What Drives Labour Productivity in the Ageing Agriculture of Thailand?

Waleerat Suphannachart[1]

Abstract

Thailand has particularly low labour productivity in agriculture as compared to industry and services. The situation is worrisome as the country population is increasingly ageing amidst the slow pace of structural transformation and the confronting middle-income trap. It is thus the purpose of this paper to investigate factors affecting labour productivity in the agricultural sector of Thailand taking into account the role of population ageing. The error correction modeling technique and time series data during 1970-2014 are employed to examine sources of the agricultural labour productivity. The results show that major factors positively influencing the agricultural labour productivity are the capital-labour ratio, land-labour ratio, research budget-labour ratio, and education level. However, there is no statistical evidence that the population ageing variable has a significant impact on the productivity. The results highlight the importance of physical capital accumulation, farm size, agricultural research, and human capital investment.

JEL: J24, O13

Keywords: Labour Productivity, Population Ageing, Thai Agriculture

1. Introduction

Thailand has particularly low labour productivity in agriculture as compared to industry and services (Figure 1). The situation is worrisome as the country population is increasingly ageing amidst the slow pace of structural transformation and the middle-income trap. In particular, Thailand is expected to become an aged society with 20 percent of total population aged 60 years and above in 2025 which is much earlier than other ASEAN countries (except Singapore). The country's GNI per capita is still in the upper-middle-income group and so it is highly likely that the aged society will be reached before the country can raise her income per capita out of the current income group (Tangkitvanich and Bisonyabut, 2014, United Nations, 2013). In addition, the large dispersion of productivity across sectors in Thailand suggests large potential aggregate productivity gains from the labour reallocation across sectors but the transformation process appears to have slowed down (Klyuev, 2015).

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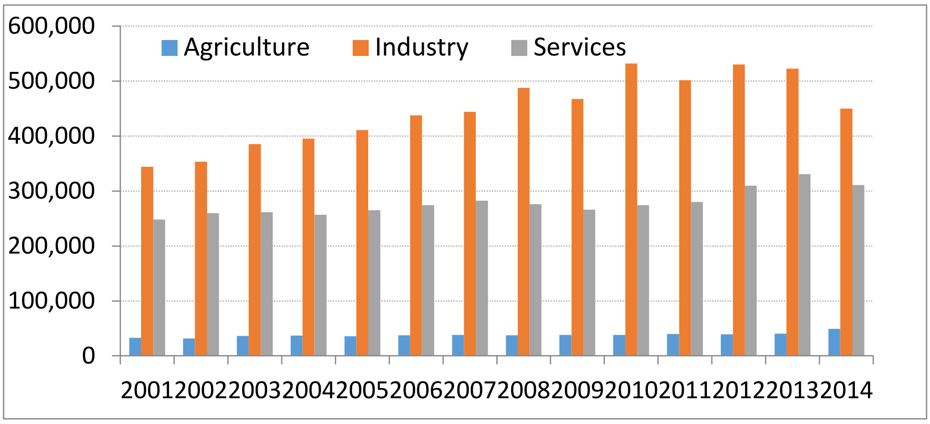
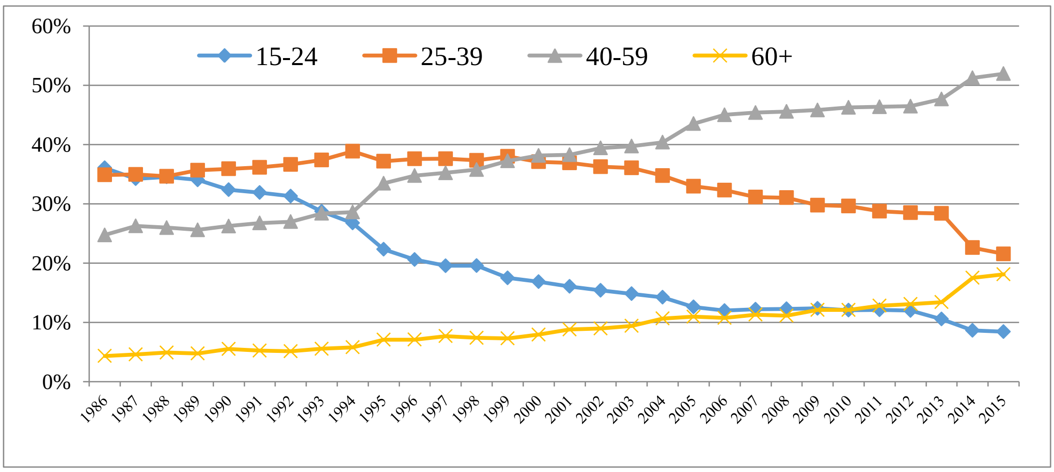
Figure 1: Value Added per Worker in Agriculture, Industry and Services



Source: Author's calculation based on National Economic and Social Development Board (NESDB)'s GDP measured as real value added and National Statistical Office (NSO)'s Labour Force Survey.

