

2018

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Wang, C., Zhang, Z., & Fei, X. (2018). Efficiency and risk in sustaining China's food production and security: Evidence from micro-level panel data analysis of Japonica rice production. *Sustainability*, 10(4), 1282. doi:[10.3390/su10041282](https://doi.org/10.3390/su10041282)

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Article

Efficiency and Risk in Sustaining China's Food Production and Security: Evidence from Micro-Level Panel Data Analysis of Japonica Rice Production

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Received: 2 April 2018; Accepted: 18 April 2018; Published: 21 April 2018



Abstract: Sustainable food production and food security are always challenging issues in China. This paper constructs a multi-element two-level constant-elasticity-of-substitution (CES) model to assess technological progress in, and its contribution to, japonica rice production in China. The results show that the speed of technological progress in the production of japonica rice on average was 0.44% per annum in 1985–2013, and technological progress has contributed significantly to the growth of japonica rice production in China. Robustness checks show that the results appear to be sensitive to which sub-sample is used. Labour and some other inputs are found to be significant but negative, especially during the middle sampling period of 1994–2006 and in eastern and western regions. This has important policy implications on the impact of rural-to-urban migration and farmers' human development.

Keywords: China's food policy; sustainable food security system; japonica rice production; two-level CES function; technological progress

1. Introduction

In recent decades rapid population growth and urbanization have made food security one of the most important global issues. According to Alexandratos and Bruinsma [1] and the United Nations (UN) [2], the world population is predicted to grow from 6.9 billion in 2010 to 8.6 billion in 2030, 9.8 billion in 2050 and 11.2 billion in 2100, while food demand is predicted to increase by 50% by 2030 and 70% by 2050. The main challenge facing the agricultural sector is how to sustain the global food production system to ensure food security and meet the projected increase in food demand, given rising resource constraints for agricultural production, yields slowing down and climate change (see Popp et al. [3,4]). Ultimately, global food production capacity will be constrained by the amount of farmland and water resources available and suitable for crop production and by biophysical limits on crop growth (Van Ittersuma et al. [5]). For instance, Popp et al. [4] maintain that there are growing opportunities and demands for the use of biomass to provide additional renewables, energy for heat, power and fuel, pharmaceuticals and green chemical feedstock. Burchi and De Muro [6] propose a capability-based analysis of food security by highlighting the importance of factors such as participation in household decision making and empowerment, and distinguishing between the capability to be food secure and functioning of food security. Studies have shown that average farm yields have reached 75–90% of the yield potential ceiling (Cassman et al. [7]; Grassini et al. [8]), and it becomes very difficult to further raise yields and have significant breakthroughs in the

genetic improvement of photosynthesis or drought tolerance (Fischer and Edmeades [9]; Hall and Richards [10]).

In China, sustainable food production and food security have always been listed as a top policy priority. It is widely believed that food security is related to national stability, independence and social stability. Hence, achieving food security and safety and maintaining the stability of domestic food production have been the major focus of Chinese agricultural policy (See Peng et al. [11]; Gautam and Yu [12]). Feeding one fifth of the world's population with rising incomes from less than a tenth of its arable land and freshwater is posing significant challenges to Chinese policy makers, while China's domestic food production and food security status will have large effects on the global food stability and security. This issue becomes even more prominent when considering recent rapid urbanization and industrialization, decline in arable farmland, a rapidly ageing urban population and other resource constraints in China. Several studies have shown that rice and maize yields appear to have plateaued or become stagnant in China and other major grain production areas (Brisson et al. [13]; Cassman et al. [7]); Van Wart et al. [14]), and farmland in China declined by about 11% between 1978 and 2006 (Fleming [15]). Some suggest that China should import more land-intensive food to reduce pressure on its already strained land and water resources, and others express fear over the fact that China's long-term dependency on foreign exports will fuel food-price increase and worsen the food insecurity status in many resource-poor countries (Wang et al. [16]; Liang et al. [17]; Ghose [18]). All these factors cast doubt on the possibility of continuing to rely on the traditional way of farming, such as increasing inputs of labour and expanding cultivated land and irrigation. Many advocate the need for "sustainable intensification" of agricultural production focusing on increasing production efficiency while minimizing economic and environmental costs (Godfray et al. [19]; Garnett et al. [20]). Thus, it has become increasingly important to link agricultural production efficiency and productivity with the sustainability of agriculture and the food security system, especially in the case of China.

