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MEASURING RETURNS TO SCALE AMONG VEGETABLE PRODUCERS UNDER TECHNOLOGICAL CHANGE: AN EVIDENCE FROM CHINA

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ABSTRACT

Chinese vegetable industry is rapidly progressing as the vibrant pillar of the rural economy. The imperatives of returns to scale under technological change in the domain of vegetable production are gaining much attention of researchers and policy makers. This research endeavor is aimed to estimate of returns to scale under technological scenario. The return to scale and technological change indexes were calculated by employing survey data collected through primary sources. First, the constant return to scale point was estimated by BCC-DEA model. Then, based on Malmquist-DEA, the total factor productivity of vegetables was calculated for a time series of 2009 to 2016, and the technological progress index is decomposed. Then, the effects of technological progress on the same scale and different scales were determined respectively. The results reveal that most of the vegetable production at present is in the trajectory of small scale cultivation with increasing return to scale. The technical progress index of small-scale planting was better than that of larger scale planting in recent years. Therefore, considerable importance should be put to small-scale growers in vegetable technology popularization. Moreover, the promoting effect of technological progress on production efficiency varies with the difference of acreages. Hence, the possible policy guidance for further improving vegetable production efficiency has been articulated.

Keywords: Return to scale; technological change; DEA model; fresh produce; China.

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INTRODUCTION

Fresh vegetable produce along with its smooth supply has gained great importance in recent years. As the staple foods in China, the supply fluctuation in vegetable could put much effluence and effect on the society especially for people's daily lives. Vegetables are also the most competitive export varieties in China's agricultural products. The vegetable exports have continued to increase in recent years. In 2017, both export and trade surpluses were about 15 billion dollars (MOA, 2018), which accounted for a large proportion of annual agricultural trade deficit of 50 billion dollars. As one of the few competitive agricultural products, vegetables play an important role in the balance of trade of agricultural products. In the process of realizing the strategy of rural revitalization and constructing the modern agricultural industry system, the coexistence of periodical oversupply and shortage becomes one of the urgent problems to be solved. This requires supply-side structural reform and speeding up the construction of modern agricultural production system. Vegetables are the most advantageous agricultural products and the most important source for increasing farmers' income in China. This is also an important part of accelerating the process of establishing a stronger agriculture (Chongguang and Hui; 2017; Ji *et al.,* 2016).

In recent years, China's vegetable industry has rapidly developed into a pillar industry of rural economy. Does this productivity growth come from Increasing Return to Scale (IRS) brought about by the expansion of vegetable scale of operations? If IRS existed in vegetable production, besides scale efficiency (SE), is it mainly driven by technology progress (TP) or by pure technology efficiency (PTE)? The answer leaves great policy significance. If the former is the case, it shows that vegetable production should continue to monitor the expansion of the scale of operations at present. If the latter is the case, then more attention should be paid to resource inputs and factors substitution. Moreover, flexible adjustment should be made according to factor endowment in order to rationally allocate input factors and adopt new inputs and processes. These two are completely different, and also are the urgent questions that the changing Chinese vegetable industry needs to respond. However, existing researches of relevant nature mainly focuses on rice and other field crops (Guo and Ding, 2016; Wang *et al.,* 2017; Xu *et al.,* 2011). The research combining IRS and PTE from the perspective of vegetable industry is hardly available in the existing body of literature.

An increasing trend of research has been analyzed the connection between vegetables and fruits, usage of agricultural land and production of food at the scale of various spatial. For instance, a study has been conducted in United States and results revealed that Willamette Valley in Oregon production had enough food to meet approximately 10 to 30 percent vegetable for the population in the study area (Giombolini *et al*., 2011). Moreover, in another study it was estimated that share of consuming vegetables and fruits will increase by the population then land would be allocated to higher values crops in New York (Peters *et al*., 2012). Anang *et al*., (2016) conducted a study to analyze scale, technical efficiency by applied data envelopment analysis (DEA) in Ghana and found that farm size has substantial positive impact on scale efficiency. Their study also revealed that number of farmers found increasing return to scale in the study area. Further, they found that other socio-economic factors, such as gender, head of household, irrigation, access to credit and extensions' visit were responsible to increase efficiency. An important thing which can be noted that in agriculture sector small scale farmers are predominance due to producing small land cultivation in developing countries including China. From the perspective of neo-classical economists' advantage can be taken by farmers to increase production and scale efficiency. It is consider that a farm maybe technical efficient but not efficient in scale. It shows that maybe farm are using with best management practices but not getting the benefits of scale economy. Hence, scale efficiency notion is dominant in small households' agriculture sector where, maybe existence of likelihood and economies of scale (Anang *et al*., 2016).