In the agricultural sector, the employment share has continuously declined since 1980s while the number of elderly workers has increased. The number of workers aged 40-59 years old and 60 years and above have increased continuously while those of 15-24 years and 25-39 years age groups have declined markedly (Figure 2). The proportion of agricultural workers aged 60 years and above has exceeded 10 percent since 2004 and has continued rising afterwards. The majority of agricultural labour is in the age group of 45-59 years old. This poses challenges to the country's quality growth notably in terms of improving farm efficiency and aggregate productivity as old aged farmers tend to have health concerns and limitations in adopting new technologies. The structural transformation process of reallocating elderly workers from less productive agriculture to more productive sectors could be slower or even stagnant.

Figure 2: Agricultural Labour Force Classified by Age Group



Source: Thai Labour Force Survey, National Statistical Office

Labour productivity is often used as an index of production efficiency and an index of increase in income (Shintani, 2003). It is an important indicator of a country's living standard as it implies an average income (or output) a worker earns. Aggregate productivity can be improved through a reallocation of labour from a lower to a higher productivity sector (structural transformation), which help boost overall economic growth. If factors explaining such a low agricultural productivity can be identified then the sluggish structural transformation could be revived and hence the overall productivity and economic growth can be raised. It is also crucial to investigate the effect of population ageing on labour productivity and to identify factors that drive labour productivity growth that could potentially offset the economic burden caused by a declining employment.

A number of studies have investigated factors affecting labour productivity (Kumar and Russell, 2002, Wye and Isamail, 2012, Guest, 2011, Valerio, 2014) but a link between labour population ageing and agricultural labour productivity still received little attention. Particularly, there is still no empirical evidence in the case of Thai agriculture. This study aims to fill this gap in the literature by investigating factors affecting labour productivity in the agricultural sector of Thailand using the newly compiled time-series data set during 1970-2014. The population ageing variable is also tested for its role on the productivity. Policy recommendation is expected to be drawn in order to shed light on how to enhance labour productivity particularly in the ageing economy.

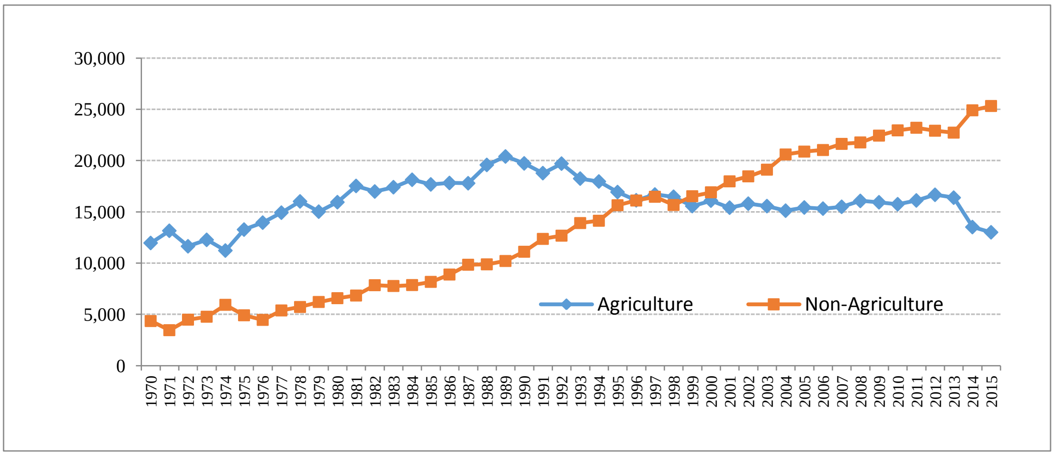
The remaining of the present paper reviews the background of Thai agricultural employment with an emphasis on the labour productivity, followed by literature review of labour productivity determinants studies and discussions on the model specifications and source of data used in this paper. Research findings are presented next and finally is the conclusion and policy implication.