Rice is one of the most important food staples in China, accounting for about 20% of the total crop area harvested (Chen et al. [21]) and about 65% of total staples consumption (Peng et al. [11]). Rice can be categorized into two main types, indica and japonica. With the rapid rise in incomes and private wealth as well as a higher standard of living in China, rice consumers have become increasingly concerned about the quality of the rice they consume. As compared to indica and other rice varieties, japonica rice is mostly preferred and considered as premium quality rice in China, and demand for japonica rice has been rising rapidly in recent years. However, continuous expansion of japonica rice production has been constrained by declining arable land, labor and capital as well as other natural resources, and it will increasingly become difficult to continue relying on resource inputs to expand production. This implies that, in order for China to maintain its sustainable farming system and ensure the stability and security of the food supply, technological progress will be the major driving force for increasing agricultural productivity and promoting agriculture development. It is therefore essential to ask the question of to what extent China's japonica rice production growth is due to technical efficiency and technological progress. According to the European Union (EU) [22], total factor productivity (TFP) is the main indicator to measure changes in productivity and TFP growth is defined as the ratio between the change in production volumes over a considered period and the corresponding change in inputs (or factors) used to produce them, and hence measures the growth in productivity over a given time span. An increase in TFP reflects a gain in output quantity which is not originating from an increase in input use.

The purpose of this paper is to adopt an improved multi-element two-level constant-elasticity-of-substitution (CES) production function to measure the technical efficiency and technological progress and its contribution to japonica rice production using cross-provincial panel data from China from 1985 to 2013. In particular, we intend to assess the rate of scientific and technological progress and to measure its contribution rate in japonica rice production in China by using panel data at provincial level. We will also shed light on the impact of the relevant agricultural policies on technological progress and contribution rate across the regions, and draw

policy implications for how to sustain japonica rice production in China. This paper is among the first to assess the contribution of science and technological advances to japonica rice production in China using an improved multi-factor two-level CES production function and provincial panel data across China. This study has important implications for China's long-term agricultural policy and development strategy.

The rest of the paper is structured as follows: Section 2 provides a brief literature review. Section 3 discusses the analytical framework and data sets employed in this study. In Section 4 we analyze the estimation results. Finally, Section 5 concludes.

2. Literature Review

Numerous studies empirically examine the effects of science and technological progress on agricultural production, and many advocate that the sustainable intensification of agricultural production focusing on technological progress and increasing production efficiency is the key to ensuring the sustainability of agriculture and food security (Tilman [23]; Godfray et al. [19]; Garnett et al. [20]; EU [20]). Shankar and Thirtle [24] estimate a damage-control specification and a conventional Cobb–Douglas production function to assess pesticide productivity and transgenic cotton technology in South Africa, and find evidence that the main potential contribution of the new technology is to enable farmers to realise lost productivity resulting from under-use. Popp et al. [3] provide a thorough review of pesticide-related productivity. Crost et al. [25] estimate a production function using a fixed-effects model to control for selection bias, and report that efficient farmers in India adopt Bt cotton at a higher rate than their less-efficient peers. Neumann et al. [26] explore the yield gap of global grain production by combining an econometric approach with spatial analysis, and report that the rapid increase in global food supplies over the past 50 years was mainly due to enhanced agricultural intensification and introduction of new technologies. Most recently, Ma et al. [27] estimate a standard production model and a damage-control model to assess the effects of Bt cotton use on productivity in Pakistan, and report that the yield-enhancing inputs (fertiliser and labour) have a strong effect on cotton productivity and all Bt variables reduce yield losses alongside insecticide use. In addition, Binswanger-Mkhize and Savastano [28] report that rapid urbanization and population growth have put farming systems under stress in Sub-Saharan African countries during the past two decades, and fallow areas have disappeared, but cropping intensities remain very low. They also find that the use of organic and chemical fertilizers is too low to maintain soil fertility and the process of intensification across these countries appears to have been weak. There has been little evidence of Boserupian agricultural intensification with respect to cropping intensity, area farmed, or irrigation. Sheahan and Barrett [29] also report that, although the use of inorganic fertilizer and agro-chemicals remains relatively low on average in Sub-Saharan Africa, the use rates are actually quite high in some countries and regions within countries, which may relate to the fact that input use is no higher on cash-crop plots than on those cultivated mainly with staple cereals. Villano et al. [30] employ a stochastic production frontier framework to examine the impact of modern rice technologies on farm productivity while disentangling technology gaps from managerial gaps in the Philippines, and find that the adoption of certified seeds has a significant and positive impact on productivity, efficiency and net income in rice farming. On the other hand, using a new micro-level dataset from four African countries, McCullough [31] finds that individuals participating in agriculture tend to devote fewer hours to agriculture, on average, than individuals participating in other sectors, and the returns to an hour of labor supplied outside of agriculture are about 1.4 times as high as returns to an hour of agricultural labor on average in these countries.

