Full Length Research Paper

Productivity growth, technical efficiency, and technical change in China's soybean production

Wei SI* and Xiuqing WANG

College of Economics and Management, China Agricultural University, Beijing, 100083, China.

Accepted 20 October, 2011

A stochastic frontier production function (SFPF) is specified to examine productivity growth, technical efficiency, and technical change in China's soybean sector. A panel data set of 12 major soybean-producing provinces across the nation during the period of 1983 to 2007 was used. Results indicate that total factor productivity for China's soybean production increased by 1.5% annually, with productivity growth, mainly, from technological progress. However, both technical efficiency and technical progress showed a decreasing trend through time. Clearly, market liberalization has produced negative impact on China's soybean productivity.

Key words: Stochastic frontier production function, total factor productivity, technical efficiency, technical change, China, soybean production.

INTRODUCTION

In recent decades, the role of soybean in China's food system has experienced significant changes following the nation's gradual move to open up its soybean market in the 1990s. Average import quantity climbed by 30% annually from 1996 to 2009 with the rapid decline of selfsufficiency from 92.4 to 25.2% at the same period. To date, soybean market is the highest liberalized market (merely 3% of import tariff) among China's agricultural products. Given China's speedy economic development, it can be confirmed that soybean demand will continue to rise in the future.

Interestingly, the rising demand has failed to drive the development of domestic soybean production. On the contrary, the soybean-planting area has a shrinking trend. Yield of soybean is sluggish compared with wheat, maize, and rice (Aubeert and Zhu, 2000), Soybean is gradually fading from China's grain self-sufficient program, and the number of scientists and institutions dedicated to soybean research continues to decline. Approximately 500 researchers are, directly, involved in soybean

JEL classification: Q11, O13, O33, O47.

research. But, soybean production is, increasingly, becoming unfavorable in the current economic and policy environment.

This study attempts to determine the reason behind the transition of China's soybean productivity growth from absolute self-sufficiency to high import dependence. Faced with growing land resource scarcity and import pressure, does China have the potential to raise soybean output by increasing total factor productivity? If this is possible, where does output potential originate and how high is this potential?

A substantial research has been dedicated to the productivity and efficiency of China's agricultural production (McMillan et al., 1989; Lin, 1992; Fan, 1991; Fan, 1997; Mao and Koo, 1997; Yao and Liu, 2000; Tian and Wan, 2000; Jin et al., 2002; Chen et al., 2008). However, few studies attempted to measure the total factor productivity (TFP), technological change (TC), and technical efficiency (TE) of Chinese soybean crop through time using translog stochastic frontier production function approach (SFA). Evidently, filling this gap in literature is beneficial in gaining a better understanding of the present status and prospects for China's soybean economy.

The main objectives of this study are: (a) to measure the TFP, TE, and TC of Chinese soybean crop over the past 25 years through the SFA model; (b) to investigate

^{*}Corresponding author. E-mail: siwei@cau.edu.cn. Tel: +86-10-62738579. Fax: +86 -10- 62738710.

the growth trend of TFP, TE, and TC over time; (c) to identify factors that can promote soybean productivity; and (d) to compare differences in TE, TC, and TFP among major soybean-producing provinces.

METHODOLOGY

Theoretical framework

Stochastic frontier production function approach (SFA)

Since the advent of SFA, it has been widely used to analyze technical efficiency. With its flexible translog specification as its main advantage, the method does not only estimate technical efficiency directly but also analyzes the effect of exogenous variables on technical inefficiency in one step instead of the commonly used multi-stage estimation approach (Lin, 1992).

A number of methods can be utilized for estimating SFA. Based on previous studies (Aigner et al., 1977; Meeusen and van den Broeck, 1977; Battese and Coelli, 1995), the model can be specified in the following basic form:

$$y_{it} = f(x_{it}, t; \beta) \exp(v_{it} - u_{it})$$
 (for i=1,2,...,n; t=1,2,...,T) , (1)

Where y_{it} represents the output of i-th production unit in time t; $f(\Box)$ denotes the production function of i-th production unite in time t; X_{it} is the input vector; t is a time trend serving as a proxy for technical change; β presents the vector of unknown parameters to be estimated; U_{it} is a non-negative random variable associated with technical inefficiency; and v_{it} is the statistical noise.

