【論文】

Environmental Efficiency and Employment in China's Soybean Farming Sector

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［キーワード］environmental efficiency, Egaitsu-Shigeno type production function, soybeans, biochemical technology, mechanical technology
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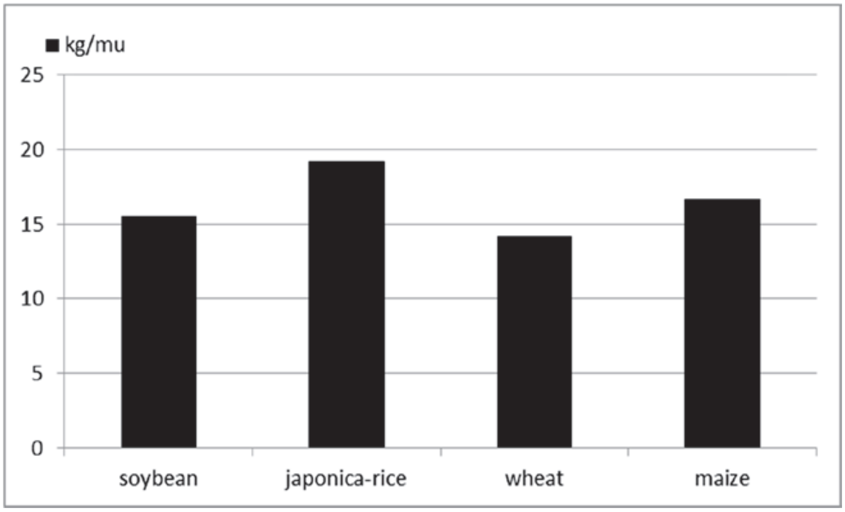
1. Introduction

The purpose of this study is to concurrently measure environmental efficiency and over-employment in China's soybean farming sector using regional panel data from 2000 to 2012. We accomplish this by conducting a stochastic frontier analysis (SFA) on the Egaitsu–Shigeno (E-S) type production function, which allows us to distinguish between biochemical (BC) technology (an indicator of environmental efficiency and waste price) and mechanical (M) technology (over-employment). We establish that there is a relationship between estimated environmental efficiency and the two independent variables, rural per-capita income and waste price, which indicates if the effect of rural development and waste levels on environmental efficiency may be observed at a provincial level in this sector.

Figure 1　Nutrition Balance



Source: CNFPCBD

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Table 1 The Ranking of The Harvested Area in China

(ha)

		2000		2006		2012
1	Rice, paddy	29961890	Rice, paddy	29294650	Maize	34949000
2	Wheat	26653290	Maize	26970880	Rice, paddy	30297000
3	Maize	23056270	Wheat	22961450	Wheat	24139000
4	Soybeans	9306760	Soybeans	9304400	Vegetables, freshnes	9650000
5	Rapeseed	7494360	Vegetables, freshnes	8300000	Rapeseed	7300000
6	Vegetables, freshnes	6660000	Rapeseed	5984000	Soybeans	6750000
7	Sweet potatoes	5815080	Seed cotton	5815700	Potatoes	5429000
8	Groundnuts, with shell	4855310	Potatoes	4214520	Groundnuts, with shell	4700000
9	Potatoes	4723430	Groundnuts, with shell	3955800	Seed cotton	4700000
10	Seed cotton	4041000	Sweet potatoes	3663000	Sweet potatoes	3472600

Source: FAOSTAT

We focus on soybeans for three reasons. First, considering the process of biological fixation in addition to the use of chemical fertilizers, soybean farming is a sector that could have a positive nutrition balance[1].

Second, soybean farming could use nutrients in intermediate goods (chemical fertilizer) and arable land (biological fixation) in BC process and so, like applying cost minimization problem, we could resolve nutrient minimization problem to estimate environmental efficiency in our empirical methodology. Third, being one of China's top ten crops by cultivated land area indicates that soybean farming has a significant effect on China's rural economy. Although the cultivated land area has decreased since the late 2000s, the output to land ratio has increased (Figure 4). Focusing on the soybean farming sector enables us to establish how the change to the "land-saving method" has affected environmental efficiency and resulted in over-employment.

There are two approaches to measuring environmental efficiency that employ data envelopment analysis (DEA); they produce input–output models that include both undesirable and desirable goods as variables. The key difference lies in whether weak disposability is imposed on the undesirable goods.

Färe *et al*. (1989), Chung *et al*. (1997), and Färe *et al*. (2004) assume that the undesirable outputs are weakly disposable. However, Coelli *et al*. (2007) and Hoang and Coelli (2011) measure total factor productivity (TFP) by

1 Nutrition balance is measured by subtracting nutrient outputs from nutrient inputs in the agricultural production process. We consider a positive nutrition balance to be a primary factor of environmental waste in the agricultural sector. For the method of estimation of nutrition balance, see Hoang and Alauddin (2009).

assuming that polluting agricultural materials are strongly disposable; additionally, they employ the nutrient balance method (NBM), which measures net agricultural pollution by subtracting nutrient outputs from nutrient inputs.

While the aforementioned studies measure environmental efficiency through DEA and linear programming, it is also possible to use SFA (Van Meensel *et al.,* 2010; Hoang and Nguyen, 2013). SFA affords two major advantages; it does not require balanced panel data (which is useful for our own study as China's regional data is rarely balanced) and it allows one to analyze the error term in the estimation of the production frontier. Van Meensel *et al.* (2010) compare the environmental efficiency estimations from DEA and SFA using data on pig furnishing in Flanders; they define feed use and the number of rotations as inputs, indicating that their production function accounts for only BC technology. Van Meensel *et al.* (2010) also utilize the NBM in their examination of the BC process. For our own study, we are able to reflect the entire BC process in our environmental efficiency estimation by taking into account nutrients produced by bacterial nitrogen fixation rather than just seeds and fertilization.[2]

Studies that examine environmental efficiency in China include Kaneko and Managi (2004), Managi and Kaneko (2006), Managi and Kaneko (2009), and Fujii *et al.* (2010); they do so by using DEA and focus on the secondary industry rather than the primary. However, there are few studies that focus on agriculture, and as such, we seek to fill this gap in the literature by using the NBM to measure environmental efficiency in China's agricultural sectors.

It should be noted that waste's shadow price index is a clear indicator of the cost of waste reduction and is thus useful in the development of tax and subsidy policies. Coelli *et al.* (2007) measure the waste price with optimal cost and nutrition values obtained from DEA, a method that our study employs as well.

In examining factors that explain environmental efficiency, we gained useful insight from some studies that estimate an environmental Kuznets curve (EKC) when considering environmental efficiency measures. Taskin and Zaim (2001) test whether the EKC hypothesis holds by examining the relationship between GDP per-capita and environmental efficiency estimates in 49 countries. Färe and Grosskopf (2003) confirm the EKC hypothesis using data from the OECD countries from 1971 to 1990. Managi and Jena (2008) employ Indian industrial panel data to estimate the EKC. GDP or GDI per capita is used as explanatory variable to calculate macro environmental efficiency in several studies. However, our estimated environmental efficiency is limited to the soybean sector. Therefore, our study examines the relationship between estimated environmental efficiency and rural personal income, which is a more limited concept than national income per-capita, and focuses on the relationship between increase in rural income and environmental efficiency. Additionally, the effect of shadow waste price of soybean farming on environmental efficiency is also established. The relationship between waste social cost and environmental efficiency has not been examined and we could gain some empirical suggestions for environmental policy.

2 According to Shindo et al. (2003), rice, soybeans, and pulses grow through biological fixation. However, according to our estimation, the biological fixation for rice farming per arable land is significantly lower than that for soybeans.

It should be noted that the E-S production function that we employ is also capable of measuring over-employment through the M process. Ohkawa (1960) states that if one industry's marginal productivity of labor (MPL) is lower than others industries', then that industry will exhibit over-employment. This over-employment indicates an inefficient use of labor input in the M process and is one of the main factors of rural poverty.