Recently, there have also been some country studies of several Asian countries that find similar results. Gautam and Yu [12] study comparatively agricultural TFP growth in China and India, and report that this is mainly propelled by technological advances in these two countries but efficiency has been stagnant or has even deteriorated. They conclude that, faced with similar challenges of limited resources and growing demand, improving productivity will be the only way to meet long-term food

security in China and India. Using a front line demonstration on potatoes in India, Mishra et al. [32] report that technological progress and the adoption of improved agricultural technologies are essential to reverse the trend of wide extension gaps for potato output. Iliyasa et al. [33] employ the Malmquist productivity index method to analyze the efficiency of technological change in Malaysia, and find that technological change and efficiency changes are important contributors to TFP growth in aquaculture production. Gao and Song [34] use DEA, Moran's I and the Theil index to measure technical efficiency in China's food production using provincial panel data spanning from 1978 to 2012, and find that the improvement of efficiency in grain production is mainly driven by the rising contribution rate of agricultural science and technology. They further confirm that since 2000, technological progress has gradually replaced the physical inputs of human capital and resources in driving China's food production growth (Gao and Song [34]). Similar findings are also reported in several recent studies. For instance, Liu et al. [35] use the logarithmic mean weight divisive method (LMDI) to explore the factors that have dominant impacts on grain production using data from 347 counties in China's Huang-Huai-Hai region, and conclude that technological progress, cultivated land balance, and the optimization of the regional planting structure should be enhanced to sustain the growth trend of grain production in this region. Yang et al. [36] apply the Malmquist-DEA model to study China's TFP growth in grain production, and report that there was a continuing decline in the TFP index at an annual rate of 0.7% even during the so called "seven consecutive years harvest period", which is largely due to the significant drop in the average annual index of technological progress. Using provincial panel data in 1985–2010 from China with an improved CES production function, Jiang et al. [37] report that the contribution made by science and technology to grain production accounts for about 52% of China's grain production increase during the period in 1985–2010, a rate closer to that in the developed countries. Liu et al. [38] report similar findings using data from Hebei province. EU [22] reports that productivity in the EU has increased over time, with a growth rate surpassed by 1% per year between 1995 and 2005, and around 0.8% between 2005 and 2015.

There are a few studies focusing on technical efficiency in rice production, especially japonica rice production in China given its importance in sustaining the country's food security. These studies (for instance, Chen et al. [39]; Lin et al. [40]; Xu et al. [41]) mostly focus more on the development trends, seed-breeding skills and technical aspects of rice production, and a few on the technical efficiency and contribution of scientific and technological progress in rice production (Tian et al. [42]; Liu et al. [43]). For instance, Chen et al. [39] provide a comprehensive review of the breeding research progress for China's super high-yield japonica rice, and conclude that cultivating and promoting super high-yield hybrid rice is still considered to be one of the most effective strategies for improving rice yield in northern China. Lin et al. [40] compare the yield and main quality traits of japonica rice with that of other rice varieties including hybrid japonica rice, and find that japonica rice has some obvious advantages in terms of yield and quality. Using Solow's growth model, Tian et al. [42] estimate the contribution of technological progress to China's rice production and report that technological progress contributed over 20% to China's rice production growth during the period in 1978–2008. Liu et al. [43] confirm that technological progress plays a much more important role than China's climate policy and other factors in driving rice production. This paper will be among the first few to assess the contribution of science and technological advances to japonica rice production in China using an improved multi-factor two-level CES production function and provincial panel data.

3. Model Specification and Data Sources

3.1. Model Specification

The process of japonica rice production involves the adoption of different levels of farming technology, equipment and inputs. In order to appropriately measure technological change and its contribution to japonica rice production, we consider three-factor inputs including capital goods, labor and others such as fertilizer, seeds etc., and develop an improved two-level nested CES

production function a la Sato [44] and Henningsen and Henningsen [45] in this study. Recently, León-Ledesma et al. [46] investigate if a simultaneous identification of the capital–labor substitution elasticity and the direction of technical change is feasible, and find that jointly modeling the production function and first-order conditions is superior to single-equation approaches. In order to reduce the complexity of measuring for excessive variables, all the variables in this study are measured per unit of land. Let Z_{it} be the first level production function value of japonica rice production in province i in year t , and Y_{it} denotes the yield of japonica rice produced by three inputs production in province i in year t . The two-level CES function is then specified as follows,

$$Z_{it} = [\omega K_{it}^{-\theta_1} + (1 - \omega)L_{it}^{-\theta_1}]^{\frac{1}{\theta_1}}, \quad (1)$$

$$Y_{it} = Ae^{\gamma t} [\psi Z_{it}^{-\theta} + (1 - \psi)F_{it}^{-\theta}]^{-\frac{m}{\theta}}. \quad (2)$$

where K_{it} denotes the input of capital equipment and mechanical power in japonica rice production in province i in year t ; L_{it} is the input of labor in province i in year t ; F_{it} denotes the input of fertilizer, seed and other material inputs in province i in year t ; ω and ψ denote the distribution parameter related to input i ; θ and θ_1 is the substitution between inputs; γ is the efficiency parameter representing the speed of annual technical progress of japonica rice production; and A denotes comprehensive benefit index, including the impact on the yield of japonica rice due to the improvement of the input quality and the management level. Mechanical elements mainly include machinery and livestock, and labor elements included self-casting workers and employees, indicating the amount of labor in the production per unit of planting acreage. Hence, $Ae^{\gamma t}$ denotes the multiple of output increase due to the improvement of technology level, and m denotes the scale factor, indicating non-constant return when $m \neq 1$.