Statistical noise arises from the inadvertent omission of relevant variables from vector X_{it} , as well as from measurement and approximation errors associated with the choice of functional form. A non-negative random variable u_{it} indicates that output values are bounded by the stochastic (that is, random) variable exp $[f(x_{it}) + v_{it}]$, and u_{it} truncated at zero as $N(m_{it}, \sigma_u^2)$. Random error V_{it} can be positive or negative; thus the stochastic frontier output tends to be evenly distributed above and below the

deterministic part of the frontier, and $v_{it} \sim N(0, \sigma_v^2)$. The term $m_{it} = z_{it} \delta$ defines an index of technical inefficiency; \boldsymbol{z}_{it} represents the vector of variable which may influence efficiency of a production unit; and δ is the corresponding parameters vector to be estimated. These parameters indicate the impacts of variables

The technical efficiency index of the ith production unit in year t can be calculated using the following formula:

$$EFF_{it} = E(y_{it} * | u_{it}, x_{it}) / E(y_{it} * | u_{it} = 0, x_{it}),$$
⁽²⁾

Where E (.) is used to calculate the expectation. When y_{it} a

dependent variable of the SFA model is, y_{it} * becomes the actual output. On the other hand, y_{it} * is exp (y_{it}) when the dependent variable is in logarithm.

Decomposition of total factor productivity

Productivity growth is attributed to technical efficiency, technical change, scale efficiency change, and allocation efficiency. Change of total factor productivity can be measured by arithmetic product (summation) of the above four effects. For deterministic production frontier function, the following formula may be utilized:

$$y_{it} = f(x_{it}, t; \beta) \exp(-u_{it}), \qquad (3)$$

The meaning of Equation (3) is consistent with that of Equation (1). According to Equation (3), technical changes of i-th production unite in time t is defined as follows:

$$TC_{it} = \frac{\partial \ln f(x_{it}, t; \beta)}{\partial t}.$$

If technical change drives the production frontier to shift upward, downward or remain constant, TC indexes can be greater than, equal to, or less than "0," respectively. If the value of TC is greater than "1," it implies the existence of technical progress.

A firm can enhance productivity through approaching the frontier by more efficient use of inputs. According to Equation (3), technical efficiency changes of i-th production unite in time t is obtained through the following:

$$TEC_{it} = -\frac{\partial u_{it}}{\partial t}.$$

Technical efficiency decreases, stays constant, or increases with changing time, making the value of TEC greater than, equal to, or less than "0," respectively. Technical efficiency indicates that a firm moves either toward the production frontier or far away from it, and that technical efficiency per se can change with time.

Productivity change can be represented as the difference between the value of rates of output change and input change by employing the Divisia index:

$$TFP_{it} = y_{it} - X_{it} = y_{it} - \sum_{i=1}^{n} S_{it} x_{it} , \qquad (4)$$

Where y_{it}^{\Box} denotes output change rate; $y_{it}^{\Box} = (\frac{1}{y_{it}})(\frac{dy_{it}}{dt});$

S_{it} is the expense share of input factor x_{it} ; $S_{it} = \frac{W_{it}x_{it}}{F}$. $E = \sum w r$ (The and total

$$v = \sum_{i} w_{it} x_{it}$$
 (the total expense share); and $v = (w, w) > 0$

 $w = (w_1, \dots, w_n) > 0$ denotes input price vector. After complete differential to Equation (4), Equation (5) can be obtained as follows:

$$TFP_{it} = TC_{it} + (\varepsilon - 1)\sum_{i=1}^{n} \left(\frac{\varepsilon_{it}}{\varepsilon}\right) X_{it}^{\Box} + \sum_{i=1}^{n} \left[\left(\frac{\varepsilon_{it}}{\varepsilon}\right) - S_{it}\right] X_{it}^{\Box} + TEC_{it}$$
(5)

in z_{it} on technical efficiency.

Where ε_{it} is the output elasticity of input variable and ε is the scale efficiency. In Equation (5), total factor productivity is decomposed into the technical change, scale change, allocation efficiency change, and technical efficiency¹. In empirical research, if data of input price cannot be obtained, allocation efficiency will not be measured and calculation of total factor productivity is merely limited to the estimation of technical efficiency, scale efficiency, and technical change.