Additionally, when a developing economy surpasses Lewis' turning point, there will cease to be over-employment and the real wage will increase. According to Minami (1973), the most effective means of determining whether this point has been reached is to estimate the production function and compare the real wage rate with the estimated marginal productivity of labor; if the real wage rate is greater, then the economy has yet to clear the turning point. Finding the Lewis turning point is not the objective of our study; however, prior studies, which estimate the production function, and establish the Lewis turning point, could give us useful empirical suggestions.

Studies that estimate production functions often evaluate the entire agricultural sector (Hondai and Ra, 1999; Islam and Yokota, 2008; Minami and Ma, 2010); however, it may be beneficial to focus on a single crop as one cannot account for the disparities in farming technologies when examining such a wide variety of crops. For instance, Inada and Yamamoto (2010) estimate the C-D production function for China's japonica rice farming sector using regional panel data (as we do in our study). In contrast to previous studies, they do not use the value-added approach but rather the production approach. As such, they are able to add intermediate goods as dependent variables, which increase the risk of multicollinearity. This, in turn, causes their estimated results to be partially insignificant. Our E-S production function requires fewer dependent variables to separate BC technology from M technology and thus yields more accurate results.

The rest of this study is organized as follows: Our empirical model is presented in the Section 2. Section 3 describes the data. Sections 4 and 5 report the results of our statistical and empirical analyses, respectively. In Section 6, we draw our conclusions and provide policy implications.

2. Theoretical background and methodologies

2.1 E-S production function and nutrient minimization problem

Under the assumption that product and production factor markets are perfectly competitive, the conventional agricultural production function may be written as follows

$$Q = f(K, L, M, S) \tag{1}$$

where Q, K, L, M, and S represent output, capital stock, labor power, intermediate goods, and arable land. Additionally, other production factors can be substituted or supplemented into this function. Egaitsu and Shigeno (1983) assume that there are a set of intermediate goods and arable land and a set of labor power and capital stock in Equation (1); the former set represents BC technology and the latter M technology. We assume that the production factors in the set are substituted, while outputs produced by the set are fully supplemented. Consequently, the E-S production function may be written as

$$Q = \min(F(K, L), G(M, S)) \tag{2}$$

If the E-S production function is a C-D type, we are able to write

$$Q = AM^{\alpha}S^{\delta} \tag{3}$$

$$Q = BL^{\beta}K^{\gamma} \tag{4}$$

A farmer's cost minimization problem (subject to (3) and (4)) can be written as follows

$$\text{Min} \quad TC = mM + sS + wL + rK \text{ such that } Q = AM^{\alpha}S^{\delta} \text{ and } Q = BL^{\beta}K^{\gamma} \tag{5}$$

where TC indicates total cost and m, s, w, and r represent every production factor's price. We obtain the optimum set of production factors by solving the following Lagrangian

$$\mathcal{L} = mM + sS + wL + rK - \lambda_1(Q - F) - \lambda_2(Q - G) \tag{6}$$

$$\frac{\partial \mathcal{L}}{\partial M} = m + \lambda_1 \frac{\partial F}{\partial M} = 0 \tag{7}$$

$$\frac{\partial \mathcal{L}}{\partial S} = s + \lambda_1 \frac{\partial F}{\partial S} = 0 \tag{8}$$

$$\frac{\partial \mathcal{L}}{\partial L} = w + \lambda_2 \frac{\partial G}{\partial L} = 0 \tag{9}$$

$$\frac{\partial \mathcal{L}}{\partial K} = r + \lambda_2 \frac{\partial G}{\partial K} = 0 \tag{10}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_1} = Q + F = 0 \tag{11}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_2} = Q + G = 0 \tag{12}$$

From the conditions in Equations (7)–(10), we get equilibrium conditions for the production factor market:

$$\frac{m}{s} = \frac{F_M}{F_S} \tag{13}$$

$$\frac{w}{r} = \frac{G_L}{G_K} \tag{14}$$

where F_M, F_S, G_L, and G_K are each production factors' marginal productivity. Furthermore, Equations (11) and (12) yield the equilibrium condition for the BC and M technologies.

$$F = G \tag{15}$$

Based on Equations (13) and (14), we confirm total cost is minimized when both BC and M technologies are at their optimal points, that is, when their production quantities are equal.

Environmental efficiency is found by applying the cost minimization problem to the BC technology process. We assume that environmental performance is determined by the nutrient minimization process. If TN represents total nutrients and m_n and s_n are the nutrients per production factor, we may rewrite the cost minimization problem as a nutrient minimization problem, which an environmentally efficient soybean farm would solve (we assume that nutrients are only in arable land and intermediate goods).

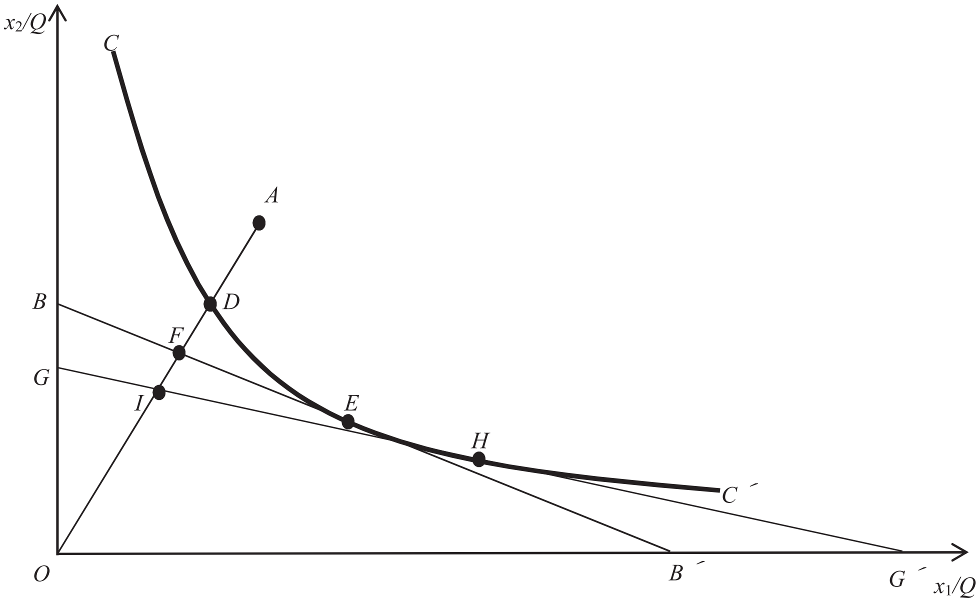
$$\min \quad TN = m_n M + s_n S \text{ such that } Q = AM^{\alpha}S^{\delta} \text{ and } Q = BL^{\beta}K^{\gamma} \tag{16}$$

The equilibrium condition for nutrients is expressed as

$$\frac{m_n}{s_n} = \frac{F_M}{F_S} \tag{17}$$

We employ Farrell's (1957) methodology in the actual estimation. In Figure 2, CC' is the unit isoquant curve and GG' is the isocost line. If a soybean farm produces at point A, they could proportionally reduce all of their production factors and produce more efficiently in terms of both BC and M technologies by producing at point D instead. Technical efficiency (TE) is expressed as the ratio between DO and AO.

Figure 2　Technical Efficiency, Environmental Efficiency, and Cost Efficiency



Source: Farrell's (1957) Diagram 1

Cost is minimized in the BC and the M processes at point *H*, though not in terms of *TE* at point *D*. Point *I* is equally as expensive as point *H* and features a proportional reduction in production factors as compared to point *A*. The allocative efficiency (*AE*) (*TE* evaluated by the production cost) of point *D* is given by the ratio of *IO* to *DO* in the BC or the M processes. Cost efficiency (*CE*) is the ratio of *IO* to *AO*. The ratios are related as follows:

$$TE\ (=\frac{DO}{AO})\ \times AE\ (\frac{IO}{DO}) = CE\ (=\frac{IO}{AO}) \tag{18}$$

We can measure these efficiencies in regard to either the BC or the M processes.