As Y_{it} is a CES function in Z_{it} and Z_{it} in turn is a CES function of K and L , following Sato [44] we call Y_{it} a two-level CES function in K and L . Now we take the natural log of Equation (2) and use the second-order Taylor series expansions at $\theta = 0$ to obtain:

$$\ln Y_{it} = \ln A + \gamma t + \psi m \ln Z_{it} + (1 - \psi)m \ln F_{it} - \frac{1}{2}\theta m \psi (1 - \psi) \left(\ln \frac{Z_{it}}{F_{it}} \right)^2. \quad (3)$$

Similarly, for Equation (1) we have the Taylor expanded form as follows,

$$\ln Z_{it} = \omega \ln K_{it} + (1 - \omega) \ln L_{it} - \frac{1}{2}\theta_1 \omega (1 - \omega) \left(\ln \frac{K_{it}}{L_{it}} \right)^2. \quad (4)$$

Combining Equations (3) and (4), we obtain Equation (5),

$$\begin{aligned} \ln Y_{it} = & \ln A + \gamma t + m\omega\psi \ln K_{it} + m(1 - \omega)(1 - \psi) \ln L_{it} + m(1 - \psi) \ln F_{it} \\ & - \frac{1}{2}m\theta_1\omega(1 - \omega)\psi \left(\ln \frac{K_{it}}{L_{it}} \right)^2 - \frac{1}{2}m\theta\psi(1 - \psi) \left(\ln \frac{K_{it}}{F_{it}} \right)^2. \end{aligned} \quad (5)$$

We use a_j as the composite parameter to represent the different combinations of distribution and substitution parameters and add an error term to Equation (5). We then have the two-level or nested CES production function for japonica rice specified as follows,

$$\ln Y_{it} = \alpha_0 + \alpha_1 t + \alpha_2 \ln K_{it} + \alpha_3 \ln L_{it} + \alpha_4 \ln F_{it} + \alpha_5 \left(\ln \frac{K_{it}}{L_{it}} \right)^2 + \alpha_6 \left(\ln \frac{K_{it}}{F_{it}} \right)^2 + \varepsilon_{it}, \quad (6)$$

From Equation (6) we have 7 parameters, a_j ($j = 0, 1, \dots, 6$), for 7 primitives, $A, m, \gamma, \theta, \theta_1 \psi, \omega$, from Equation (5). The contribution rate of technical progress to the yield growth of japonica rice can be calculated based on the following equation,

$$R_{it} = \frac{\gamma_{it}}{y_{it}} \times 100\% = \frac{\gamma_{it}}{\sqrt{\frac{Y_{it}}{Y_{ib}} - 1}} \times 100\%. \quad (7)$$

In formula (7), R_{it} is the contribution rate of technological progress in province i at year t ; γ_{it} denotes the speed of technology progress in province i at year t ; y_{it} denotes the average growth rate of japonica rice yield in province i at year t ; Y_{it} denotes the japonica rice yield during the reporting period from province i ; and Y_{ib} represents the japonica rice yield during the based period from province i .

3.2. Data Description

All data used in this study were obtained from China's National Bureau of Statistics: Statistics on Agricultural Costs and Returns, various issues; Sixty Year Agricultural Statistics; Statistical Yearbook of China, various issues; Yearbook of Agricultural Statistics, various issues; as well as several official government websites. All datasets were collected over the period from 1985 to 2013. There are several reasons for choosing this sample period and, among others, data availability is one of the most important considerations. This period also witnesses the rapid growth of japonica rice production in China. This study focuses on 12 provinces in China, including Heilongjiang, Jilin, Liaoning, Hebei, Jiangsu, Zhejiang, Anhui, Shandong, Henan, Hubei, Yunnan, Ningxia, and so on. These regions are not only the major farming areas for China's grain production, but also for japonica rice production, with the latter accounting for more than 60% of China's total japonica rice production. In order to reduce the unnecessary complexity of the measurement issue, all the input and output variables in this study are measured in terms of per unit of farming land. Finally, we take 2000 as the base year for those variables proxied with the form of index numbers. Table 1 presents the key descriptive statistics of our sample. To ensure all the series are stationary, we have conducted the panel unit root test by applying the Levin–Lin–Chu (LLC) test and the Fisher–augmented Dickey–Fuller (ADF) test. The results (available upon request from the authors) confirm that all the series are stationary.

Table 1. Descriptive statistical information.