Empirical model

It is assumed that a non-neutral technical efficiency exists within the process of China's soybean production. Translog stochastic production frontier referenced from Battese and Coelli (2005) is defined as follows:

$$\ln q_{ii} = b_0 + \sum_{n=1}^{N} b_n \ln x_{nit} + \frac{1}{2} \sum_{n=1}^{N} \sum_{j=1}^{N} b_{nj} \ln x_{nit} \ln x_{nit} + \sum_{n=1}^{N} b_m t \ln x_{nit} + \frac{1}{2} b_n t^2 + b_i t + v_{ii} - u_{ii}$$

$$i = 1, 2, \dots, 12, t = 1, 2, \dots, 25$$
(6)

Where q_{it} denotes the soybean yield (kg/mu) of ith soybean production province in year t; x_{nit} represents the input variable of four input factor (labor, seed, fertilizer, machine) in year t; b is the parameters vector to be estimated; t is time trend accounting for technical progress; v_{it} is the random error term; and u_{it} pertains to technical inefficiency factors. It is assumed that v_{it} and u_{it} are independent, following the normal distribution with mean zero and

 $\operatorname{variance}_{\mathbf{S}^{::}} \sigma_{v}^{2}$

Simultaneous estimation procedure provided by Battese and Coelli (1993, 1995) will be employed to obtain the estimated parameters of the SFA model as well as the technical inefficiency function. Technical efficiency of agricultural crops is affected by biological factors, human resources, and socioeconomic conditions (Tian and Wan, 2000). In view of data availability and Chinese soybean farming characteristics, the following variables have been included in the inefficiency function to explain inter-province efficiency differences:

1. Average education level of rural laborers (EDU). This is measured through the proportion of rural laborers with high school education or above. Better-educated rural laborers are expected to be in a better position to utilize existing technologies, thus possessing the capability to attain higher technical efficiency (Battese and Coelli, 1995). With the expanding income gap between urban and rural areas, rural laborers, especially those who are well-educated, are more inclined to work off-farm in China. Therefore, the effect of educational attainment level on the efficiency of soybean production is worth discerning.

2. Average level of farming mechanization (MKW). This is measured by the share of total farm machinery power of sample provinces in the national total machinery power. In cropping practice, subsoil shattering and field management with high horsepower machines can improve soybean unit productivity. Therefore, mechanization level is expected to produce a positive effect on technical efficiency.

3. Per capita land possession (PAR). Farm size affects soybean production efficiency. Per capita land possession is anticipated to produce a positive effect.

4. Proportion of cultivated land area to effective irrigation facilities (PIR). Soybean growth is highly sensitive to water, thus favorable irrigation condition comprises important bases for sound soybean crop production. In general, production efficiency is higher in areas equipped with better irrigation and drainage facilities.

5. Proportion of natural disaster-hit areas to total agricultural crop planting areas (DHA). Natural disasters include drought, flood, wind-hails, and frost. Logically, natural disasters produce a negative effect on soybean production efficiency.

Since China opened up its soybean market in 1990s, yield has not significantly improved in the succeeding years. This paper attempts to examine whether production technical efficiency has improved since 1996. Policy dummy variable (PDW) is included in the function to pool observation of the effect of market-oriented reforms on technical efficiency. Given this argument, the efficiency function is specified as follows:

$$m_{ii} = d_0 + d_1 EDU_{ii} + d_2 MKW_{ii} + d_3 PAR_{ii} + d_4 PIR_{ii} + d_5 DHA_{ii} + d_6 PDW_i + d_7 T_{ii}$$
(7)

T is the time trend variable representing the overall influence of factors not included in the model on technical efficiency; d is the parameter to be estimated

If variable T is negative in Equation (7), it implies that technical efficiency is gradually improved throughout the observation period.

Coelli (2005) posited that total factor productivity growth could be achieved by decomposing technical change and technical efficiency change. According to empirical results obtained in SFA model, TEC and TC per province, as well as the corresponding indices, can be obtained, respectively. Malmquist TFP growth rate is the product of these two indices².

The TEC index of the i-th firm from s-th period to t-th period is specified as follows:

$$TEC_{it} = \frac{TE_{it}}{TE_{is}},$$
(8)

 TE_{is} and TE_{it} represent technical efficiency of the i-th firm in time s and t, respectively, as measured in SFA model.

The TC index is directly obtained from estimated parameters in SFA model by time partial derivatives of production function in time s and t. The TC index is the exponential function of the algebraic mean of logarithmic derivative in time s and t:

$$TC_{it} = \exp\left[\frac{1}{2}\left(\frac{\partial \ln q_{is}}{\partial s} + \frac{\partial \ln q_{it}}{\partial t}\right)\right].$$
(9)

Malmquist TFP growth index is the product of Equations (8) and (9).