If x_1 and x_2 in Figure 2 represent the arable land and the intermediate goods in the BC process, and BB′ represents the iso-nutrient line, then TE, environmental allocative efficiency (EAE), and environmental efficiency (EE) are the ratios of *DO* to *AO, FO* to *DO,* and *FO* to *AO,* respectively. Furthermore,

$$TE\ (=\frac{DO}{AO})\ \times EAE\ (=\frac{FO}{DO}) = EE\ (=\frac{FO}{AO}) \tag{19}$$

Using Equation (19) in conjunction with SFA, we are able to measure the production efficiency while taking into account the environmental factor.

In estimating these efficiencies, we may obtain the optimal sets of production factors, which, according to Coelli *et al.* (2007), may then be used to find the shadow price of waste. Consequently, Figure 2 indicates the following

$$P_w = \frac{TC_E - TC_H}{TN_H - TN_E} \tag{20}$$

where P_w represents the shadow price of waste, which is the monetary cost (factoring in the reduction in environmental optimal points) of reducing nutrients. By measuring the price of pollutants, we may better understand the cost of environmental conservation, which would, in turn, be useful in the development of regional agricultural policies.

From the estimation of the M process' efficiency, we may determine optimal sets of capital stock and labor. We define over-employment as the difference between real labor power and optimal labor power at the cost minimizing point. If, in Figure 2, the production function reflects M technology and x_1 and x_2 represent capital stock and labor power, the rate of over-employment (ROE) is

$$\mathrm{ROE} = \frac{L_A - L_H}{L_A} \tag{21}$$

2.2 SFA

In order to estimate the production function, and thereby the environmental efficiency and other indexes, we utilize SFA as it can be applied to unbalanced panel data and allows us to include an error term. By transforming Equations (3) and (4) into logarithms, we are able to obtain our SFA model for the production frontier:

$$lnQ_{it} = lnA + \alpha lnM_{it} + \delta lnS_{it} + v_{it} - u_{it} \tag{22}$$

$$lnQ_{it} = lnB + \beta lnL_{it} + \gamma lnK_{it} + v_{it} - u_{it} \tag{23}$$

where i, t, v, and u represent the region, time, error term, and inefficiency, respectively. We use Greene's (2005) true fixed effect (TFE) model and true random effect model (TRE) for the estimation. lnA in Equation (22) is given by the TFE model

$$lnA = a_i \tag{24}$$

where a_i is a time invariant effect on the i region. In the TFE model, the error term, v, is assumed to be normally distributed, while the inefficiency, u, is exponentially distributed.

In Equation (25), lnA is given by the TRE model

$$lnA = a + \omega_i \tag{25}$$

where ω_i is a random, region-specific effect. Again, the error term, v, and inefficiency, u, are assumed to be normally and exponentially distributed, respectively.

We measure TE and EE with the aforementioned models. For example, if $lnQ_{it} - v_{it} = ln\bar{Q}_{it}$ and the actual ratio of intermediate goods to arable land is $\frac{M_{it}}{S_{it}} = c_{it}$, then TE_{BC} (the efficiency of BC technology) is the ratio of a set of M^{te} and S^{te} (that simultaneously realize $\bar{Q}_{it}$ and c_{it}) to a set of observed M_{it} and S_{it}.

$$TE_{BC} = \frac{mM^{te} + sS^{te}}{mM + sS} \tag{26}$$

Similarly, TE_M is

$$TE_M = \frac{wL^{te} + rK^{te}}{wL + rK} \tag{27}$$

To measure EE, we solve the nutrient minimization problem (Equation (16)) to obtain the nutrient function,

$$lnTN_{it} = n_0 + n_1 lnm_{n,it} + n_2 lns_{n,it} + n_3 ln\bar{Q}_{it} \tag{28}$$

where

$n_0 = ln(\alpha + \delta) - (lnA + \ln(\alpha^{\alpha}\beta^{\beta}))/(\alpha + \delta)$

$n_1 = \frac{\alpha}{\alpha + \delta}, n_2 = \frac{\delta}{\alpha + \delta}$

$n_3 = \frac{1}{\alpha + \delta}$

By using Equation (28), we can find the nutrient minimizing set.

$$M_{it}^{ee} = n_1 m_{n,it}^{-1} TN_{it} \tag{29}$$

$$S_{it}^{ee} = n_2 s_{n,it}^{-1} TN_{it} \tag{30}$$

$$EE = \frac{m_n M^{ee} + s_n S^{ee}}{m_n M + s_n S} \tag{31}$$

We may also derive cost functions that can be minimized with respect to either the BC or the M process and thereby obtain the *CE*.

$$CE_{BC} = \frac{mM^{ce} + sS^{ce}}{mM + sS} \tag{32}$$

$$CE_M = \frac{wL^{ce} + rK^{ce}}{wL + rK} \tag{33}$$

Kopp (1981), Bravo-Ureta and Rieger (1991), Sharma *et al.* (1999), and Singh *et al.* (2001) decompose cost efficiency as well, though they ignore time invariant fixed effects and random effects (which Greene's (2005) panel model allows us to account for).

2.3 The examination of explanatory variables on environmental efficiency

Based on equation (19), we estimate equations 34–36 as follows:

$$TE_{it} = a_0 + a_y lny_{it} + a_{yy}(lny_{it})^2 + a_{p_w} p_{w,it} \tag{34}$$

$$EAE_{it} = b_0 + b_y lny_{it} + b_{yy}(lny_{it})^2 + b_{p_w} p_{w,it} \tag{35}$$

$$EE_{it} = c_0 + c_y lny_{it} + c_{yy}(lny_{it})^2 + c_{p_w} p_{w,it} \tag{36}$$

where y indicates the per-capita income in the rural areas of each province. Considering the nonlinearity of the relationship between several efficiencies and rural per-capita income, we include y^2 in the estimated equations. We include the shadow price of waste, P_w, to test the effect of the regional pollution level on efficiencies.

3. Data

The Compilation of National Farm Product Cost-Benefit Data (CNFPCBD) is a national sample survey that details the production costs of several agricultural products; we rely on it for regional soybean farming data in our estimation of the production function.

As the CNFPCBD records data in units per mu, we must modify the values for our study. Furthermore, we must estimate arable land data for all periods except 2000–2003.

3.1 Production function estimation through SFA

- Output: annual soybean production
- Intermediate goods: total expenditure on chemical fertilizer, seeds, pesticides, and other goods

These values are expressed in constant 2007 prices calculated with the China Rural Statistical Yearbook's (CRSY) price index.

- Capital input: capital service

Capital service is the total capital cost of machinery, draft animals, and depreciation expressed in constant 2007 prices (CRSY).

- Labor input: days of labor.

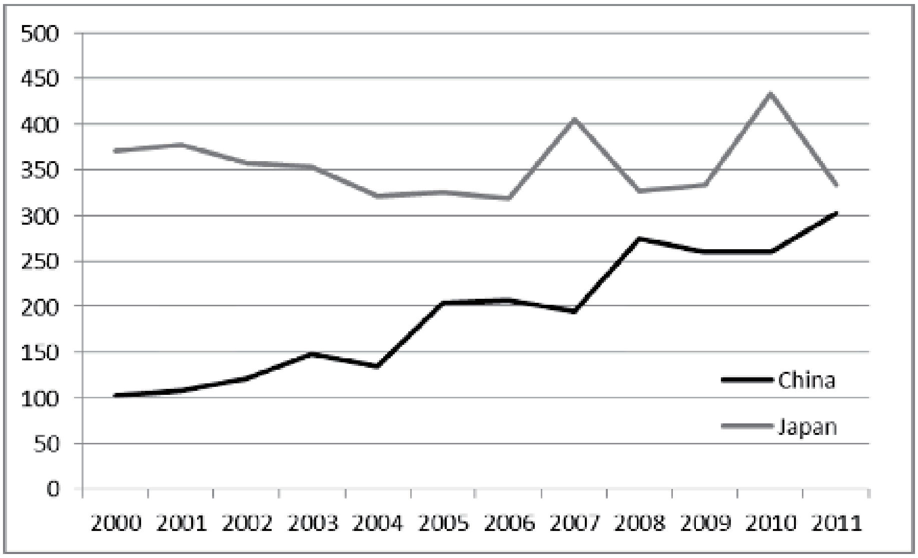
One day of labor is assumed to be eight hours.