Variable	Average	Maximum Value	Minimum Value	Standard Deviation	Observations
$\ln(Y_{it})$	6.114	6.425	5.606	0.169	348
$\ln(K_{it})$	3.045	5.465	−0.117	1.228	348
$\ln(L_{it})$	2.638	3.740	1.284	0.509	348
$\ln(F_{it})$	3.285	4.697	2.209	0.487	348
$\ln^2(K_{it}/L_{it})$	2.833	17.266	2.12×10^{-6}	3.350	348
$\ln^2(K_{it}/F_{it})$	2.180	19.661	9.37×10^{-6}	2.959	348

Note: The unit of machinery, livestock and other mechanical power cost (C) is (yuan/mu); the unit of the amount of labor (L) is (one working day/mu); the unit of seeds, fertilizer and other material cost (F) is (yuan/mu); the unit of Japonica rice yield (G) is (kg/mu).

4. Empirical Results and Analysis

To investigate technological change and its contribution to japonica rice production, we estimate a range of panel data models for different sub-sample periods and regions from 1985 to 2013. The models are estimated with panel least square (PLS), mixed effects (ME), fixed effects (FE) with both province and year, and random effects (RE). Using a panel FE model is advantageous because FE can control for unobserved time invariant region-specific effects. We also estimate random effects to capture the influence of unobserved factors that may produce heterogeneity across the countries. We conduct the

F-test (Wald test) and the Hausman test to determine the significance and choice of the models. Table 2 reports the estimation results of the random effect, fixed effect and mixed effect model.

Table 2. Estimation results of the constant-elasticity-of-substitution (CES) production function for japonica rice.

Coefficient	RE	FE	ME
a_0	5.740 *** (50.815)	5.829 *** (49.381)	5.079 *** (68.708)
a_1	0.004 ** (2.055)	0.004 (1.622)	0.003 ** (2.076)
a_2	0.061 *** (4.522)	0.061 *** (4.374)	0.108 *** (7.737)
a_3	−0.011 *** (−3.73)	−0.031 *** (−9.830)	−0.117 *** (−6.052)
a_4	0.048 ** (2.373)	0.040 * (1.944)	0.109 *** (5.297)
a_5	−0.002 *** (−7.010)	−0.003 *** (−9.860)	−0.004 *** (−5.897)
a_6	0.0004 * (1.971)	0.002 (0.359)	0.008 (1.303)
Observations	348	348	348
Adjusted R^2	0.591	0.780	0.571
F	84.470 ***	73.316 ***	77.931 ***

Note: RE refers to random effect, FE to fixed effect and ME to mixed effect. ***, **, * indicate the level of significance at the 1%, 5% and 10%, respectively.

As it can be seen in Table 2, the coefficients of capital equipment and mechanical power, fertilizer and the squared ratio of capital and fertilizer are all positive and significant, with the exception of the squared capital fertilizer ratio in fixed-effect and mixed-effects estimations. The result suggests that a 1% increase in mechanical power input will lead to a 0.061% increase in japonica yield, while with a 1% increase in fertilizer input the japonica yield rises by 0.048%. It is interesting to note that the labor input coefficient is negative and significant at the 1% level in all the estimations, implying that an increase in labor input will reduce the yield of japonica rice. This finding seems contrary to our causal observation. One possible explanation is that the production of japonica rice in China is mostly managed by small-scale family farming units. Due to its scarce arable land and the abundance of manpower, farming in China has always been very labor-intensive. Hence, it is not surprising to note the declining labor productivity in the production of japonica rice. Another possible explanation is that, as small-scale family farmers are more risk averse, they tend to be reluctant to adopt quality seeds and new agricultural technologies in the production of japonica rice. Although intensive farming practices can generate relatively high yield, over-reliance on increasing inputs of labor in farming can be counter-productive. The finding is consistent with Mishra et al. [32] and Liu et al. [43]. This, together with the low estimate of the capital terms coefficient, seems to reaffirm Solow's [47] conclusion that accumulation of capital and an increase in the labor participation rate had a relatively minor effect on growth, and cannot explain all the growth of japonica rice in the past few decades. It also suggests that traditional farming practices with a sole reliance on increasing inputs of capital and labor will not be sustainable in the long term, and emphasis should be given to continuous improvement in seed quality, farmer skill, technological progress and the adoption of technologies for sustainable farming systems.

Using the estimates in Table 2, we will be able to identify the primitives in the multiple element two-level CES function and determine technological progress in the production of japonica rice. Table 3 reports the results. The results show that the speed of technological progress in the production of japonica rice on average is 0.44% per annum in the sample period in 1985–2013. According to Chinese statistics, the average yield of japonica rice per unit of farming land in the 12 provinces concerned was 297.91 kg in 1985, and rose to 436.76 kg in 2013, with an average annual growth rate of about 1.33%.

This study finds that technical progress has contributed significantly to the growth of japonica rice production in China, with a rate accounting for 33.13% from 1985 to 2013.

Table 3. Identified distribution and substitution parameters and technical progress in China's japonica rice production.