Data issues

Data on soybean input and output employed in the estimation of frontier production function are obtained from the Agricultural

¹ For more detailed information, please refer to the following: Umbhakar, S. C., Knox Lovell, C.A., 2003. Stochastic Frontier Analysis. Cambridge University Press. pp. 282-285.

² The composition of TFP is a controversial topic. Due to input price data unavailable, this study doesn't discuss the allocation efficiency and scale efficiency .For more detailed information. Please refer to "Coelli,T.J., Rao,D.S.P., O'Donnell,C.J., & Battese, G.E., 2005. An Introduction to Efficiency and Productivity Analysis, 2nd edition, New York: Springer Publishers.pp.291-293.

Product Cost and Revenue Materials Compilation from 1983 to 2007, as designed by the National Development and Reform Commission. A detailed description of the survey and discussion of data have been provided (Han and Feng, 1991; Tian and Wan, 2000). This study estimated the model with balanced panel data. In view of data completeness, materials were selected from 12 provinces including Hebei, Shanxi, Inner Mongolia, Jilin, Liaoning, Heilongjiang, Jiangsu, Anhui, Shandong, Henan, Shaanxi and Yunnan. The soybean-cultivated areas of the said provinces collectively constitute 82.5% of total soybean growing area in China, accounting for 80.4% of national soybean production.

Both input and output are quantitative indices on mu basis (Chinese area unit, approximately 0.067 hectare). Output is measured by yield, while labor input is measured using standard work day of labor spent on production. Seed input refers to quantity sown (kg/mu)³, while chemical fertilizer input is measured using standard weights obtained by converting actual weights into a certain standard(kg/mu). Meanwhile, machinery power input refers to the share of machinery cost on direct operation cost discounted by production inputs price index reported in the Statistical Yearbook of the National Bureau of Statistics of China (NSB, 1984-2008). In this study, input and output data were mean-corrected prior to estimation.

Observations of explanatory variables of technical inefficiency functions are found in the provincial averages corresponding to sample provinces. These data were obtained from the Fifty Years Statistics Compilation of New China, China's Agricultural Yearbook, and China's Statistical Yearbook, published by NSB. As noted by Tian and Wan (2000), observation variables in inefficiency functions are not household unit observations. Consequently, the two data sets may not be completely correspondent; this may result in certain biases in the estimation of results.

RESULTS

Estimation of the SFA model

This study employed one-step regression method to simultaneously estimate the translog SFA model and the inefficiency function model discussed earlier. Front 4.1-xp software was utilized for this purpose (Coelli, 1994). Table 1 presents the estimation results for soybean, with parameter estimates for the SFA model reported on the left side of the table. Meanwhile, those for inefficiency function are reported on the right side of the table.

Judging by the likelihood value and t-ratios reported in Table 1, the empirical models perform well. Given that γ is highly statistically significant at the 1% level; thus, it can be concluded that technical inefficiencies do exist in China's soybean production. This implies that the translog stochastic production frontier model is adequate for modeling the Chinese soybean economy.

In Table 1, the coefficient of time is 0.02, indicating an average technical progress of 2% per year. The coefficient of time squared is negative, indicating that the rate of technical progress declines at a mild decreasing rate through time. These results are consistent with observed facts on China's soybean economy. Coefficients of time interacting with labor, fertilizer, and machinery are

positive and nearly zero, implying that technical change is triggered by labor, fertilizer, and machinery saving. However, the coefficient of time interacting with seed is negative, suggesting over-use during the observed periods. Visually, this indicates that the isoquant is shifting inwards at a faster rate over time in the laborintensive part of input space. This is possibly a consequence of relative cost of labor which rises along with China's continuous economic development.

As the variables were mean-corrected prior to estimating the SFA model, first-order parameters were interpreted as elasticities at the sample mean. When any of the three input factors (labor, seed, and fertilizer) increased by 10%, soybean yield increased by approximately 11, 0.2 and 13%, respectively. It should be noted that negative elasticities are obtained for machine input; in the authors' view, data selection may be responsible for this result. Further, the sum of elasticities of the four inputs (labor, seed, fertilizer, and machine) is 0.24, suggesting very sharply decreasing returns to scale at the sample mean data point.