- Arable land:

For the 2000–2003 period, we are able to use planted area values from the CNFPCBD. After 2004, we estimate the values with the following equation.

$$\begin{aligned} &\mathrm{t}_{\,individual\ farm\ in\ province\ i's\ planted\ area\ of\ soybeans\ in\ a\ specified\ year} \\ &= \mathrm{average}\left(\frac{individual\ farm\ in\ province\ i's\ planted\ area\ of\ soybeans}{total\ soybean\ planted\ land\ in\ province\ i}\right) * t_{\,total\ soybean\ planted\ area\ in\ province\ i's\ specified\ year} \end{aligned}$$

Figure 3 Real Fertilizer Expenditure to Land Ratio (Constant International Dollar/Ha)



Sources: CNFPCBD and the Ministry of Agriculture, Forestry, and Fisheries (MAFF)

The average between 2002 and 2003 is used. The data on the total area of soybean cultivation is obtained from the CRSY.

3.2 Measurement of EE and over-employment

- Nutrients in the intermediate goods: total nutrients (i.e., nitrogen, phosphoric acid, and potassium) included in chemical fertilizers (CNFPCBD), seeds (China Food Composition (CFC)), and arable land (estimated using Shindo's (2012) method)
- Price of intermediate goods: implicit deflator of intermediate goods
- Price of capital input: implicit deflator of capital services
- Real Wage: wages of hired-laborers in the regional soybean farming sector deflated by the consumer price index (China Statistical Yearbook (CSY))

3.3 Estimation of factors explaining several efficiencies

- Real per-capita income in rural areas: per-capita income in rural areas deflated by the consumer price index (CSY)

4. Statistical Analysis

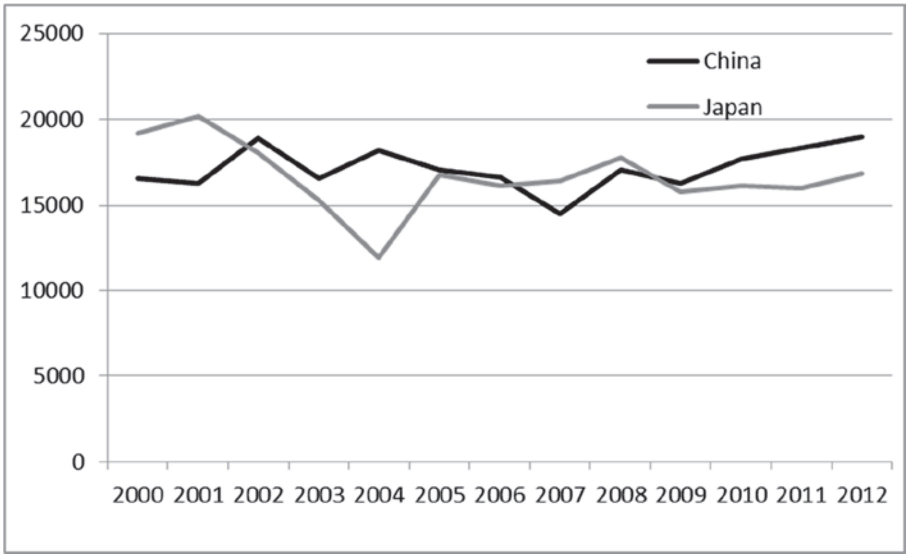
As Japan has transitioned from a developing to a developed economy (surpassing Lewis' turning point (Minami, 1973) and finishing the second export substitution (Ohkawa and Kohama, 1989)), we may compare its data with that of China in order to determine China's current stage of development and thereby supplement our empirical estimation.

Figure 3 shows real expenditures on chemical fertilizer per Ha of arable land in Japan's and China's soybean farming sectors from 2000 to 2011[3].

Though Japan's fertilizer expenditure to land ratio has trended downward, China's

3 It is difficult to obtain comparable data on the nutrient content of Japan's and China's soybean fertilizers, so we instead compare the monetary value. The local currencies are converted using the World Bank's purchasing power parity estimations.

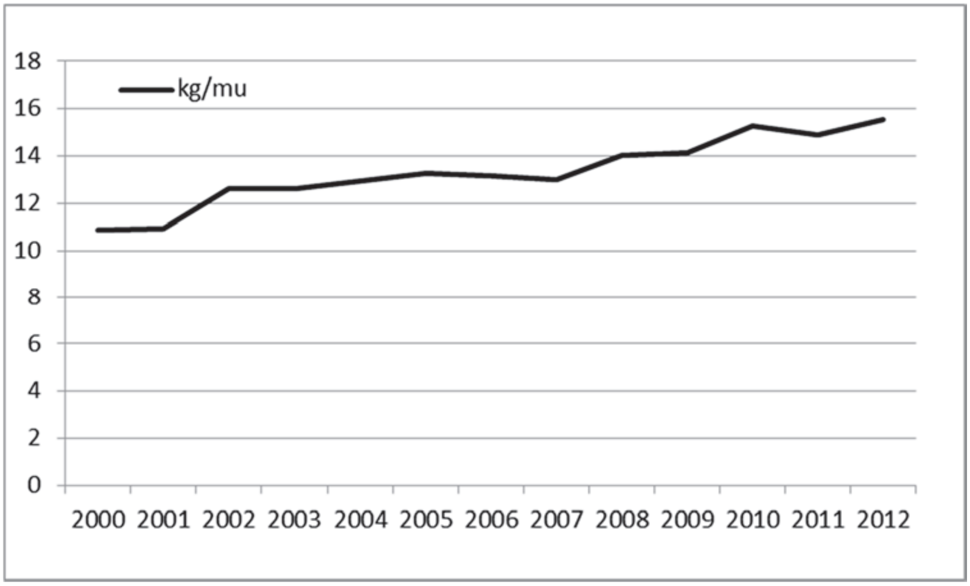
Figure 4　Soybean Output to Land Ratio (Hg/Ha)



Source: FAOSTAT

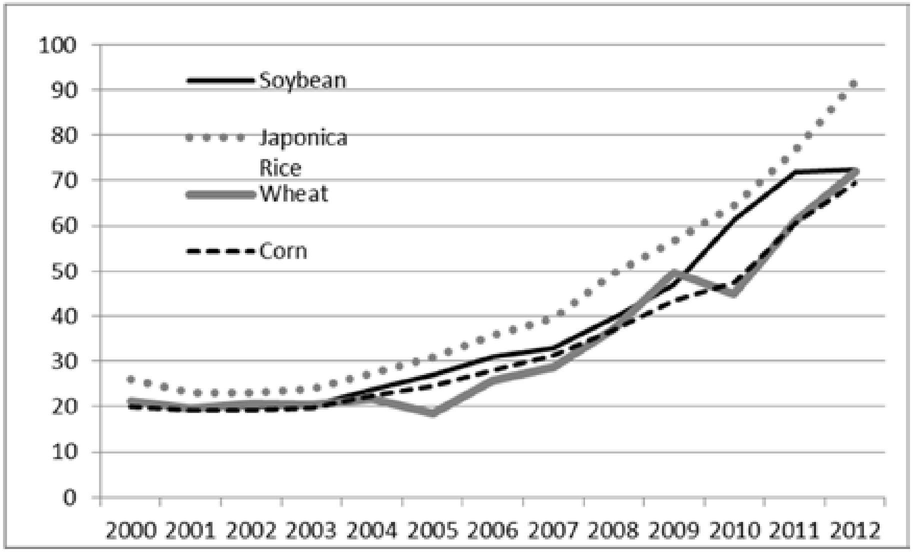
has trended upward to where the two nearly converged in the late 2000s. Reflecting this trend, China's output to land ratio has come to exceed Japan's (Figure 4). As arable land is relatively scarce in East Asian countries, increasing the output to land ratio is integral for agricultural development. Unfortunately, fertilizer usage tends to pollute arable land and ground water. Furthermore, on soybean farms, increases in the output to land ratio raise the nutrient to land ratio by means of biological fixation, thus exacerbating the pollution

Figure 5　Nutrient Balance in the Soybean Farming Sector (2000-2012)



Sources: CNFPCBD

Figure 6 Real Wage Rate of Hired -Labor in China's Farming Sector (Yuan/day)



Sources: CNFPCBD and CSY

problem. As a result, the estimated average nutrition surplus per mu during 2000–2012 in the soybean farming sector has increased from 11 kg to 16 kg (Figure 5).