2. Background of Thai Agricultural Employment and Labour Productivity

Thai agriculture has long been a major source of employment generation. Over the period of 1970-2015, agricultural employment accounted for more than half of total employment for almost three decades. However, since the early 1980s, the share of agricultural employment in total employment has declined. This declining trend of agricultural employment is in line with the structural change of the Thai economy that has shifted from agricultural-based to industrialized, attracting agricultural labour towards industries and services. Figure 3 shows the number of agricultural workers has declined while that of non-agriculture increased.

The process of reallocating workers from less productive agriculture to more productive sectors (or structural transformation) had continuously proceeded since the industrial expansion of the 1980s but slightly reversed during the 1997-1998 financial crises when a number of industrial workers had moved back to the agricultural sector. After the crisis, structural transformation proceeds slowly. Since 2004 onwards the number of employment in agriculture started to pick up slightly notably during 2011-2012. This is partly due to the rise in agricultural product prices. However, the agricultural labour force has dropped since 2014 which is in line with the downward trend of agricultural commodity prices.

Figure 3: Numbers of Employed Persons in Agriculture and Non-Agriculture (Thousand persons)



Source: Labour Force Survey (LFS), National Statistical Office (NSO).

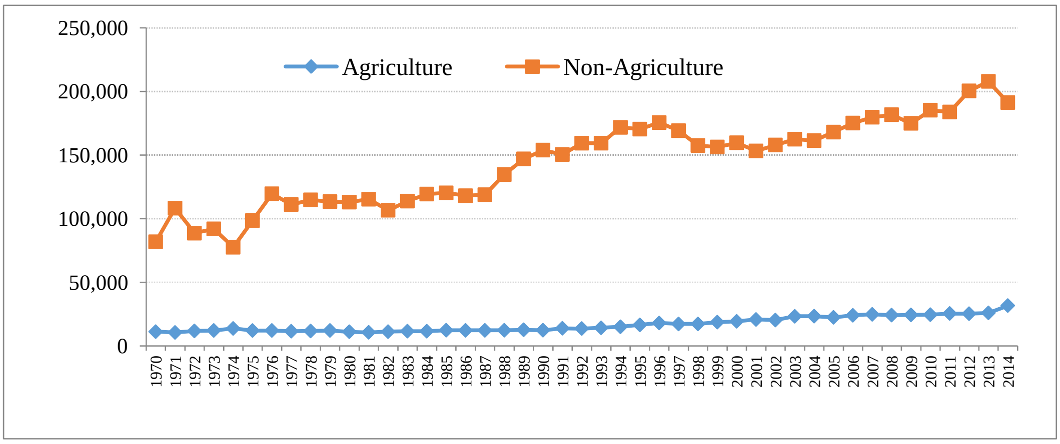
Using the newly compiled data set, the agricultural labour productivity measured as real annual output divided by number of employed workers during 1970-2014 is shown in Table 1. In general, the level of productivity in the non-agricultural sector is about nine-fold higher than in the agricultural sector. This means an agricultural worker receives an average annual income of 16,826.26 Baht or approximately $480.75 per person per year (US$ 1 = 35 Thai Baht) while a non-agricultural worker receives an average annual income of 143,966.02 Baht (approximately $4,113.31 per person per year). However, the average annual growth rate of productivity in agriculture is higher than those of non-agriculture. Output per worker in the agricultural sector has increased at the rate of 2.35 percent per year between 1970 and 2014. Such a rate is quite high compared with the average annual rate of growth of labour productivity in the non-agricultural sector, estimated at 1.93 percent. Table 1 shows these calculations and presents labour productivity in various sub-periods. It indicates output per worker in both the agricultural and non-agricultural sectors has increased but that of agriculture has risen more rapidly particularly since the 1990s. Figure 4 illustrates the changes in labour productivity in both the agricultural and non-agricultural sectors over the study period.

Table 1: Labour Productivity and Annual Growth Rate, 1970-2014

	Output per worker (Baht per person per year)		Growth rate (percent per year)	
	Agriculture	Non-Agriculture	Agriculture	Non-Agriculture
1970-1980	11,919.03	101,716.25	-0.05	3.22
1981-1990	11,988.10	124,776.25	1.00	3.09
1991-2000	16,450.72	162,914.11	4.47	0.37
2001-2014	24,406.00	177,334.90	3.52	1.29
1970-2014	**16,826.26**	**143,966.02**	**2.35**	**1.93**

Source: Author's calculation

Figure 4: Labour Productivity in Thailand, 1970-2014 (Unit: Baht per person per year)