The change trend of elasticities' can be obtained by evaluating the relevant sample means of the four inputs from 1983 to 2007; results are presented in Table 2. Evidently, different inputs resulted in different trends in elasticities. For example, elasticities of labor and fertilizer rose over time. In contrast, elasticities of seed declined uniformly. Meanwhile, elasticities of machinery tended to be small and negative through the years.

Tian and Wan (2000) study obtained similar conclusions for rice and corn crops in China. As the scholars pointed out, enhanced ability to make choices in agricultural operations for rural labor is the major cause behind the rising labor input elasticities in China's agricultural economy. Owing to uncertain margins of planting soybean, farmers in recent years have exhibited unwillingness to input reasonable amount of chemical fertilizers in China's northeast spring sowing soybean provinces. Further, farmers in summer sowing provinces seldom use chemical fertilizers for continuous or intercropping farming system. Hence, elasticities of fertilizer reflect an increasing trend, only next to labor input.

In terms of the technical inefficiency model, all efficiency variables are highly significant, with the exception of EDU. Rural laborers' educational attainment level appears to have resulted in a lower level of efficiency, being consistent with the observation that welleducated laborers are predisposed to work off-farm in China. This implies that soybean production will face tougher challenges with laborers' continued migration from rural to urban areas.

Estimated parameters of mechanical power (MKW) and per capita land areas (PAR) both produce positive effects on technical efficiency. The latter implies that scale economy exists in soybean production. In other words, percapita area of arable land is higher than the average national level in China's northeast soybean producing provinces such as Heilongjiang and Jilin. This encourages

 $^{^{3}}$ Mu is the traditinal unit of land measurement used in China. 1 mu is equal to 1/15th of a hectare.

Explanatory variable	Coefficient	Estimate	t-ratio	Explanatory variable	Coefficient	Estimate	t-ratio
Constant	b ₀	0.228	7.802	Constant	d ₀	0.028	0.159
Labor	b1	0.108	2.583	EDU	d ₁	0.018	0.931
Seed	b ₂	0.017	0.291	MKW	d ₂	-9.040	-2.632
Fertilizer	b ₃	0.131	6.091	PAR	d ₃	-0.105	-2.987
Machine	b ₄	-0.023	-1.504	PIR	d_4	-0.655	-3.032
Time	bt	0.020	5.768	DHA	d₅	1.483	3.508
Labor-squared	b ₁₁	0.053	0.362	PDW	d ₆	0.393	2.394
Labor × Seed	b ₁₂	-0.589	-2.781	Time	d ₇	0.022	1.537
Labor × Fertilizer	b ₁₃	-0.118	-1.983		$d_7 \sigma^2$	0.083	3.101
Labor × Machine	b ₁₄	0.087	2.076		γ	0.878	18.715
T × Labor	b _{1t}	0.002	0.282	Log-likelihood v	95.278		
Seed-squared	b ₂₂	-0.212	-0.558	Mean efficien	0.814		
Seed × Fertilizer	b ₂₃	-0.111	-1.241	Number of observations		300	
Seed × Machine	b ₂₄	0.117	1.742				
T × Seed	b _{2t}	-0.037	-2.912				
Fertilizer-squared	b ₃₃	0.068	2.197				
Fertilizer × Machine	b ₃₄	-0.018	-0.863				
T × Fertilizer	b _{3t}	0.006	1.299				
Machine-squared	b ₄₄	0.011	0.519				
T × Machine	b _{4t}	0.002	0.512				
T-squared	b _{tt}	-0.001	-1.104				

Table 1. Estimates of stochastic frontier production and inefficiency function.

Table 2. Output elasticities for soybean in China, 1983 to2007.

Year	Labor	Seed	Fertilizer	Machine
1983-1989	-0.065	0.071	0.102	-0.040
1990-1995	0.085	0.007	0.091	-0.014
1996-2001	0.175	-0.001	0.126	-0.004
2002-2007	0.264	-0.018	0.210	-0.024

a higher level of efficiency.