We believe that when the economy passes the turning point, it has a significant impact on over-employment in the soybean farming sector. Minami (1973) states that, in order to determine whether a country has surpassed Lewis' turning point, one must examine (i) wages and the marginal productivity of labor (MP_L) in the subsistence sector, (ii) the correlation between the two, (iii) the movements in the subsistence sector's real wages, (iv) changes in the wage differentials, and (v) the elasticity of labor supply between the subsistence and capitalist sectors. We use China's and Japan's data to examine (iii) and (iv).[4]

Figure 6 shows the real wage rates in China's soybean, japonica rice, wheat, and corn farming sectors. We use the real wage rate of hired labor as the proxy for the real wage rate. As Minami (1973) suggests, the real wage rate of long-term contract labor would be a preferable proxy, but the CNFPCBD combines short-and long-term laborers in its hired-labor data. The resulting wage rate is thus slightly higher as it reflects the seasonal rise in short-term laborers' wages during the harvest. Taking this limitation into account, we use data on labor power per hour.

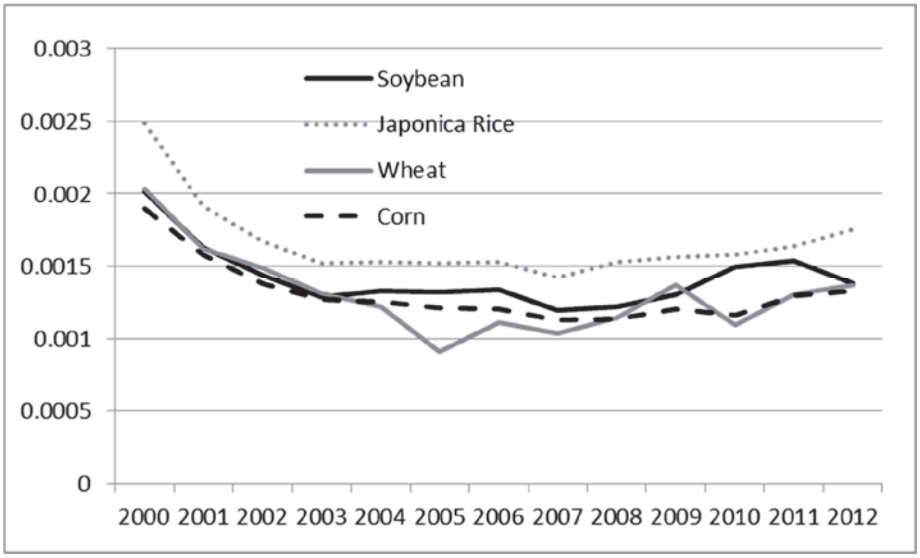
In the early 2000s, the real wage rate in China's farming sector was constant, though later in the decade it rose rapidly.

The average growth rate over this period was 14.4 percent, which is roughly double Japan's growth rate from 1961 to 1969 (i.e., the period during which it reached its turning point and over-employment in agriculture became nonexistent).[5]

4 Minami (1973) states that (i) is the most rigorous test for finding the turning point, but it requires us to estimate the production function, which we do not do until the next section.

5 According to Minami (1973), the growth rate of annual contractors' and daily workers' real wages was 7.15% and 7.27% from 1961 to 1969, respectively.

Figure 7　Wage Differentials between the Crop Farming and Urban Sectors



Sources: CNFPCBD and CSY

According to Minami (1973), wage differentials between unskilled labor and skilled labor may be used to determine the turning point. We define unskilled laborers as crop farmers (the data for whom is recorded as daily pay) and skilled laborers as urban workers (annual salaries), and present the resulting wage differentials in Figure 7.

During the early 2000s, the wage in the soybean and other crop farming sector decreased relative to that in the urban sector, whereas it increased later in the decade; these trends in the real wage rate and wage differentials would suggest that China surpassed Lewis' turning point and over-employment in these sectors became nonexistent. However, the rapid increase in the farming sector's real wage often reflects not only increased MP_L but also improvements in the subsistence level. Additionally, the wage differential is also affected by the relative demand and supply of unskilled and skilled labor. Furthermore, the exist of the over-employment in farming sector affects relative supply but not demand. Therefore, to confirm over-employment, we must estimate the E-S production function.

5. Estimation results

5.1 Production function

Before estimating the production function, we must confirm whether our panel data is stationary (non-stationary data may yield spurious correlations). Consequently, we employ the Fisher-type panel unit-root test as it is suitable for our unbalanced panel dataset.

Table2 shows that the null (all panels contain unit roots) is rejected in both the Augmented Dickey–Fuller (ADF) test and the Phillips and Perron (PP) test, which include a time trend and subtract cross-sectional means from the series. Thus, we conclude that our dataset is stationary.

We employ Belotti *et al.*'s (2012) methodology and sfpanel for STATA in our estimation of the production function. Table 3 shows the estimation results of the stochastic frontier production function. In both the BC and M production functions (i) all of the coefficients'

Table 2 Results of Panel Unit Root Test (H0: All panels contain unit roots)

	ADF test							
	Inverse chisquared		*Inverse normal*		*Inverse logit t*		*Modified inv. chi-squared*	
	statistics	*p-values*	*statistics*	*p-values*	*statistics*	*p-values*	*statistics*	*p-values*
lnQ	49.6725	0.01	−2.0278	0.02	−2.4485	0.01	2.8961	0.00
lnM	48.1211	0.01	−2.2151	0.01	−2.5738	0.01	2.6888	0.00
lnS	47.5753	0.01	−1.4189	0.08	−1.8616	0.03	2.6159	0.00
lnK	49.8330	0.01	−2.6514	0.00	−3.1420	0.00	2.9176	0.00
lnL	56.7160	0.00	−2.2890	0.01	−2.6255	0.01	3.8373	0.00
	PP test							
	Inverse chisquared		*Inverse normal*		*Inverse logit t*		*Modified inv. chi-squared*	
	statistics	*p-values*	*statistics*	*p-values*	*statistics*	*p-values*	*statistics*	*p-values*
lnQ	88.0217	0.00	−4.9436	0.00	−5.8507	0.00	8.0207	0.00
lnM	121.2031	0.00	−6.0551	0.00	−8.3556	0.00	12.4548	0.00
lnS	201.9714	0.00	−7.9505	0.00	−14.3440	0.00	23.2479	0.00
lnK	142.7486	0.00	−5.5836	0.00	−9.5460	0.00	15.3339	0.00
lnL	113.5214	0.00	−3.9955	0.00	−7.0905	0.00	11.4283	0.00

(a) We use one lag in each test.