Source: Author's calculation

3. Literature Review

A number of studies, mostly concentrated on industry and overall economy, have investigated factors affecting labour productivity and found the attributable factors are largely a matter of empirical evidence (Kumar and Russell, 2002, Wye and Isamail, 2012, Guest, 2011, Valerio, 2014). The majority of previous studies suggest that total factor productivity (TFP); as in technology advancement, innovation, R&D and skilled labour, and capital intensity; particularly ICT-induced capital deepening, are key sources of labour productivity growth (Wye and Isamail, 2012). In addition, the reallocation of labour from the agricultural sector to the nonagricultural sector is a key to contributor to overall labour productivity growth. Ilmakunnas and Miyakoshi (2013) investigated factors affecting TFP in the ageing economy using the case of manufacturing industries in some OECD countries and found that among the low-skilled the ageing process is a negative driver of productivity, but among the high-skilled it is a positive driver. Tombe (2015) is among the few studies focusing on agriculture. He argued that trade is the key factor explaining why agriculture's share of employment so high and its productivity so low in poor countries. In particular, agricultural trade costs account for one fourth of aggregate productivity differences between rich and poor countries (Tombe, 2015).

Regarding the implications of ageing population Serban (2012) suggested that the effects of unfavourable demographic conditions on labour market can be partially over passed by education in all developed and developing countries all over the world. The population ageing will moderately decrease the rate of economic growth in developed countries while it will not significantly impede the pace of economic growth in developing countries (Bloom et al., 2010). On the contrary, Rigo et al. (2013) provided firm-level data evidence on the Belgian economy that the age structure of firms is a key determinant of their productivity and the ageing workforce will have a significant negative impact on firms' performance and labour markets. Guest (2011) investigated the link between population ageing and labour productivity using data for the United States and Australia and found that population ageing will shift expenditure towards goods with relatively high capital intensity. The labour productivity was simulated to rise by 1-4 percent per annum by 2050 which might partially offset the negative effect of ageing on living standards.

Similar to the international studies, the majority of Thai studies have concentrated on labour productivity of the overall economy but Thai agriculture received little attention. For example, Kajanakaroon (2001) investigates the determinants of the long-run labour productivity growth model in Thailand and found the changes in export-labour ratio growth and physical capital-labour ratio growth have a significantly positive effect on the labour productivity growth in Thailand. Santipollavut et al. (2007) also confirm that physical capital investment is an important factor affecting the labour productivity along with formal and informal education and promotion of physical and mental labour's health. Suphannachart (2013) found capital-labour ratio, land-labour ratio, and research budget-labour ratio are major factors positively influencing the labour productivity of Thai rice production during 1984-2010. Thus far there has not been a study that investigates the role of population ageing on labour productivity in the agricultural sector of Thailand.

4. Methodology and Data

The labour productivity determinant model is specified based on the agricultural production function that includes land, labour and capital as conventional inputs that explain agricultural output. As labour productivity is a partial productivity the amounts of other inputs may vary, increases in output per worker can result from either increase in the use of other conventional inputs (land and capital) or to changes in technology. Besides the conventional inputs, other explanatory variables are chosen based on the concept used to analyse agricultural productivity developed by Evenson (2001) that specifies a partial productivity measure as a function of climate factors, soil quality factors, technological factors (such as agricultural research and extension), infrastructure (such as irrigation), and farmer skills. In addition, the other potential drivers of labour productivity reviewed in the literature, namely TFP and trade, are also taken into account. Since the investigation of labour productivity determinant is also a matter of empirical study, some potential explanatory variables have two alternative measures which are investigated and selected in the regression analysis. Thus, the model employed in this study can be written in a stylized form as shown in equation (1).

$$QL = f(KL, AL, IL, Tech, Trade, Edu, Age, Weather) \qquad (1)$$

where *QL* is denotes agricultural labour productivity, *KL* denotes agricultural capital per worker (capital-labour ratio), *AL* denotes agricultural land area per worker (land-labour ratio), *IL* is denotes infrastructure factor represented by irrigation, *Tech* denotes technology factors represented by agricultural research expenditure and total factor productivity (TFP), *Trade* denotes trade factors represented by trade openness and agricultural exports, *Edu* denotes farmer education and skills, *Age* denotes population ageing, and *Weather* denotes weather or natural factors.

The expected relationships between agricultural labour productivity and the explanatory variables are as follows. Capital input enhances a worker to produce more output and should increase the productivity. Land input also allows a worker to cultivate more output thereby expecting to raise the productivity. Irrigation is an important source of water supply during dry seasons. It also facilitates the adoption of new technology like modern rice varieties thereby raising the productivity. Technology is expected to raise the productivity as it enables farmers to produce more output using the same or fewer inputs. Trade enhances market competition as well as expanding market size through export. It is expected to raise the productivity. Education is recognized as a mean of improving labour quality which can increase efficiency in the use of physical capital and adoption of technology. Better educated workers are expected to contribute positively to productivity.