Primitive Parameters	A	γ	ω	θ_1	ψ	θ	m
Values	312.19	0.004	1.22	−0.30	0.51	−0.03	0.10
Contribution rate of technological progress							R_{it} : 33.13%

Note: γ_{it} refers to the technical progress speed; R_{it} refer to the contribution rate of technical progress.

4.1. The Dynamics of Japonica Rice Output and Technological Progress

Since the late 1970s, China's agricultural sector and farming system have undergone a series of reforms, aiming at improving the efficiency of resources allocation and promoting agricultural and rural production technology productivity. To assess the dynamic impacts of various reform measures and policy changes on the growth of japonica rice production, we divide the whole sample period into three: the first period covers 1985 to 1993 to catch the effects of the primary reform in agriculture during the early reform era; the second period spans from 1994 to 2006 to reflect the impact of implementing the new policy measures on current agricultural and rural economic development on 5 November 1993; and the third sub-sample period ranges from 2007 to 2013 to allow for the effects of adopting various fiscal subsidies measures in the agricultural sector since 2006. We re-estimate the models using the new sub-sample data to measure the technological progress and its contribution rate over the different sub-sample periods. Table 4 reports the estimation results.

Table 4. Estimation results for different sub-sample periods.

Coefficient	RE	RE	FE
	1985–1993	1994–2006	2007–2013
a_0	4.917 *** (5.567)	5.199 *** (4.254)	5.946 *** (19.787)
a_1	0.007 *** (6.262)	0.002 *** (8.345)	0.013 *** (2.977)
a_2	0.263 *** (7.983)	0.101 *** (4.587)	0.055 ** (2.145)
a_3	0.080 * (1.700)	0.071 ** (2.409)	−0.038 *** (−3.470)
a_4	0.057 *** (4.196)	0.124 *** (3.477)	−0.044 *** (−3.934)
a_5	0.035 *** (2.737)	0.008 *** (6.341)	−0.007 *** (−3.945)
a_6	0.012 *** (5.032)	−0.031 *** (−3.451)	−0.008 ** (−2.811)
Obs.	108	156	84
R^2	0.424	0.442	0.890
Adjusted R^2	0.389	0.420	0.862
F	12.366 ***	19.677 ***	31.383 ***
Fixed effect F test	18.993 ***	19.795 ***	12.161 ***
Hausman test	0.000	4.238	20.902 ***

Note: ***, ** and * indicate the level of significance at the 1%, 5% and 10%, respectively.

It can be seen from Table 4 that all the coefficients are statistically significant over the three sub-periods. The estimated coefficient of capital equipment and mechanical power has a positive sign for all the sub-sample periods while all of the rest of the variables have positive signs only for the first two sub-periods except the capital–fertilizer ratio. By contrast with the results for the whole

sample period, the coefficients of labour and fertilizer inputs as well as the squared capital-labour and capital-fertilizer ratios become negative during the third stage of development from 2007 to 2013. The findings reaffirm that over-reliance on increasing physical inputs in japonica rice production cannot be sustained in the long term, and can be counter-productive.

Using the estimates in Table 4, we then identify the primitives in the multiple element two-level CES function and determine technological progress in the production of japonica rice during each of the sub-sample periods. We report the results in Table 5. As can be seen in Table 5, the speed of technological progress in the production of japonica rice varies across the sub-periods, with a V-shape over time. The period 2007–2013 witnessed the fastest progress in technology in China’s japonica rice production, followed by the 1985–1993 period, while the period 1994–2006 was the worst when China experienced negative growth in technology. The finding is consistent with that in Zhang [48] for the national economy. There are several reasons to explain this pattern of technological progress. First, China’s agricultural reform started in the late 1970s. The initial success of China’s agricultural reform was remarkable and led to a rapid increase in agricultural productivity and growth through the early 1990s, a result of which has been the rapid progress in technology in China’s japonica rice production during the period in 1985–1993. Second, with the increasing demand for quality and variety of agricultural products and rapid urbanization in the 1990s, the Chinese agricultural sector experienced a sharp decline in both arable farmland and rural labour force. The popularity among and interest of farmers in adopting new rice farming technology was also affected, a result of which has been the decrease both in rice output and technological progress in japonica rice production in the period 1994–2006. Finally, since the early 2000s, China has implemented its New Blueprint for Rural Reform and Development, including a series of new agricultural policies and favourable measures, to build a new countryside. These policies and measures have stimulated farmers to adopt new agricultural technologies and improve efficiency, and also reduced the costs of using quality rice seeds and production. This led to the rapid expansion of rice output and technological progress in japonica rice production in the period 2007–2013.

Table 5. Identified distribution and substitution parameters and technical progress.