Table 3 Regression Estimates (2000-2012, n=159)

	BC Technology				M Technology			
	Fixed Effects		*Random Effects*		*Fixed Effects*		*Random Effects*	
	Estimates	*Standard Error*	*Estimates*	*Standard Error*	*Estimates*	*Standard Error*	*Estimates*	*Standard Error*
a			5.5567***	0.3102			2.4565***	0.0727
α	0.2262***	0.0484	0.3090***	0.0526				
δ	0.7150***	0.0433	0.6810***	0.0492				
β					0.4361***	0.0294	0.4934***	0.0344
γ					0.4345***	0.0413	0.4396***	0.0269
σ_u	0.1544***	0.0202	0.1486***	0.0182	0.1513***	0.0257	0.1322***	0.0232
σ_v	0.0410***	0.0148	0.0579***	0.0118	0.0907***	0.0185	0.1173***	0.0155
$\lambda(=\frac{\sigma_u}{\sigma_v})$	3.7633***	0.0324	2.5654***	0.0264	1.6677***	0.0413	1.1271***	0.0349
	Statistics	p-value			Statistics	p-value	Statistics	p-value
Hausman test	12.52	0.00			3.33	0.19		
CRS test	4.08	0.04					7.16	0.01

(a) *** Statistically significant at the 1% confidence level; ** Statistically significant at the 5% confidence level; * Statistically significant at the 10% confidence level signs are as expected, (ii) all of the parameters are statistically significant, and (iii) are below one, indicating that there are diminishing returns to scale (DRS). Based on the Hausman test, the estimation results from the TFE model of the BC function and those from the TRE model of the M function are selected to measure EE and over-employment.

In order to confirm the validity of (iii), we use the Wald test to see whether there are constant returns to scale (CRS) (see Table 3). The CRS hypothesis is rejected for both the BC and M functions, which actually seem to exhibit DRS.

Our estimation results for $\alpha+\delta$ are similar to those of previous studies; that is, Japan and China enjoy CRS (or DRS that are near to CRS). However, the estimation results for $\beta+\gamma$ indicate that Japan enjoys increasing returns to scale (IRS) to a greater degree than China. In contrast to previous studies, our results suggest that China's soybean farming sector has not exploited the IRS in the M process.

5.2 Estimation results for TE, EAE, EE, AE, and CE

The regional arithmetic means of TE, EAE, EE, AE, and CE are shown in Table 5. The average EE value across all of the provinces is 0.8269, indicating that China's soybean farming sector has been environmentally inefficient since 2000. Inner Mongolia, for example, could reduce the quantity of nutrients by about 33% while maintaining the same level of production, while Shandong could reduce its nutrient level by 11%. This, in turn, indicates a regional disparity in EE. We estimate each province's potential for nutrient reduction by subtracting the optimal number of nutrients from the real number of nutrients. The province with the greatest potential for reduction is Heilongjiang with 32 kg, while the other provinces vary between 0.09 kg and 2.6 kg. In every province, there is greater potential for reduction through TE (accounting for 67 percent of the reduction for EE) than there is through EAE.

According to the CE in the BC process, China has also been inefficient in terms of cost minimization since 2000 with a potential to

Table 4 Previous Studies' Results

Articles	Country	Data	Period and sector	α	δ	$\alpha+\delta$	β	γ	$\beta+\gamma$
Egaitsu and Shigeno (1983)	Japan	Cross section	1957 – 1979 Japonica rice	0.14–0.26		CRS	0.48–1.32	−0.13–0.88	1.17–1.36
Egaitsu (1985)	Japan	Cross section	1957 – 1980 Dairy farming	0.60–1.05	0.06–0.41	0.98–1.11	0.44–1.26	0.30–0.78	1.13–1.61
Shirasago (1986)	China	Cross section	1980 Agriculture	0.35	0.58	0.93	0.55	0.53	1.09
Shirasago (1991)	China	Cross section	1981 – 1987 Agriculture	0.33–0.58	0.40–0.63	0.95–1.04	0.43–0.53	0.46–0.57	0.98–1.01
Komagata (1998)	China	Panel	1991 – 96 Agriculture	0.67		CRS	0.36	0.61	0.97

(a) CRS indicates the assumption that $\alpha+\delta=1$.

(b) Egaitsu's (1985) α is the output elasticity of feed, while δ is the output elasticity of dairy cow stock.

Table 5 Arithmetic Means of TE, EAE, EE, AE, and CE by Region and Time-series Variations (2000 − 2012)

	TE BC	EAE BC	EE BC	AE BC	CE BC	TE M	AE M	CE M
Anhui	0.8721	0.9944	0.8671	0.8667	0.7579	0.8767	0.6595	0.5787
Yunnan	0.8503	0.9529	0.8121	0.7464	0.6313	0.8823	0.6765	0.5964
Henan	0.8676	0.9818	0.8517	0.9254	0.8008	0.8275	0.7074	0.5783
Hebei	0.9067	0.9702	0.8792	0.9036	0.8186	0.8809	0.7648	0.6727
Jilin	0.8967	0.9527	0.8551	0.9239	0.8289	0.8829	0.8195	0.7238
Hubei	0.7907	0.9515	0.7540	0.8882	0.7010	0.8263	0.7402	0.6172
Jiangsu	0.7510	0.9412	0.7182	0.8813	0.6559	0.8285	0.5647	0.4644
Shanxi	0.8533	0.9214	0.7894	0.8187	0.6968	0.8763	0.7295	0.6391
Shandong	0.9019	0.9865	0.8899	0.8756	0.7885	0.8934	0.6025	0.5372
Chongqing	0.8881	0.9854	0.8754	0.7896	0.7083	0.8724	0.2501	0.2133
Inner Mongolia	0.7065	0.9378	0.6672	0.8761	0.6240	0.8471	0.8023	0.6792
Heilongjiang	0.8821	0.9371	0.8274	0.9137	0.8081	0.8911	0.9146	0.8147
Liaoning	0.8970	0.9646	0.8658	0.9481	0.8497	0.8932	0.8440	0.7531
Shaanxi	0.8697	0.9421	0.8212	0.8913	0.7767	0.8829	0.7423	0.6526
Total	0.8596	0.9595	0.8269	0.8799	0.7572	0.8720	0.7120	0.6200
	TE BC	EAE BC	EE BC	AE BC	CE BC	TE M	AE M	CE M
2000	0.8188	0.9681	0.7959	0.8850	0.7249	0.8488	0.7378	0.6251
2001	0.8014	0.9643	0.7754	0.9041	0.7231	0.8234	0.7518	0.6184
2002	0.9027	0.9712	0.8774	0.8792	0.7954	0.8690	0.7240	0.6331
2003	0.7849	0.9544	0.7511	0.8602	0.6730	0.8128	0.7307	0.5997
2004	0.8685	0.9521	0.8296	0.7609	0.6629	0.8764	0.7127	0.6213
2005	0.8440	0.9593	0.8128	0.8278	0.6989	0.8902	0.7072	0.6314
2006	0.8520	0.9553	0.8175	0.8184	0.6934	0.8497	0.7254	0.6109
2007	0.7785	0.9414	0.7355	0.8558	0.6638	0.8702	0.6871	0.5915
2008	0.8894	0.9703	0.8631	0.8584	0.7653	0.9237	0.6753	0.6234
2009	0.8583	0.9518	0.8194	0.9203	0.7879	0.8909	0.6872	0.6101
2010	0.9368	0.9625	0.9020	0.9465	0.8871	0.9040	0.6960	0.6314
2011	0.9342	0.9622	0.8991	0.9558	0.8930	0.9135	0.6838	0.6250
2012	0.9459	0.9619	0.9096	0.9547	0.9026	0.8935	0.7179	0.6428
Total	0.8596	0.9595	0.8269	0.8799	0.7572	0.8720	0.7120	0.6200

reduce total costs by 24 percent. In contrast to previous studies, we find that the CE in the BC process is higher than the EE (Van Meensel *et al.*, 2010; Hoang and Nguyen, 2013). This would seem to indicate that the soybeans farming sector is affected by a smaller amount of fertilizer than the other crops. The arithmetic mean of TE in terms of the M process is 0.87 and the index is similar to that of the BC; however, there is less regional variation in the former (coefficient of variation=0.099) than there is in the latter (coefficient of variation=0.14). Furthermore, a one-way analysis of the variance rejects the hypothesis that the TEs in both processes are identical at the 0.6 percent level. The M process' AE and CE are significantly lower than the BC process', which suggests that M technology production factors are over-used to a greater extent than BC technology factors.