This paper reviewed the existing research on agricultural return to scale and technological progress. It has also put forward some of the testable research hypothesis based on fundamental economic theory. Secondly, measuring the Total Factor Productivity (TFP) by Malmquist-DEA method, the corresponding relationship between different production scales and production efficiency was calculated to verify the hypothesis of existence of returns to vegetable scale. Then, the index of technological progress and technological efficiency was separated from TFP to analyze the main reasons for the growth of TFP. The possible relationship between technological progress and return to scale was also traced. Finally, policy suggestions to promote vegetable production efficiency have been discussed at the end of this manuscript.

Hypothesis: H_1: There is IRS in vegetable production. The improvement of vegetable production efficiency may be affected by return to scale. Recently, the vegetable production scale is mainly affected by two aspects. First is the technological progress of the industry itself together with the large-scale planting spontaneously by the market. China's vegetable industry has been in constant change and evolution, and its production mode, production scale and technology levels are constantly changing. So, optimal production and scale of operation are actually changing. Overall, with the formation of the main producing areas and the gradual deepening of the specialization of production and marketing, its scale of operation shows an expanding trend. It is not uncommon for field vegetable planting to be larger than 100 mu[1] in the main producing areas (Zhang *et al.,* 2018). Secondly, there is an inherent demand for scale due to the change of population structure, urbanization and rising labor costs.

In recent years, with the decrease of comparative income of planting land and the increase of working opportunities in cities, abandonment of farming has occurred in many places, and the trend of large-scale land has been formed spontaneously (Chen, 2013; Cui *et al.,* 2016). Vegetables, as important agricultural products for farmers to increase their income, are also facing similar internal demand of large-scale (Chen and Chen 2018). Under this interactive background, we need to see whether there an increase in return to scale in vegetable production? Under the background of large-scale transfer of farmland management rights, should vegetable, as one of many kinds of agricultural products, also fall in large-scale category? To answer these questions, it must first study whether the current vegetable production scale is still in the increasing interval of return to scale.

H_2: Technological progress has stronger affect in large-scale than small-scale production.

The role of technological progress in vegetable production efficiency may vary according to the differences of operational scale. Economic structural growth is usually driven by technological progress and factor substitution. On the premise that the market is mature and responsive, factor substitution will achieve equilibrium in some period of time and show the growth of total factor productivity, which is continued till the next technological progress. Lin,(2011) pointed out that the endowment structure and structural improvement of production factors are the inherent essential conditions of economic growth. Decomposition of TFP growth in different directions can find the direction of efficiency improvement and decomposition of technological progress is one of them, which is also the classic method of many DEAs (Fare *et al.,* 1994; Yan and Wang 2004). For the technological progress in the growth of vegetable production efficiency, it can analyze and compare the differences of technological progress index under different planting scales to find out the possible influence of scale difference on technological progress.

[1]Mu is used as local unit of agricultural land in China where 1 hectare equals 15 Mu.

MATERIALS AND METHODS

Data sampling and variables: In the evaluation of agricultural production efficiency, the main input is usually divided into two aspects including input of labor and input of means of production (Fang and Zhang 2010; Guo *et al.,* 2010). Previous researches have mostly been using man and animal power, machinery, sowing area, seedling and various chemical fertilizers and pesticides as inputs variables(Coelli and Rao 2005), annual output or output value as outputs variable (Quan, 2009; Zhu *et al.,* 2015). Combining with the existing research methods, this paper selected the annual gross income of farmers as the output index, and labor, seedling, fertilizer, pesticides as the input index, as shown in Table 1.

Table 1. Selection of Input and Output variable.

