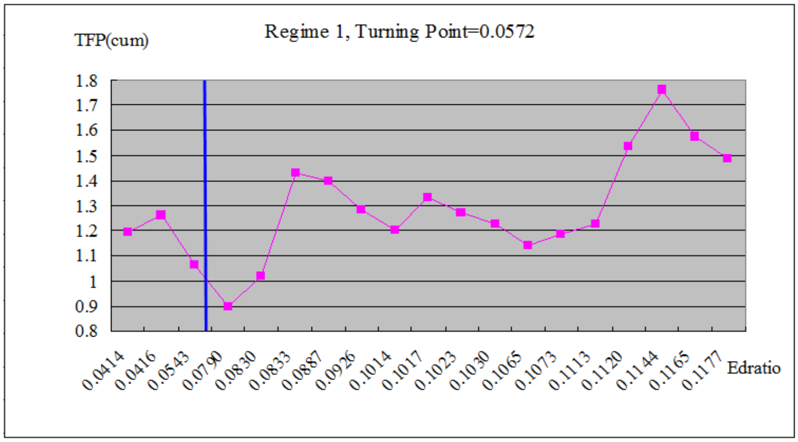

Figure A3 (a). Effects of Education – South Korea

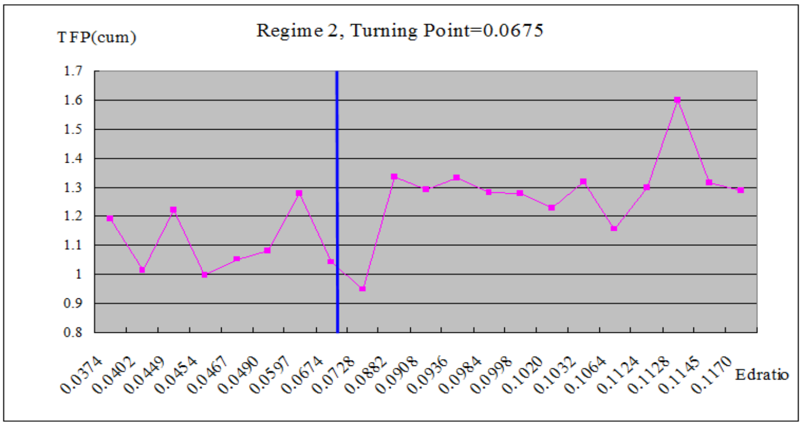

Figure A3 (b). Effects of Education – South Korea

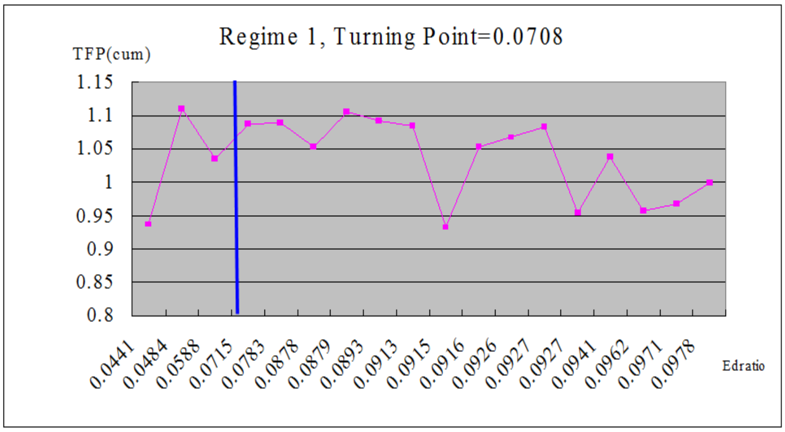

Figure A4 (a). Effects of Education – Taiwan

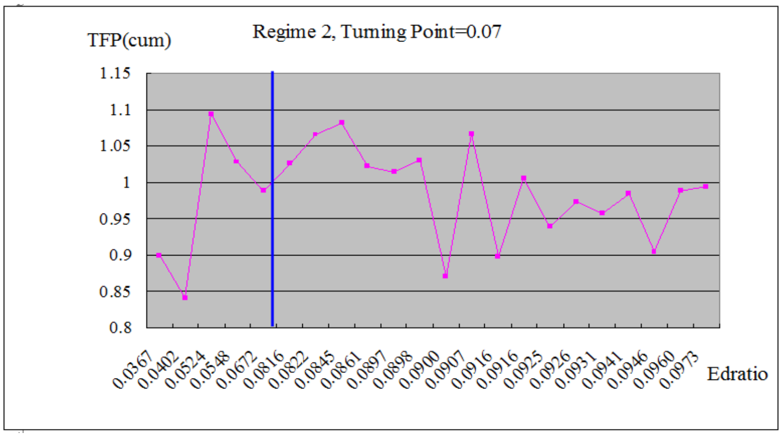

Figure A4 (b). Effects of Education – Taiwan