Regarding the variable measurement and data sources, agricultural labour productivity (the dependent variable) is measured as real output (at 1988 fixed-prices) divided by the number of employed workers. Labour input is represented by the number of employed persons in the agricultural sector (crops, livestock, fisheries and forestry). Although the total working hours is a preferable flow measure of labour input, the number of workers employed is used instead because it was found that hours reported in agriculture were a mixture of both on- and off-farm work, which includes non-agricultural activities (Tinakorn and Sussangkarn, 1996, p.55). It is obtained from the Labour Force Survey (LFS) conducted by the National Statistical Office (NSO). Labour input includes those of age 15 and over working in the fields during the survey period in the rainy season (July-September) when the agricultural population is most active in the fields. This comprises both self-employed (farm owner-operator, family labour employees) and private workers (contract or hired labour).

For the potential factors affecting the labour productivity identified in equation (1) the data series are mainly obtained from the official sources. Note that the data series representing ageing farmers or proportion of agricultural workers aged 60 years or over (*Age*) are available from 1986 onwards. Thus, the inclusion of *Age* variable covers a shorter period. The models are estimated separately with and without this ageing variable. The models that include *Age* employs data from 1986-2014 while the models that exclude *Age* cover a longer period of 1970-2014. Summary of data sources and definition is shown in Table 2 and the descriptive statistics of the relevant variable are summarized in Table 3. Explanations on the explanatory variables are briefly described as follows.

Capital is measured as agricultural net capital stock per unit of labour (KL). The capital stock net of annual depreciation in the overall agricultural sector comprises both public and private capital, mainly including construction costs of the irrigation system, agricultural machinery and equipment, farm buildings and imported breeding livestock. The data are obtained from the National Economic and Social Development Board.

Land is measured as amount of land used in agricultural production per unit of labour (AL). The data are obtained from the Office of Agricultural Economics.

Infrastructure is represented by accumulated irrigation area per worker (IL). The data are obtained from the Office of Agricultural Economics.

Technology factors are represented by public agricultural research per worker (RL) and, separately, TFP. ***Public agricultural research*** is measured as real government budget expenditure on the R&D activities of the Ministry of Agriculture and Cooperatives, where almost all agricultural research occurs. The budget data are from the Bureau of the Budget under the office of the Prime Minister. ***TFP*** is measured using the growth accounting method, which means that it is a residual of output growth after subtracting labour, land and capital growth, weighted by their respective factor income shares. Detailed explanations on the TFP measurement method is provided in Suphannachart and Warr (2012, 2011). The TFP data series were extended to cover the period of 1971 to 2014 in Suphannachart (2016).

Trade factors are represented by export-labour ratio (XL) measured as the ratio of agricultural exports to total number of agricultural labour and, separately, trade openness (TO) that is measured as the percentage share of agricultural imports and exports in total agricultural output. Import and export values of agricultural commodities are obtained from the Office of Agricultural Economics. Data on agricultural output are obtained from the National Economic and Social Development Board.

Education is measured as the percentage share of the agricultural labour force with upper secondary education in the total agricultural labour force. Agricultural workers with at least upper secondary education are considered higher educated groups of workers thereby representing human capital in the agricultural sector. The numbers of agricultural labour classified by education attainment are obtained from the Labour Force Survey conducted by the National Statistical Office.

Population ageing is represented by shares of agricultural labour force aged 60 years and over (Age). The data is obtained from Thailand Labour Force Survey of the National Statistical Office.

Weather factors are represented by annual average rainfall measured in millimeters (Rain), using data obtained from the Office of Agricultural Economics (OAE) and, separately, the share of the rice harvested area in planted area (W). Since rice is the most important crop for the Thai economy and its planted area dominates total agricultural land, the share of the rice harvested area is used as a proxy for drought or flooding. A reduction in the ratio implies an occurrence of flooding, drought or bad weather conditions. An increase in the ratio implies good weather conditions or no natural disasters. The data are also obtained from the OAE.