Type	Variable name	Definition
Input variable	X1	Number of labor input (man-days)
	X2	Fuel tool fee (Yuan)
	X3	Crop planting area (mu)
	X4	Seedling input fee (Yuan)
	X5	Pesticide input fee (Yuan)
	X6	Fertilizer input fee (Yuan)
	X7	Manure input fee (Yuan)
Output variable	Y1	Total annual income (Yuan)

Multilevel mixed sampling method was employed to get representative sample data of main vegetable producing areas in China. There are six major vegetable producing areas. Firstly, several extension stations of vegetable industry system were selected from the main vegetable producing areas in China. Then, the average and representative counties from the regional selected extension stations were selected. Finally, some vegetable growers were randomly selected from specific counties to do the investigation. Questionnaires were sent to various stations through the large-scale vegetable industry system. These were filled out by the targeted respondents and submitted to the system uniformly. Finally, with data collection by the organization staff of laboratory of industrial economics, 5121 questionnaires of vegetable farmers were employed for this analysis.

Returns to scale in DEA method: There are different assumptions of return to scale in many diversified model applications of Data Envelopment Analysis (DEA), such as Constant Return to Scale (CRS) or Variable Return to Scale (VRS), etc. Different DEA models usually fit to different assumptions only (Ma, 2010). For instance, CCR-DEA model is generally assumed to be CRS, while BCC-DEA model is to be taken as VRS (Yang *et al.,* 2013). Malmquist efficiency index could be decomposed into Technical Efficiency Change (TEC) and TP. It could further be divided into PTE and SE under the VRS assumption (Nin *et al.,* 2003; Zhang and Gui 2008), i.e.

$$\mathrm{MI} = \mathrm{TEC} * \mathrm{TP} = \mathrm{PTE} * \mathrm{SE} * \mathrm{TP}$$

The popular explanation is that the improvement of production efficiency is through the action of management decision-making ability and technological progress. The former indicates the ability of resource allocation and optimum of its operational scale.

DEA is used to analyze the efficiency of firm(s) which is a non-parametric approach and used by previous scholars (Barros, 2005; Wöber, 2007). According to the idea, we can make a distinction between the role of technological progress and resource allocation ability by panel data analysis (Gucheng, 2009). In practical application, it should take full account of its hypothetical premise requirement of return to scale and select specific DEA models, according to varying conditions. Existing literature on return to scale generally adopted the Malmquist-Index method designed by Stem Malmquist in 1953 which had been decomposed into TEC, TP and SE (Coelli and Rao 2005; Guojun *et al.,* 2013). Then the efficiency analysis of different types of DMUs in different periods is carried out. Hence, we have used the above methods to testify the research hypothesis.

RESULTS AND DISCUSSION

Descriptive statistics of the used variables: The descriptive statistical characteristics of the used variables in present study are shown in table 2. Further, figures 1 (a) and (b) show according to the frequency distribution of planting area and annual gross income.

Table 2. Descriptive statistics of samples.

Item	Mean	Std	Median	3/4 quarter
Number of labor input (man-days)	782.1	108.0	50	114.6
Fuel tool fee (yuan)	1844.8	141.3	190	430.1
Crop planting area (mu)	181.7	53.8	4.2	10
Seedling input fee (yuan)	4510.9	279.4	265	740
Pesticide input fee (yuan)	2789.2	234.6	250	600
Fertilizer input fee (yuan)	4955.7	208.6	600	1228.8
Manure input fee (yuan)	3647.9	245.2	300	600
Total annual income (yuan)	75280.3	659.0	15750	31192.5

It can be seen in table 2 that the given situation of the farmer shows small and medium-sized farms. A significant difference existed between the samples. From the perspective of crop planting area, 75 percent of the farmers planted less than 10 mu, with a median of 4.2 mu, while the average value was 181.7 mu, with a standard deviation of 53.8 mu. It can be seen that most of the open-field farmers planted on a small scale, but some farmers operated on a larger scale. This is showing a coexistence of more small-scale planting and a small number of large-scale planting. Descriptive statistics of other indicators also show similar kind of features. For example, in the three items of fertilizer input, farm manure input and annual total income, the 3/4 quarter and median of the samples also show that the size of most of the three samples is not large. The mean deviation is 3/4 quarter and the standard deviations are large. This also indicates that there are a few large-scale growers in the samples.