Soybean crop is sensitive to natural climate conditions. Provinces with favorable agricultural production conditions, such as better irrigation and drainage facilities, tend to be most efficient. Parameters coefficient of the effective irrigation ratio (PIR) variable is negative and natural disaster (PDW) variable is positive, verifying this inference. Estimated coefficient of dummy variable is positive, indicating that liberalization of the soybean market created a significant negative impact on technical efficiency improvement. Likewise, coefficient of time trend variable in the inefficiency functions is positive, indicating the absence of obvious technical efficiency improvement for the soybean crop in the past 25 years. Individual

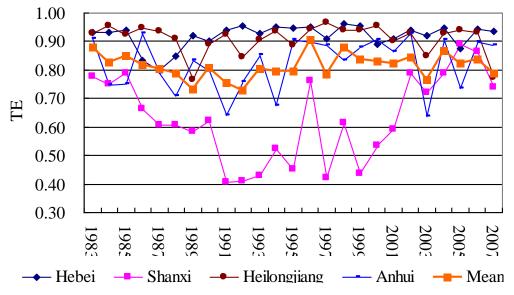


Figure 1. Evolution of technical efficiency, 1983 to 2007.

Table 3. Average	cumulative ch	hanges of	f TE,	TC, a	and TFI	o in	China's	soybean-
growing provinces,	1983 to 2007.							

	TEC	тс	TFPC
Hebei	0.007	1.997	2.004
Shanxi	-0.207	3.380	3.173
Inner Mongolia	-2.438	1.956	-0.482
Jilin	-0.743	2.817	2.074
Liaoning	-0.844	2.882	2.038
Heilongjiang	-0.771	2.113	1.342
Jiangsu	0.104	0.844	0.948
Anhui	-0.103	1.021	0.918
Shandong	0.449	2.649	3.098
Henan	0.025	1.318	1.343
Yunnan	-0.867	1.128	0.261
Shaanxi	-0.814	2.103	1.288
Mean	-0.517	2.017	1.501

These are annual average cumulative percentage changes calculated for each province in each pair of adjacent years.

provinces' technical efficiency levels provide further explanation for the discussion. National average technical efficiency from 1983 to 2007 is estimated to be 0.82, ranging between 0.62 to 0.92 and recording no significant improvement over the years. In other words, an average soybean yield falls 8 to 38% short of the maximum possible level.

Figure 1 demonstrates the evolution of technical efficiency for individual provinces through time⁴. Traditional soybean production provinces, such as Hebei and Heilongjiang, possess a higher level of technical efficiency owing to long-term technical accumulation which is very close to the frontier. On the other hand, certain provinces, such as Shanxi and Shaanxi, exhibit lower and unstable technical efficiency changing pattern for the poor agricultural production conditions. Wide efficiency differentials across provinces comprise an indication of substantial potential for efficiency improvements in soybean production.

Decomposition results

Table 3 shows the annual average growth rates of TE,

⁴ Not all sample provinces are illustrated in Figure 1 for easy identification.

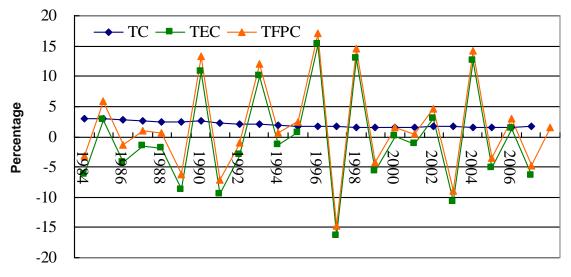


Figure 2. Annual cumulative change measures of TEC, TC, and TFPC for soybean in China.

TC, and TFP for each province. Collectively, TFP increased by 1.5% from 1983 to 2007, owing to the 2% upward shift in technology and 0.5% decrease in the TE. Thus, the TC growth rate of 2% is consistent with the result estimated by the SFA model. Further, Table 3 reveals that TE has failed to record an improvement, even decreasing by 0.5% through time. This again proves the conclusion obtained from the previous SFA model.

The TE growth rates of all observed provinces have experienced varying degrees of decline, with the exception of Jiangsu, Shandong, Henan, and Hebei. Shandong province records a significant increase of 0.5%. The most rapid decrease at 2.4% is recorded by Inner Mongolia. Results of this study further reveal that TE growth decreases by approximately 0.8% per year for three major spring sowing soybean provinces in northeast China, namely, Heilongjiang, Jilin, and Liaoning. A slight decline occurs in Anhui province as well, which is another main summer sowing soybean province in central China.