Table 2: Summary of the data sources, 1970-2014

Variable	Definition	Data source
Output	GDP at 1988 prices (value added) in agriculture (million Baht)	National Income of Thailand, National Economic and Social Development Board (NESDB)
Labour	Number of employed persons age 15 and above working in agriculture (persons)	Labour Force Survey, National Statistical Office
Land	Land used in agricultural production (rai)	Office of Agricultural Economics
Capital	Net capital stock at 1988 prices in agriculture (million Baht)	National Economic and Social Development Board
Irrigation	Accumulated irrigation area (rai), including small, medium and large scale irrigation projects	Office of Agricultural Economics
Research expenditure	Research budget expenditure allocated to the Ministry of Agriculture and Cooperatives (million Baht)	Bureau of the budget
TFP	Agricultural total factor productivity measured as a residual of output growth that cannot be explained by land, labour and capital. The TFP growth rates were converted into indexes	Suphannachart and Warr (2011, 2012) and Suphannachart (2016)
Export	Value of agricultural exports (million Baht)	Office of Agricultural Economics
Trade openness	Share of agricultural imports and exports in total agricultural output.	Office of Agricultural Economics
Education	Shares of agricultural labour force with upper secondary education level	Labour Force Survey, National Statistical Office

Ageing farmers	Shares of agricultural labour force aged 60 years and over	Labour Force Survey, National Statistical Office (1986-2014)*
Rainfall	Amount of regional rainfall (millimetre)	Office of Agricultural Economics
Weather condition	Rice harvested as share in total rice planted area.	Office of Agricultural Economics

Note: *The data on number of employed persons classified by age are available from 1986 onwards.

Table 3: Summary statistics of variables in the labour productivity determinant models (1970-2014)

Variables	Obs	Mean	Std.Dev.
Labour Productivity: lnQL	45	9.678	0.324
Capital-labour ratio: lnKL	45	10.313	0.480
Land-labour ratio: lnAL	45	2.089	0.095
Irrigation area-labour ratio: lnIL	45	0.488	0.297
Research-labour ratio: lnRL	45	3.411	0.751
TFP: lnTFP	44	0.222	0.104
Export-labour ratio: lnXL	45	9.662	1.239
Trade openness: lnTO	45	0.106	0.432
Education: lnEdu	45	0.443	1.712
Ageing farmers: lnAge	29	-2.510	0.389
Rainfall: lnRain	45	7.103	0.269
Weather and natural factor: lnW	45	-0.062	0.025

Note: all variables are expressed in natural logs.

With regards to the estimation method, applying the standard OLS method to non-stationary data series can produce a spurious regression while first-differencing that ensures stationary data series can overlook some meaningful level information. To guard against the possibility of a spurious relationship while maintaining the level information, two main approaches offer reasonable solutions. First is the co-integration approach pioneered by Engle and Granger (1987) and later improved by studies such as Johansen (1988) and Phillips and Hansen (1990). The Engle and Granger pioneering method is appropriate when dealing with non-stationary data that are integrated of the same order – that is, all data series are integrated processes of order 1. Second is the unrestricted error correction modeling (ECM) method developed by Hendry and his co-researchers (Davidson et al., 1978, Hendry et al., 1984, Hendry, 1995). Under the ECM, the long-run relationship is embedded within a detailed dynamic specification, including both lagged dependent and independent variables, which helps minimize the possibility of estimating a spurious regression. It has been argued that the ECM method developed by Hendry (1995) can legitimately be applied to data series that are integrated of different orders, provided the resulting specification makes economic sense (Athukorala and Sen, 2002).

The first step of the estimation process is to conduct standard unit root tests on each variable. The Augmented Dickey-Fuller (ADF) test is employed in this study to test the time-series properties of the data series. The ADF tests the null hypothesis of non-stationarity against the alternative of stationarity (Banerjee et al., 1993). The results in Table 4 shows the variables used in this study is a mixture of stationary series or I(0) and nonstationary series that are integrated of order 1 or I(1). Since the data series are integrated of different orders, the error correction modeling (ECM) procedure of Hendry (1995) is used in this study.

Table 4: Augmented Dickey-Fuller Test for Unit Roots, 1970-2014

Variables	t-statistics for level without time trend	t-statistics for level with time trend	t-statistics for first difference without time trend	t-statistics for first difference with time trend
QL	0.764(0)	-1.752(0)	-7.271(0)*	-7.463(0)*
KL	1.464(0)	-1.425(0)	-5.645(0)*	-6.241(0)*
AL	-2.075(0)	-2.080(0)	-7.767(0)*	-7.671(0)*
IL	-0.724(0)	-4.518(1)*	-10.420(0)*	-10.336(0)*
RL	-2.062(0)	-2.298(0)	-6.813(0)*	-6.737(0)*
TFP	-1.641(0)	-4.991(0)*	-6.652(1)*	-6.541(1)*
XL	-2.670(1)**	-3.144(0)**	-8.090(0)*	-8.706(0)*
TO	-2.352(0)	-1.283(0)	-8.073(0)*	-8.845(0)*
Edu	-2.489(0)	-1.808(0)	-7.208(0)*	-7.599(0)*
Age	-0.664(0)	-3.602(0)**	-5.135(0)*	-5.475(1)*
Rain	-2.108(0)	-2.075(0)	-8.965(0)*	-9.261(0)*
W	-6.471(0)*	-6.340(0)*	-10.343(0)*	-10.217(0)*