Primitive Parameters	Period	A	γ	ω	θ_1	ψ	θ	m
Values	1985–1993	137.43	0.007	0.76	−0.97	0.84	−0.40	−0.4
	1994–2006	181.87	−0.003	0.59	−0.49	0.58	0.87	0.29
	2007–2013	385.20	0.013	3.00	−0.12	−1.00	0.40	−0.02
Contribution rate of technological progress R_{it}	1985–1993	34.31%						
	1994–2006	26.9%						
	2007–2013	147.16%						

4.2. Technological Progress Across the Regions

Given the diverse natural and socio-economic environment across China, it is believed that region-specific factors would also play an important role in japonica rice production. To further assess the region-specific impacts on the technological progress and japonica rice production nexus, we divide the 12 sample major rice-production provinces into three regions, i.e., the eastern, central and western regions. The eastern region includes the provinces of Liaoning, Hebei, Jiangsu, Zhejiang, and Shandong; the central includes Heilongjiang, Jilin, Anhui, Henan, and Hubei; and the western region includes Yunnan and Ningxia. It is worth noting that after re-grouping our sample, the panel dataset has been transformed into one with a long-time series and short cross-sectional data, i.e., panel data with large T and small N. The typical complications of TSCS panel data are heteroskedasticity and autocorrelation. The conventional way to deal with heteroskedasticity and correlated errors is to use the feasible generalized least squares (FGLS) technique, but FGLS has been found to be less efficient and tends to underestimate standard errors (Beck and Katz [49]). In this study we use the panel-corrected standard error (PCSE) to address panel heteroskedasticity and include a lagged

dependent variable in the model to address serial correlation. Table 6 reports the estimation results for the three sub-regions. We further identify the primitives in the multiple element two-level CES function and determine the technical progress in the production of japonica rice for each sub-region. We report the results in Table 7.

Table 6. Estimation results at the regional level.

Coefficient	Eastern Region	Central Region	Western Region
a_0	5.881 *** (34.290)	5.538 *** (4.164)	7.066 *** (24.480)
a_1	0.007 (1.762)	0.003 ** (2.270)	0.0003 * (1.871)
a_2	0.051 * (1.953)	0.097 *** (5.12)	0.017 *** (3.417)
a_3	−0.079 * (−1.67)	0.008 ** (2.051)	−0.249 *** (−4.31)
a_4	0.086 ** (2.05)	0.049 * (1.920)	−0.015 ** (−2.237)
a_5	−0.014 *** (−3.35)	−0.005 * (−1.830)	−0.028 *** (−3.630)
a_6	−0.009 * (−1.806)	0.002 ** (2.234)	0.021 ** (2.320)
Observations	145	145	58
R^2	0.926	0.924	0.936
wald	112.562	119.951	107.915
ρ	0.385	0.358	0.249

Note: Eastern including Liaoning, Hebei, Jiangsu, Zhejiang, Shandong; Central including Heilongjiang, Jilin, Anhui, Henan, Hubei; Western including Yunnan, Ningxia. ***, **, * represents the significant level of 1%, 5% and 10% respectively.

As can be seen in Table 7 and also from Table 6, the eastern region has the fastest growth of technological progress in japonica rice production during the whole sample period from 1985 to 2013, with an average growth rate of 0.7% for technological progress and 43.75% for the technological contribution. This is followed by the central region, where the rate of technological progress and the contribution rate are 0.3% and 24%, respectively. The western region has the lowest technical progress rate and contribution rate with the former being 0.03% and the latter 3.37%, respectively. There are several possible reasons for these regional differences in technological progress and contribution rate. Among others, the well-established social and economic environment and favourable natural farming conditions in the eastern region, and to some extent also in the central region, are the major factors explaining why these regions have higher technological progress and contribution rates. By contrast, the economy of the western region is poorly developed largely due to its backward infrastructure and poor natural endowments. It is financially difficult for the farmers in the western region to adopt new agricultural technologies and use quality rice seeds and production, a result of which has been the lowest technological progress in japonica rice production.

Table 7. Identified distribution and substitution parameters and technical progress at regional level.

Primitive Parameters	Region	A	γ	ω	θ_1	ψ	θ	m
Values	Eastern	359.14	0.7%	−1.67	0.15	−0.50	−0.4	0.06
	Central	255.57	0.3%	0.93	1.5	0.68	−0.12	0.16
	Western	1181.41	0.03%	−0.09	2.80	0.89	2.3	−0.25
Contribution rate of technological progress R_{it}	Eastern	43.75%						
	Central	24%						
	Western	3.37%						