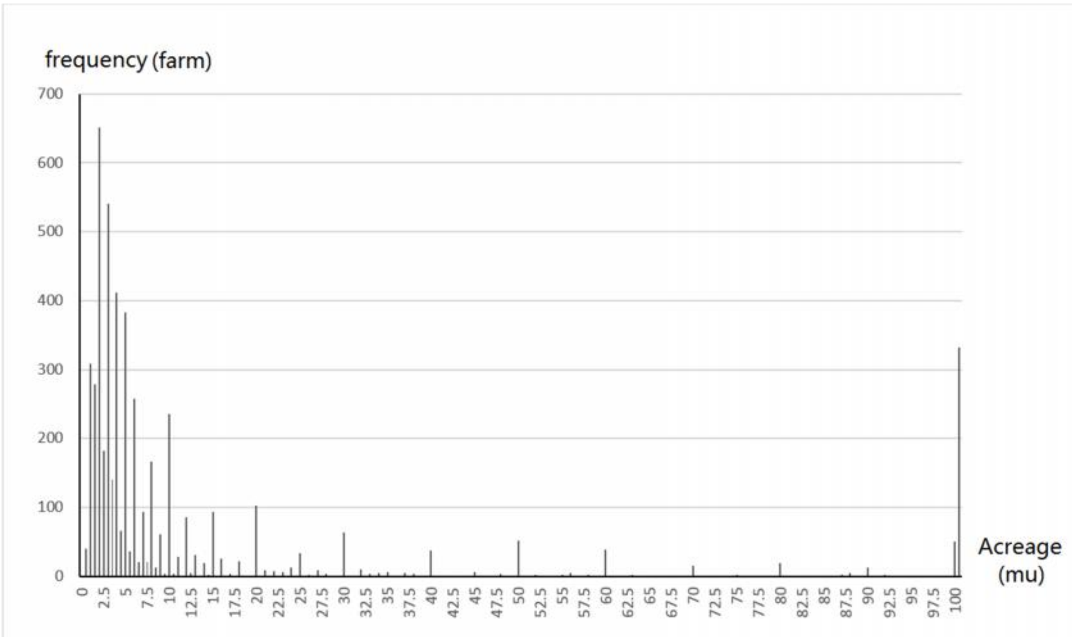

Figure 1 (a) Frequency distribution of vegetable planting acreage.

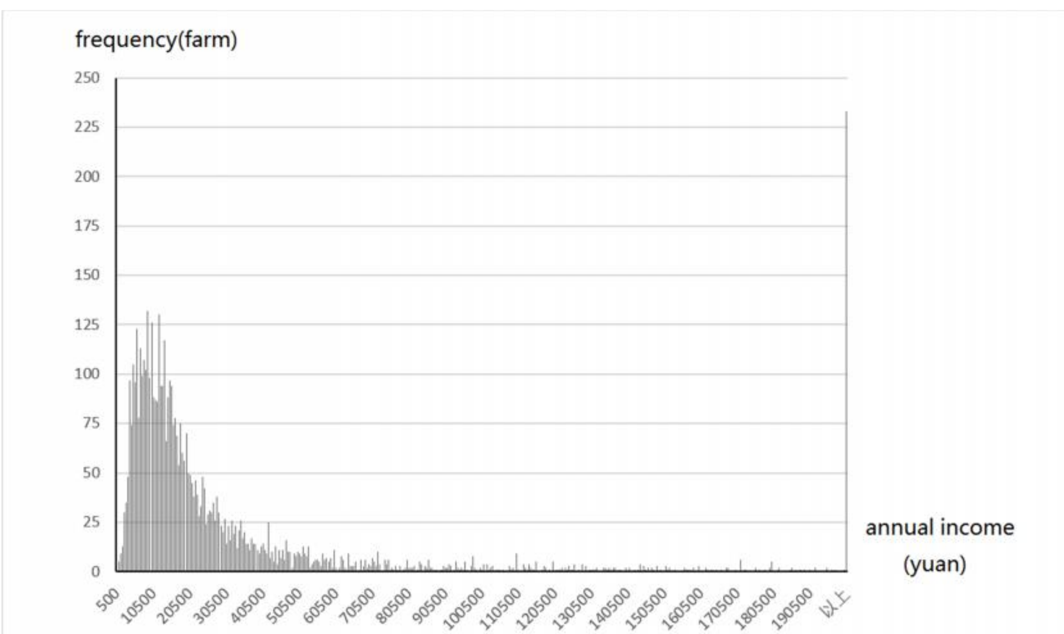

Figure 1 (b) Annual income distribution.