The time-series variations in TE, EAE, EE, AE, and CE are shown in Table 5. In the BC process, TE increased from 0.82 to 0.95 during the study period, while EAE stayed between 0.94–0.97. Consequently, TE has had a greater impact on the improvements in EE. Furthermore, while the CE decreased in the early 2000s, it eventually rose later in the decade. TE did not improve in the M process as it did in the BC process. Additionally, in the M process, AE declined during the study period, which caused CE to remain stagnant.

Table 6 reports the price of waste. In general, the cost of environmental improvement in China's soybean farming sector has increased. The cost of reducing nutrients is approximately 1.9 times higher in Henan (the province with the greatest waste price) than it is in Shanxi (the province with the lowest price), indicating that there are wide regional variations in reduction costs.

Table 6 Arithmetic Means of Pollutant Prices and the ROE by Province and Year

Province	Pw	ROE	Year	Pw	ROE
Anhui	9.2702	0.6404	2000	6.9343	0.5419
Yunnan	6.2504	0.6450	2001	6.3873	0.5538
Henan	10.3471	0.6149	2002	5.4502	0.5381
Hebei	7.0251	0.4718	2003	6.3086	0.5638
Jilin	7.9107	0.5174	2004	6.5369	0.5870
Hubei	7.1241	0.5682	2005	7.0307	0.5657
Jiangsu	7.9883	0.6979	2006	6.6705	0.5983
Shanxi	5.4573	0.5923	2007	7.4317	0.6220
Shandong	7.2146	0.6574	2008	8.7752	0.6001
Chongqing	8.0186	0.8698	2009	9.0645	0.6124
Inner Mongolia	8.3576	0.5053	2010	9.4399	0.5972
Heilongjiang	7.6879	0.3884	2011	10.2286	0.6052
Liaoning	8.2678	0.4968	2012	11.3234	0.5682
Shaanxi	5.8670	0.5817			
Total	7.6841	0.5797		7.6841	

5.3 Over-employment estimation results

The ROE estimation results are presented in Table 6. The arithmetic mean of the ROE is 58 percent. There is a 48 percentage point difference between the province with the lowest ROE (Heilongjiang at 39 percent) and that with the highest (Chongqing at 87 percent). Even though over-employment began to decrease in 2007, it has consistently remained above 54 percent, thus indicating that the labor input in Chinese soybean farming is inefficient.

5.4 Examination of the impact on environmental efficiency

Before estimating equations 34–36, we conduct Fisher's panel unit-root test in order to confirm that the series are stationary. Table 7 and 8 show the results of Fisher's panel unit- root test. From the ADF test in levels, we see that we cannot reject the null hypothesis that all panels contain unit roots. Meanwhile, the ADF test in first differences indicates that we can reject the null hypothesis in the majority of cases. The PP test in levels shows that the null can be rejected for TE, EAE, and EE and that the other variables are in most cases non-stationary. The PP tests in first differences show thay the variables of interests are all stationary. The ADF test indicates that our data for the estimation may be *I*(1). To confirm the long-term relationship between *I*(1) variables, we run Pedroni's (2004)

Table 7 Results of the Panel Unit Root Test (H0: All panels contain unit roots)

	ADF test							
	Inverse chisquared		*Inverse normal*		*Inverse logit t*		*Modified inv. chi-squared*	
	Statistics	*p-values*	*Statistics*	*p-values*	*Statistics*	*p-values*	*Statistics*	*p-values*
TE	19.8291	0.87	−0.1791	0.43	−0.1839	0.43	−1.0919	0.86
EAE	22.1900	0.77	−0.2799	0.39	−0.2668	0.40	−0.7764	0.78
EE	18.8631	0.90	−0.1650	0.44	−0.1481	0.44	−1.2210	0.89
lny	19.1951	0.89	0.0674	0.53	0.0521	0.52	−1.1766	0.88
$(lny)^2$	21.0137	0.82	−0.1182	0.45	−0.1509	0.44	−0.9336	0.82
p_w	8.6710	1.00	3.1470	1.00	3.2475	1.00	−2.5829	1.00
	PP test							
	Inverse chisquared		*Inverse normal*		*Inverse logit t*		*Modified inv. chi-squared*	
	Statistics	*p-values*	*Statistics*	*p-values*	*Statistics*	*p-values*	*Statistics*	*p-values*
TE	106.8710	0.00	−6.7509	0.00	−7.6695	0.00	10.5396	0.00
EAE	103.8412	0.00	−5.9681	0.00	−7.0793	0.00	10.1347	0.00
EE	102.9530	0.00	−6.3961	0.00	−7.2824	0.00	10.0160	0.00
lny	35.8254	0.15	0.6482	0.26	0.5301	0.30	1.0457	0.15
$(lny)^2$	35.6169	0.15	−0.6416	0.26	−0.5220	0.30	1.0179	0.15
p_w	42.4322	0.04	0.6459	0.74	−0.1495	0.44	1.9286	0.03

(a) We use one lag in each test.

Table 8　Results of the Panel Unit Root Test (H0: All panels contain unit roots)

	ADF test							
	Inverse chi-squared		*Inverse normal*		*Inverse logit t*		*Modified inv. chi-squared*	
	Statistics	*p-values*	*Statistics*	*p-values*	*Statistics*	*p-values*	*Statistics*	*p-values*
ΔTE	55.3800	0.00	−3.4962	0.00	−4.0181	0.00	4.0743	0.00
ΔEAE	51.9160	0.00	−3.3629	0.00	−3.6364	0.00	3.5939	0.00
ΔEE	47.2187	0.01	−2.8299	0.00	−3.1540	0.00	2.9425	0.00
Δlny	35.2680	0.11	−1.7287	0.04	−1.7497	0.04	1.2850	0.10
$\Delta (lny)^2$	33.9822	0.14	−1.63	0.05	−1.6204	0.06	1.1069	0.13
Δp_w	64.2338	0.00	−3.2098	0.00	−4.3373	0.00	5.3021	0.00
	PP test							
	Inverse chi-squared		*Inverse normal*		*Inverse logit t*		*Modified inv. chi-squared*	
	Statistics	*p-values*	*Statistics*	*p-values*	*Statistics*	*p-values*	*Statistics*	*p-values*
ΔTE	305.7051	0.00	−14.2337	0.00	−25.5393	0.00	37.1099	0.00
ΔEAE	187.4767	0.00	−10.6584	0.00	−15.6652	0.00	21.3110	0.00
ΔEE	273.0350	0.00	−13.1602	0.00	−22.8164	0.00	32.7442	0.00
Δlny	108.1409	0.00	−7.5542	0.00	−8.9273	0.00	10.7093	0.00
$\Delta (lny)^2$	102.3158	0.00	−7.2136	0.00	−8.4235	0.00	9.9309	0.00
Δp_w	129.7979	0.00	−7.9002	0.00	−10.7326	0.00	13.6033	0.00

(a) We use one lag in each test.

and Kao's (1999) panel co-integration tests, which show that the null may be rejected for 7 of the 12 statistics (Table 9 and 10). This suggests that the panel variables in equations 34–36 are cointegrated.

Table 11 shows the estimation results for equations 34–36. The restriction over-identifying test (used instead of the conventional Hausman test) indicates that (i) the fixed effect model is preferable.[6] The TE and EE of the system GMM reveal that (ii) the estimated parameters of *lny* are significantly positive and (iii) those of $(lny)^2$ are significantly negative. The signs of TE's and EE's estimated parameters are identical. Consequently, as increases in per-capita income in China's rural areas raise TE and EE will rise as well. However, after per-capita income peaks, TE and EE will begin to fall as income growth continues. In addition, there is a significantly negative correlation between TE and pw; thus, we conclude that lowering the cost of agricultural waste would improve TE and thereby have a positive impact on EE.

6　In our estimated results, the standard error is clustered. Consequently, we use Arellano's (1993) and Woodridge's (2002) artificial regression approach to select the fixed or random effect model.