The results in Table 6 show that the input of capital equipment and mechanical power has a positive impact on japonica yields in the central region, and has a negative impact in other regions, but the effect of labour, the capital–labor ratio and the capital–fertilizer ratio all are negative in the eastern region, and labour, fertilizer and the capital–labour ratio in the western region are also negative. This can be explained by the decline in arable farmland and rising rural surplus labour due to rapid urbanization and industrialization, as well as inappropriate use of chemical fertilizers in farming. Accompanying the process of rapid urbanization and industrialization has been massive work-related rural-to-urban migration in China over the past few decades. As a result, there has been a shortage of capable farm labour in rural areas and farm work has to be undertaken by those left-behind, mostly the elderly, women and children. They will have to increase the time spent on farm work with low efficiency. One study reports that elderly people in rural households with rural-to-urban migrants tend to work 100–200 more hours per year on farm work than those households without migrants (Chang et al. [50]). On the other hand, those left behind in rural areas normally have low education, and lack modern farming techniques and knowledge. Driven by the desire for higher yields, it has become a common practice for farmers to overuse chemical fertilizers in farming. However, over-fertilization or the use of imbalanced fertilization does not always increase crop output and contribute to high rice yield. Instead, over-fertilization may deteriorate the soil conditions and cause a series of economic and environmental problems (Ju et al. [51]). This has clearly been an issue among policy makers. In contrast, our results show that the estimated coefficient of fertilizer for the central region is positive, which seems to suggest that over-fertilization does not exist in farming in the central region. The central region is China's main grain production base where farmers are well trained in how to utilize chemical fertilizer in farming. That explains the positive coefficient of fertilizer in the regression for japonica rice production.

5. Concluding Remarks

Sustainable food production and food security have been China's top policy priority. Due to recent rapid urbanization and industrialization, decline in arable farmland, a rapidly ageing urban population and other resource constraints in Chinese agriculture, technological progress will have to be the major driving force for increasing agricultural productivity and promoting agricultural development. In this study, we have constructed an improved multi-element two-level CES production model to assess the rate of technological progress and its contribution rate in japonica rice production in China by using cross-provincial panel data from China from 1985 to 2013. The results from the whole sample estimations show that the labor input coefficient is statistically significant but negative, suggesting that increases in labor input will reduce the yield of japonica rice. Furthermore, the results from the sub-sample estimations further show that the coefficients of labor and fertilizer inputs as well as the squared capital–labour and capital–fertilizer ratios become negative only during the third stage of development from 2007. The sub-regional studies further confirm that the coefficients of labour, capital–labor ratio and capital–fertilizer ratio all are negative in the eastern region, and the coefficients of labour, fertilizer and capital–labour ratio in the western region are also negative. Finally, the results show that the speed of technological progress in the production of japonica rice on average was 0.44% per annum in the sample period in 1985–2013, and technological progress has contributed significantly to the growth of japonica rice production in China, with a rate accounting for 33.13% from 1985 to 2013. The dynamics of the speed of technological progress in the production of japonica rice show a V-shape over time, with the period in 2007–2013 being the fastest and the period in 1994–2006 the worst. It is found that the eastern region had the fastest growth of technology progress in japonica rice production during the whole sample period, followed by the central region. The western region had the lowest technical progress and contribution rates.

The empirical findings have several policy implications. First, due to rapid urbanization and industrialization there has been massive work-related rural-to-urban migration in China over the past several decades. The production of japonica rice in China is mostly managed by small-scale family

farming units, and by those left-behind in rural areas, mostly the elderly, women and children, who are incapable of farm labour and have to devote increasing labour hours to farming. Hence it is not surprising to note declining labor productivity in the production of japonica rice with low efficiency. Another possible explanation is that as small-scale family farmers are more risk averse, they tend to be reluctant to adopt quality seeds and new agricultural technologies in the production of japonica rice. Then, although intensive farming practices can generate relatively high yields, an over-reliance on increasing input of labor in farming can be counter-productive. The over-fertilization or the use of imbalanced fertilization does not always increase crop output and contribute to high rice yields. Instead, over-fertilization may deteriorate the soil conditions and cause a series of economic and environmental problems. This, together with the low estimate of the capital terms coefficient, seems to reaffirm Solow's conclusion that an accumulation of capital and an increase in the labor participation rate had a relatively minor effect on growth, and cannot explain all the growth of japonica rice in the past few decades. It also suggests that traditional farming practices with a sole reliance on increasing inputs of capital and labor will not be sustainable in the long term, and an emphasis should be placed on continuous improvement in seed quality, farmer skill, technological progress and the adoption of technologies for sustainable farming systems.

Acknowledgments: The authors wish to thank Michael McAleer, Guo Pei, Bai Junfei, Chen Qihui, Tian Weiming, Shen Yueqin, Yu Kang, and two anonymous referees for their constructive comments and suggestions. The first authors also wish to acknowledge financial support from the National Natural Science Foundation of China (41201125, 41401642); major project of the key research base of Humanities and Social Sciences of the Education Ministry (14JJD790045); Youth Fund Project of Humanities and Social Sciences of the Education Ministry (11YJC790172, 14YJC790027); Post-doctoral Fund Project (2015M571895); and Leading Project of Young and Central-Aged Academic Leaders in Zhejiang Province (pd2013244).

Author Contributions: Wang, Zhang and Fei, conceived the paper, Fei analyzed the data; Wang and Zhang wrote and finalized the manuscript. All authors read and approved the final manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

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