From the distribution chart of crop planting area in figure1 (a) and annual total income in figure 1 (b), it can be seen that more than 300 times occur in each interval between 2.5 and 6 mu of planting area, while the frequency of farmers with over 30 mu is less than 50 times and mostly less than 20 times. From the frequency distribution of annual income, the frequency between 10,000 Yuan and 30,000 Yuan is the highest. While, the frequency of more than 40,000 Yuan rapidly decreases sequentially with the characteristic that the frequency distribution is generally positive and skewed and the long tail extends to the right. A recent study conducted in Nepal regarding rice crop is supporting our results (Osti *et al*., 2017).

Existence of IRS: Firstly, the BCC-O model was applied to measure the RTS with all 5121 DMUs so as to obtain the set of DMUs on the frontier surface. Then, all the frontier and the frontier DMUs belonging to the top 75 percent of collected samples were analyzed respectively to calculate the characteristics of frontier statistics, which are shown in Table 3.

Table 3. Statistical characteristics of DMUs on BCC-O frontier.

Category	Number		Proportion		Mean Area		Std.		Median		3/4 Quarter	
	all	top75%	all	top75%	all	top75%	all	top75%	all	top75%	all	top75%
IRS	65	63	36.3	46.7	3.4	2.2	2.7	1.9	1.9	1.5	2.8	2.3
CRS	89	69	49.7	51.1	37.7	3.1	9.5	2.9	3	2	10	4.6
DRS	25	3	14.0	2.2	444.7	6.0	28.4	2.8	130	4	300	7
Total	179	135	100	100	82.1	2.8	18.5	2.6	2.5	2	10	3.8

Note: In the table, "all" refers to all DMUs at the frontier calculated by BCC-O, while "top75%" refers to the frontier DMUs calculated by BCC-O at the front 75% of all samples.

Table 3 comprehensively reflects the characteristics of sample frontier. Among all DMUs, 179 of them have excellent relative efficiency, including 65 in IRS, 89 in CRS and 25 in DRS. In terms of average of area, CRS and DRS were worked out quite different in all frontiers and 75 percent frontiers.

By descriptive statistics of the sample, we can see that most of the growers are small-scale planting area under 5 mu, of which 75 percent is under 10 mu. Moreover, from the perspective of the total frontier, the average IRS and CRS values are 3.4 and 37.7 mu respectively.. From the front 75 percent of the total, the average IRS and CRS are 2.2 and 3.1 mu respectively. Comparing all the planting conditions, the current CRS is 37.7 mu and most of the sample planting area is less than this value, while the CRS point is 3.1 mu compared with the excellent farmers of the most of the growers and most of the sample planting area is less than this value. This shows that most scale of vegetable growers are in the IRS interval, and most scale of operation of vegetable growers have the characteristics of increasing return to scale. Therefore, hypothesis 1 (H_1) has proved i.e. there exists IRS in vegetable production.

Technological progress and scale efficiency: After confirming the existence of IRS in vegetable production, in order to find out the specific sources of efficiency improvement, this paper used DEAP 2.1 to calculate Malmquist-Index. It further decomposed PTE, SE and TP to observe the role of technological progress and the change of scale efficiency. Considering that the efficiency value of DEA algorithm is essentially the relative importance of DMUs, if 5121 DMUs are first calculated according to the annual MI index and then classified according to the size of the scale, then relative value was taken as average. Therefore, groups recorded by planting area together to take year as unit. Then, groups were divided into sub-groups in the same period to calculate and compare the DMUs, i.e. average values of different areas group.

Table 4. Malmquist-Index between 2009-2016.

Year	TEC	TP	PTE	SE	TFP
2010	0.989	0.719	1.010	0.979	0.711
2011	1.026	0.638	1.030	0.996	0.655
2012	0.895	0.998	1.003	0.892	0.893
2013	1.135	1.093	1.008	1.126	1.240
2014	0.898	0.976	0.914	0.983	0.876
2015	0.962	1.028	1.063	0.905	0.990
2016	0.731	2.079	0.928	0.788	1.521
Total mean	0.941	1.006	0.993	0.948	0.946

In Table 4, TFP fluctuated gradually between 0.6 and 0.8 before 2012. After that, although there were still some fluctuations, the overall trend was upward. For the seven years total average of 1.006, TP is the most important factor to improve efficiency, while PTE is 0.993, and the technical efficiency over the years is about 1. This shows that the resource allocation efficiency in vegetable production is generally in a good state, and there is no improper allocation that some elements are too much while other parts are too little. Osti *et al*., (2017) revealed in their study that technical efficiency was lower in rice growing farmers in Nepal during both spring and monsoon season. Further, the results of their study showed that monsoon season growers found more profitable then spring season. In 2016, the TP index (2.079) increased significantly, and PTE decreased to 0.993 during the same period. This indicates that the adoption of new technologies in vegetable production has significantly promoted productivity in recent two years, but the allocation of inputs has not been optimized to the optimal proportion in time. These results are supported with an earlier study (Choo *et al.,* 2018).