Notes: 1. All variables are measured in natural logarithms. 2. * and ** denote the rejection of the null hypothesis at the 5 percent and 10 percent level, respectively. 3. Numbers in parentheses indicate the order of augmentation selected on the basis of the Schwarz criterion.

5. Results: What drives the agricultural labor productivity?

With regards to what drives the agricultural labour productivity, the estimation results using the unrestricted error correction modeling (ECM) are divided into two cases, as shown in Table 5. The first case represents a general model of labour productivity determinants without the role of population ageing. It excludes the shares of agricultural workers aged 60 or over (*Age*) as an explanatory variable covering the entire period of 1970-2014. The second case takes into account the role of population ageing by including *Age* variable covering a shorter period of 1986-2014 (due to data availability).

For the entire study period of 1970-2014, the labour productivity determinant equations are statistically significant at the 1 percent level in terms of the standard F test and perform well in terms of standard diagnostic tests for serial correlation, functional form specification, heteroskedasticity and stationarity of the residuals. The final parsimonious equations are shown in Table 5. The choice of dropping or keeping variables in the final models was statistical acceptance in terms of the joint variable deletion tests against the maintained hypothesis. The explanatory variables that have two alternative measures, namely the technology factors (represented by research expenditure and TFP) and trade factors (represented by export-labour ratio and trade openness), are all tested and only significant variables that pass the joint variable deletion tests are kept in the final model.

The final ECM results suggest that major factors affecting labour productivity in the agricultural sector of Thailand are capital-labour ratio (KL), research-labour ratio (RL), and shares of agricultural workers with upper secondary education level (Edu). The agricultural capital stock (such as machinery and equipment) is the only factor that plays a positive and significant role both in short-term and long-term. In the short run a 1 percent increase in agricultural capital per worker leads to 0.714 percent increase in agricultural productivity whereas in the long run a 1 percent increase in agricultural capital per worker raises the labour productivity by 0.57 percent. This conforms to prior expectations and previous studies as the number of agricultural labour force is declining Thai farms have become more mechanized and so the more machinery each farmer has the more output he or she can produce. Agricultural research expenditure per worker (representing technological factor) has shown to be statistically significant only in the short run. This is partly due to the very small and declining amount of agricultural research investment, the impact of research-based technology can only drive labour productivity temporarily (Suphannachart, 2015). On the contrary, an education variable representing human capital and farmers' skills has only a long-term effect on the labour productivity; a 1 percent increase in the shares of agricultural labour with upper secondary education leads to 0.095 percent increase in the productivity. As it takes time to invest in human capital the impact can be recognized only in the long run.

When the population ageing variable (*Age*) is included covering the study period of 1986-2014, the ECM results show quite similar results except that the long run impact of capital accumulation becomes insignificant while that of land size turns out significant. The capital-labor ratio and the research-labor ratio are still statistically significant in the short run but their impacts disappear in the long run. The land-labour ratio has a positive and significant impact in the long term, with a 1 percent increase in land area per worker leads to 1.092 percent increase in the labour productivity. As the number of agricultural workers have been declining while the agricultural land is roughly maintained the land area per worker has increased. Larger farm size is expected to benefit from economies of scale and more efficient uses of resources and farm management resulting in higher income per worker. The education variable is also statistically significant in the long run suggesting a 1 percent increase in the shares of agricultural labour with upper secondary education leads to 0.143 percent increase in the productivity. The magnitude of the human capital impact is larger than the first case that covers the longer period suggesting the increasingly important role of education in later periods. However, the population ageing measured as shares of agricultural labour force aged 60 or over (*Age* variable) are not statistically significant. The impact of population ageing in the agricultural sector of Thailand may not be as bad as many people expect as Thai people have longer life expectancy and become healthier than in the past. More and more agricultural workers can work beyond the age of 60 (Figure 2). Life-long farm experiences of the elderly with helps of machinery and new technology could probably compensate their health deficiency and prolong their old-age dependency.