Table 9 Results of Pedroni's (2004) Cointegration Test (H0: No cointegration)

TE

	Statistics	*p-values*	*Weighted statistics*	*p-values*		*Statistics*	*p-values*
Panel v-Statistic	−1.3547	0.9123	−3.2279	0.9994	Group rho-Statistic	3.2883	0.9995
Panel rho-Statistic	2.2000	0.9861	2.5343	0.9944	Group PP-Statistic	−16.5240	0.0000
Panel PP-Statistic	−9.8833	0.0000	−8.8530	0.0000	Group ADF-Statistic	−5.6208	0.0000
Panel ADF-Statistic	−5.6835	0.0000	−4.8038	0.0000			

EAE

	Statistics	*p-values*	*Weighted statistics*	*p-values*		*Statistics*	*p-values*
Panel v-Statistic	−1.8301	0.9664	−3.4205	0.9997	Group rho-Statistic	3.1726	0.9992
Panel rho-Statistic	1.7988	0.9640	2.6340	0.9958	Group PP-Statistic	−13.2374	0.0000
Panel PP-Statistic	−7.8456	0.0000	−5.9824	0.0000	Group ADF-Statistic	−7.1491	0.0000
Panel ADF-Statistic	−5.5376	0.0000	−6.2712	0.0000			

EE

	Statistics	*p-values*	*Weighted statistics*	*p-values*		*Statistics*	*p-values*
Panel v-Statistic	−1.8294	0.9663	−3.0383	0.9988	Group rho-Statistic	3.3982	0.9997
Panel rho-Statistic	2.4542	0.9929	2.5559	0.9947	Group PP-Statistic	−15.2790	0.0000
Panel PP-Statistic	−8.1712	0.0000	−8.8730	0.0000	Group ADF-Statistic	−5.2453	0.0000
Panel ADF-Statistic	−4.7001	0.0000	−4.9709	0.0000			

Table 10 Results of Kao's (1999) Cointegration Test (H0: No cointegration)

		statistics	*probability*
TE	ADF-Statistic	−7.3070	0.0000
EAE	ADF-Statistic	−4.2967	0.0000
EE	ADF-Statistic	−6.6937	0.0000

Table 11　Regression Estimates (2000－2012, n=159)

Dependent Variable	TE						EAE					
	Fixed Effects		Random Effects		System GMM		Fixed Effects		Random Effects		System GMM	
	Estimates	Standard Error	Estimates	Standard Error	Estimates	Standard Error	Estimates	Standard Error	Estimates	Standard Error	Estimates	Standard Error
Intercept			-2.9970	5.7524	-17.4524*	9.8319			0.1470	1.3799	-4.0676*	2.2245
lny	1.7076	2.0720	0.9074	1.4158	4.4055*	2.3822	0.3375	0.4618	0.1786	0.3515	1.0244	0.5055
$(lny)^2$	-0.0660	0.1220	-0.0509	0.0872	-0.2589*	0.1440	-0.1044	0.0288	-0.0093	0.0226	-0.0545	0.0290
p_w	-0.0255***	0.0074	-0.0229***	0.0074	-0.0264***	0.0093	-0.0012	0.0014	-0.0002	0.0014	-0.0002	0.0011
			Statistics	*p-values*		*p-values*			*Statistics*	*p-values*		*p-values*
Test for 1st order serial correlation						0.0443						0.0074
Test for 2nd order serial correlation						0.3309						0.1399
Test for restriction over-identification			808.805	0.0000					1634.413	0.0000		

Dependent Variable	EE					
	Fixed Effects		Random Effects		System GMM	
	Estimates	Standard Error	Estimates	Standard Error	Estimates	Standard Error
Intercept			-3.040	6.2991	-18.9135**	9.5652
lny	1.7913	2.2756	0.8895	1.5573	4.6431**	2.3316
$(lny)^2$	-0.0637	0.1354	-0.0485	0.0965	-0.2684*	0.1413
p_w	-0.0248***	0.0078	-0.0214***	0.0079	-0.0258**	0.0101
Test for 1st order serial correlation						0.0402
Test for 2nd order serial correlation						0.3271
Test for restriction over-identification			1011.700	0.0000		

(a) The standard errors in fixed and random effect model are clustered on provinces.
(b) The system GMM standard errors are robust.
(c) We include a time dummy variable in each equation.

6. Conclusions and policy implications

EE improved (though with regional disparities) within China's soybean farming sector throughout the study period; this is largely due to increases in TE. Meanwhile, the waste price has increased since the late 2000s. In spite of the improvement in EE, the pollution from the BC process has increased. Recently, the government has increased its direct subsidies to farmers as well those for purchasing agricultural materials. The Chinese government should take regional variations into account in their development of subsidy policies, which should focus more on conserving agricultural materials. Additionally, efforts should be made to educate farmers on the most efficient way to manage materials. For instance, multiple cropping, whereby one crop is allowed to consume the nutrients from another crop (e.g., soybeans), appears to be an effective means of reducing farm-level waste; this method may be particularly beneficial in regions where the cost of waste reduction is high. The estimation results for the equations 34–36 suggest that a policy that focuses on higher rural income could temporarily raise EE, though it would eventually decrease again. In order to improve EE and reduce waste, policies that focus on the efficient usage of agricultural materials must be implemented.

It should also be noted that the ROE in the soybean farming sector exceeds 50% in most provinces. Recently, China's government has reformed the family register (***hukou***), which disrupts transfers between rural and urban areas. Further reforms may yet reduce over-employment to a greater extent. Moreover, TE and CE have not grown as rapidly in the M process as they have in the BC process. In order to improve these efficiencies within the M process, policies that promote the transfer of labor and increase capital intensity in the farming sector should be enacted.

According to our empirical results, both BC and M production factors have been used inefficiently in China's soybean farming sector. The pollution and low income in rural areas is a direct result of the excessive use of production factors. Clearly, institutions and policies that distort the production factor market are needed to remedy this situation.

It should be noted that our research methodology could also be applied to the rice farming sector, where the rice fields are rich in nitrogen. In fact, this line of inquiry could provide useful insights into the green revolution in China's development process as the rice farming sector has seen a rapid increase in output due to the extensive use of fertilizer. Additionally, it may be beneficial for future studies to explore how the use of EE in total agriculture is more suitable for the estimation of the equations 34–36.

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Environmental Efficiency and Employment in China’s Soybean Farming Sector

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Keywords: environmental efficiency, Egaitsu-Shigeno type production function, soybeans, biochemical technology, mechanical technology
JEL Classification Numbers: O1, Q1, Q5

The purpose of this study is to measure the environmental efficiency, waste price, and over-employment in China’s soybean farming sector. We establish that there is a relationship between estimated environmental efficiency and the two independent variables, rural per-capita income and waste price, which indicates if the effect of rural development and waste levels on environmental efficiency may be observed at a provincial level in this sector.

This study relies heavily on the Compilation of National Farm Product Cost-Benefit Data as well as the Cob-Douglas production function developed by Egaitsu and Shigeno (E-S), which allows us to distinguish between biochemical (BC) technology and mechanical (M) technology. For the estimation, we apply the stochastic frontier model to Greene’s (2005) panel data.

Based on our environmental efficiency estimation, we conclude that the industry has been inefficient since 2000; however, it has since generally improved (with regional variations) due largely to technological advances. Additionally, we find that the waste price has increased since the late 2000s and that the rate of over-employment exceeded 50% in the majority of the provinces. Technical efficiency and cost efficiency have not grown as rapidly in the M process as they have in the BC process. In order to improve these efficiencies within the M process, policies that promote the transfer of labor and increase capital intensity in the farming sector should be enacted.

Furthermore, Both the technical efficiency and environmental efficiency of the system GMM reveal that the estimated parameters of log(rural per-capita) are significantly positive and those of log (rural per-capita) squared and waste price are significantly negative.

According to our empirical results, both BC and M production factors have been used inefficiently in China’s soybean farming sector. The pollution and low income in rural areas is a direct result of the excessive use of production factors. Clearly, institutions and policies that distort the production factor market are needed to remedy this situation.