The allocation efficiency still needs to be further optimized and adjusted after the technological advance, compared with Yan and Wang' research (Yan and Wang 2004)which was done from whole agricultural. On the contrary, SE showed a better trend in the first three years, and then declined year by year. This indicates that there is a gap between the current vegetable planting scale and the matching of overall conditions. The possible reason maybe that after the overall environmental changes, the CRS position of the industry could make most of the existing planting scale falls into the IRS interval. Toma *et al*., (2015) conducted a study on different countries and revealed in their study results that even though some countries are less efficient however, CRS scores increased. Hence, results of this study shows that planting scale has not been adjusted to the optimal level, which in some degree means fresh produce section has not the same industrial efficiency level (Gucheng, 2009).

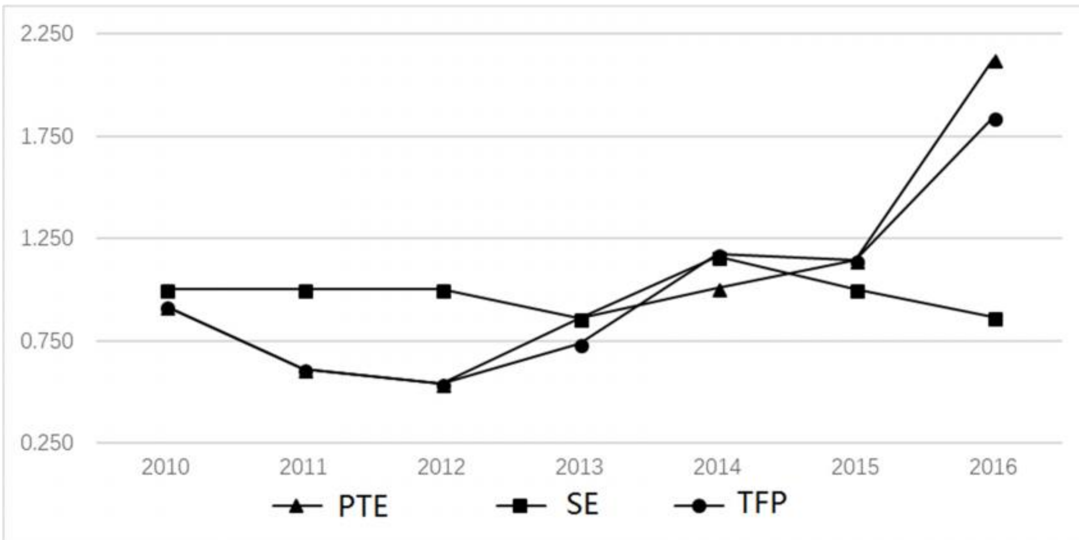

Figure 2. TP and SE of DMU with planting scale of 3-4 mu over the years.