Table 5: Factors affecting agricultural labour productivity in Thailand

Dependent variables: $\Delta \ln QL_t$				
	Ageing variable ($lnAge$) excluded (period: 1970-2014)		Ageing variable ($lnAge$) included (period: 1986-2014)	
	Estimated coefficients (t-ratios)	Long-run elasticity	Estimated coefficients (t-ratios)	Long-run elasticity
Constant	2.167 (3.348)***		6.051 (2.729)**	
$\Delta \ln KL_t$	0.714 (6.079)***		0.792 (4.692)***	
$\Delta \ln XL_t$	0.040 (0.790)		0.131 (1.643)	
$\Delta \ln RL_{t-2}$	0.030 (2.235)**		0.047 (2.124)**	
$\Delta \ln Edu_t$	0.013 (0.445)		-0.033 (-0.437)	
$\ln KL_{t-1}$	0.319 (3.436)***	**0.570**	-0.040 (-0.203)	
$\ln AL_{t-1}$	0.184 (1.069)		0.920 (3.047)***	**1.092**
$\ln XL_{t-1}$	0.046 (1.143)		0.091 (0.968)	
$\ln Edu_{t-1}$	0.053 (2.362)**	**0.095**	0.120 (2.655)***	**0.143**

$\ln Age_{t-1}$			0.153 (1.168)	
$\ln QL_{t-1}$	-0.560 (-3.646)***		-0.842 (-3.954)***	
N (no. of observations)	42		28	
k (no. of parameters)	10		11	
Adjusted R^2	0.70		0.70	
F-statistic	11.72		7.44	
S.E. of regression	0.03		0.03	
Diagnostic tests:				
$LM(1)$, $F(1, N\text{-}k\text{-}1)$	0.72 [p = 0.40]		0.00 [p = 0.97]	
$LM(2)$, $F(2, N\text{-}k\text{-}2)$	0.89 [p = 0.42]		0.69 [p = 0.52]	
RESET, $F(1, N\text{-}k\text{-}1)$	0.43 [p = 0.51]		0.57 [p = 0.23]	
JBN, $\chi^2(2)$	0.43 [p = 0.81]		0.22 [p = 0.89]	
ARCH, $F(1, N\text{-}2)$	0.00 [p = 0.96]		0.72 [p = 0.40]	
ADF	-6.60 [p = 0.00]		-7.51 [p = 0.00]	

Notes: 1. The level of statistical significance is denoted as: * = 10 percent, ** = 5 percent and *** = 1 percent. 2. Long-run elasticities can be computed by dividing the estimated coefficients of the level terms by the positive value of the coefficient of the lagged dependent variable. 3. Diagnostic tests are [numbers in square brackets are *p*-values of the test statistics]: *LM* is Breusch-Godfrey serial correlation LM test; *RESET* is Ramsey test for functional form mis-specification; *JBN* is Jarque-Bera test of normality of residual; *ARCH* is Engle's autoregressive conditional heteroskedasticity test; *ADF* is Augmented Dickey-Fuller test for residual stationarity.

6. Conclusion

In conclusion, factors those drive the labour productivity in Thai agriculture, in which its labour has become increasingly ageing, are capital-labour ratio, land-labour ratio, research budget-labour ratio, and education level. The results are generally consistent with the previous research that analyzes factors affecting labour productivity of the rice sector which occupied the largest share of the agricultural sector and found capital-labour ratio, land-labour ratio, and research budget-labour ratio are major factors positively influencing the labour productivity of Thai rice production (Suphannachart, 2013). Agricultural labours with more capital input and land area have shown to be more productive. The significant role of the research investment is also conforms to the previous finding from Suphannachart and War (2011) that shows agricultural research drives the total factor productivity in Thai agriculture. As agricultural research can improve quality of agricultural capital (including machinery) that proved significant in driving the labour productivity enhancing agricultural research investment could probably help sustain both the research and capital impact on productivity into the longer term. The role of education takes time to reap its benefit but proved significant in raising the productivity. Nonetheless, there is no statistical evidence that the rising proportion of ageing workers affects the agricultural labour productivity.

The statistical results from this study suggest that in order to enhance the agricultural productivity policy emphasis should be directed to physical capital accumulation, farm size expansion, agricultural research investment, and human capital investment. These factors are crucial for stimulating the sluggish structural transformation, boosting the aggregate productivity that sustains economic growth, and hence raising per capita income and living standard of the Thai population.

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