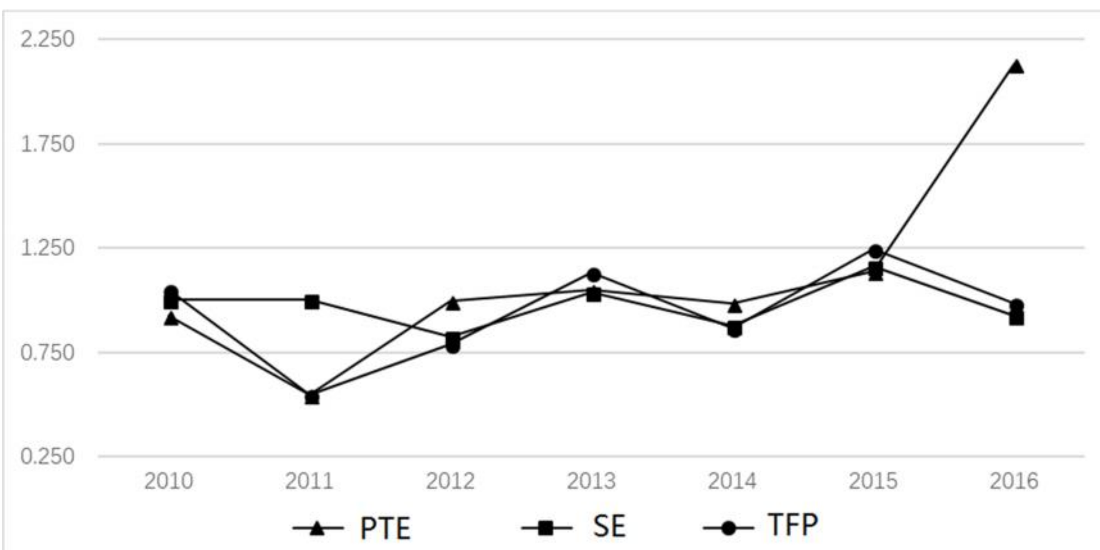

Figure 3. TP and SE of DMU with planting scale of 10-30 mu over the years

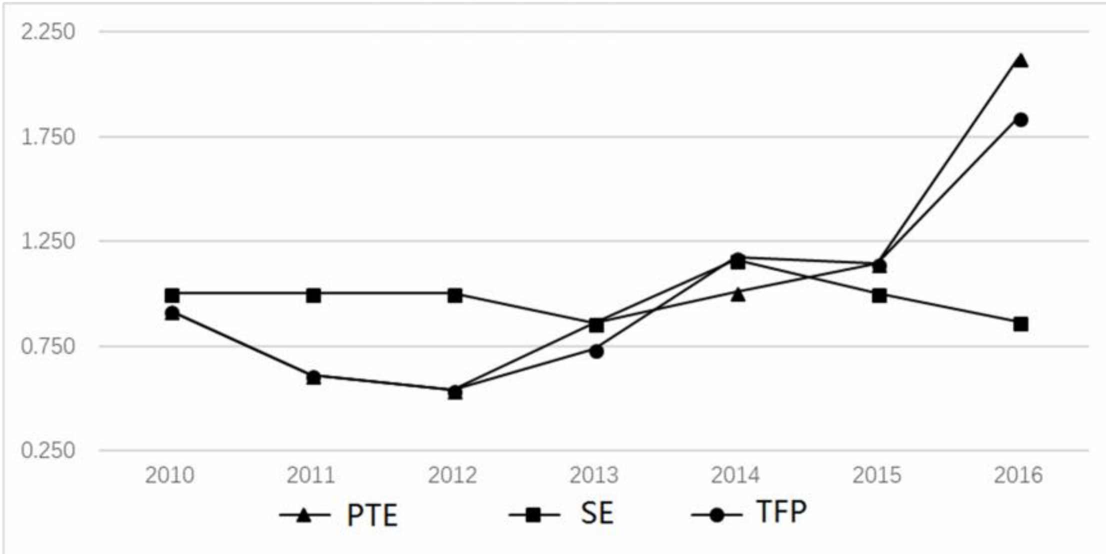

Figure 4. TP and SE of DMU with planting scale of 50-100 mu over the years.

The figures 2, 3 and 4 verify the change of efficiency index in general. In order to further compare the efficiency changes and analyze the characteristics in different planting scales, three typical planting scales of 3-4 mu, 10-30 mu and 50-100 mu DMU are selected , and their technical progress index, scale efficiency and TFP are shown in annual changes and shown in figure 2 to 4 respectively. In these figures, the technical progress index TP are connected by triangular vertex, the scale efficiency SE are connected by square top and TFP are connected by circular vertex.

Technological progress plays an important positive role in production efficiency, and the technological progress index of small planting scale is higher than DMU of large planting scale. Intuitively observing from figure 2-4, it can be seen that technological progress index, scale efficiency and TFP fluctuated between 0.75 and 1.25 in most years before 2016. The results of a previous study also shows that scale efficiency found higher than cost and allocative efficiency among rice farmers in Sri Lanka (Thibbotuwawa *et al*., 2012). Moreover before 2015, the index of technological progress in figure2 and 3 fluctuated around the level of 1, and was higher than that in figure 4. Whereas, figure 2 and figure 3 show a steady growth while figure 4 shows a rapid rise from the trough of wave in 2012. It seems that the index of DMU with small planting area is higher than that of DMU with large planting area. In 2016, the technological progress index of all planting scales has risen sharply and led to a significant increase in TFP, which confirms that China's agricultural production still has the characteristics of technological progress investment promotion as is also supported by some agro-productivity researches. It is stated in a previous study that vegetable growers operating farms under an intensive situation though it was pretty low in total agriculture sector in China (Zhang and Xue, 2005).

Table 5. Homogeneity of variance test of technological progress index.

Group	Mean	Variance	Obs. Value	Free	F Value	P(F<=f) Single	F Single Tail
A	1.1773	0.3404	20	19	3.7092	0.0032	2.1682
B	0.9117	0.0918	20	19			

In order to further verify the intuitive analytical conclusion, here we choose DMUs of 2-4 mu with small planting scale and in IRS as control group A, and 30-100, 100-500, 500-as control group B with large planting scale and in DRS as control group. It carries on the analysis of the effect of technological progress in A and B group as shown in Table 5. Firstly, the homogeneity of variance was analyzed. These results revealed that mean value of group A is 1.1773 and the variance is 0.3404, while the mean value of group B found 0.9117 and the variance is 0.0918. The P value of the homogeneity test of variance found 0.0032, much less than the significant level of 0.05, so the variance of the two groups was different. Then, an independent sample t-test method with respective variances is used to perform the mean test of technical progress. Based on the above intuitive analysis and the results of homogeneity test of variance, the original hypothesis is put forward to verify the difference of characteristics of technological progress under different business scales. Technological progress effect of small-scale planting is weaker than or equal to that of large-scale planting. Where, the alternative hypothesis: technological progress of small-scale planting is stronger than that of large-scale planting, namely, $H_0 : \overline{\mu}_A \leq \overline{\mu}_B$, $H_1 : \overline{\mu}_A > \overline{\mu}_B$. Thus, the independent sample t-test of AB control group under the premise of unequal variance is carried out, and the results are shown in Table 6.

Table 6. Independent sample t-test.

Free Degree	t Value	P(T<=t) Single Tail	t Single Tail Critical Value
29	1.8071	0.0406	1.6992

Table 6 shows that P value（0.0406 < 0.05）falls in the decline domain which means to reject H_0 and accept H_1, We can say that the average value of group A is greater than that of group B. The technological progress index of small-scale planting is higher than that of large-scale planting. In other words, the technological progress effect of small-scale planting is higher than that of large-scale planting in vegetable planting. According to the descriptive statistical results in Section 3.2, the control group A that actually falls in the IRS interval is the planting scale of the majority growers, while control group B that is in fact the part of DRS growers in the long tail interval in figure 1 (a).

Therefore, hypothesis 2 proves to be disqualified which means that at present, technological progress in large-scale planting production is weaker than that in small-scale planting production.

Conclusions: Based on the sampling data of vegetable growers from 6 primary growing areas, the return to scale and technological progress index in vegetable production were calculated by applying BCC-DEA and Malmquist-DEA models. The research hypothesis was tested mathematically. The results of study show that in the current vegetable production, most growers are in the state of increasing return to scale. Furthermore, restates show that more than 75 percent of the sample planting scale is less than 10 mu, which presented as the characteristic that most of them concentrate on small-scale planting to form a peak, while a few large-scale planting to form a right-sided peak-tail. The former 75 percent of the sample is estimated to be about 6 mu. This result indicated that in most vegetable producing areas of the country, increasing farmer's planting scale to get return to scale and improve production efficiency may still be an effective choice. Recently, the vegetable industry policy-making can be guided on the basis of the results of study, but it should be noted that even if the scale doubles here, it will be about 10 mu. This is far away from those vegetable planning of several hundred mu or several thousand mu.

Technological progress had played an important role in vegetable planting, but the diffusion and adoption of new technology was more obvious in small-scale planting, or the role of technological progress in large-scale planting needs to be played in a better way. There were a lot of labor participation links in vegetable planting process. The application of new technology and new craftwork needs workers to be more careful and responsible. Findings also revealed that the role of technological progress of small-scale planting was significantly better than that of large-scale planting. This means that in the application and promotion of new technology in vegetable industry, making small-scale planting rather than large-scale household as a breakthrough point may be more conducive to the early play of the role of new technology, although the actual technology promotion fact maybe different from what is supposed.

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