Technical change rates vary substantially from one province to another, although all sample provinces exhibit a positive technical progress trend over time. For example, technical progress rose by 2.1 to 3.4% annually in Heilongjiang, Jilin, Liaoning, Shandong, Shanxi, and Shaanxi provinces. This figure is higher than that of the mean of all sample provinces, but close to or less than 2% of the rest of observed provinces. A reasonable explanation is that these provinces benefited from numerous soybean-related technical research and extension institutions (accounting for 50% of China's total soybean research institutions) that can facilitate technical progress. However, summer sowing soybean provinces such as Anhui and Henan, which are major rural labor migrating regions, recorded a lower technical progress rate. With increasing opportunity cost and freedom of rural laborers to choose their place of work, these provinces are expected to confront greater challenges in attaining technological progress in soybean production.

Table 3 illustrates an increasing productivity growth ranging between 0.3 to 3.2% yearly among all observed provinces, with the exception of Inner Mongolia whose TFP growth rate recorded an annual decline of 0.5%. However, it must be noted that the TFP growth rate in Heilongjiang, China's largest soybean-producing province accounting for close to 40% of total soybean production, is merely 1.3% per year. This is lower than the average level of 1.5%.

The TFP index is a comprehensive effect of technical efficiency and technical change. Results of this study likewise indicate that a number of provinces, such as Shanxi and Jilin, recorded positive TFP growth rates spurred by rising technological progress, although these provinces' TE have exhibited a declining trend over the past 25 years. This implies that technical efficiency improvement for those provinces contributed to productivity growth.

Figure 2 demonstrates the whole annual change trend of TE, TC, and TFP for all soybean-growing Chinese provinces from 1983 to 1995. It must be noted that TFPC is rather stochastic through time. This is primarily due to the effect of stochastic TEC, which is most likely a consequence of natural climate factors affecting soybean yield. Meanwhile, TE growth rate exhibited a downward trend. Further, TE, TC, and TFP increased by -0.9, 1.6, and 0.7%, respectively, from 2001 to 2007, while the three indices increased by 0.3, 1.8, and 2.1% per year between 1991 and 2000, respectively. To a certain extent, these findings explain the phenomenon surrounding the gradual shrinking of China's soybean production viz-a-viz the rapid rise in domestic demand. At the same time, it clearly shows that China's agricultural market-oriented reform, especially the soybean market liberalization, has posed an immense negative impact on domestic soybean production.

SUMMARY AND CONCLUSION

This study employed provincial data to estimate technical efficiency change and its determinants for China's soybean production by SFA model over the period spanning 1983 to 2007. It measured technological progress and total factor productivity based on the estimated results of SFA model. Further, this study identified growth trend of TE, TC, and TFP. The differences in TE, TC versus TFP growth in individual provinces were investigated as well. Finally, it analyzed the evolution features of TFP, TC, and TE growth through time in the Chinese soybean economy.

Results indicate that technical efficiencies in China's soybean production have not improved in recent decades. However, it should be noted that technical efficiency growth rate has decreased over time. Technical efficiencies and their growth rates varied substantially from one province to another. In other words, wide differentials across efficiencv provinces indicate substantial potential for efficiency improvements in soybean production. Further, the elimination of trade barriers in soybean market access has produced an immensely negative impact on China's technical efficiency improvement.

All investigated provinces have recorded positive technical progress trends over time. In general, average technological growth rate was approximately 2% per year from 1983 to 2007, exhibiting a downward trend. On the other hand, total factor productivity increased by 1.5% per year. It must be noted that TFP growth is quite stochastic through time owing to the effect of stochastic TE change. Evidently, productivity growth mainly resulted from technological progress.

The soybean sector is a cross-section of agricultural market-oriented reform in China. Trade liberalization has spurred broadened impacts on China's soybean productivity. Given the growing domestic demand and surging imports, this study confirms that balancing soybean imports and domestic production is a critical issue that must be addressed by China's policymakers.

REFERENCES

- Aigner D, Lovell CAK, Schmidt P (1977). Formulation and estimation of stochastic frontier production punction models. J. Econ., 6(1): 21-37.
- Battese GE, Coelli TJ (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empir. Econ., 20: 325-332.
- Battese GE, Corra GS (1977). Estimation of a production frontier model: with application to the pastoral zone of eastern Australia. Aust. Agric. Res. Econ. Soc., 21(03): 169-179.
- Chen PC, Yu MM, Chang CC, Hsu SH (2008). Total factor productivity growth in China's agricultural sector. China Econ. Rev., 19: 580-593.
- Coelli TJ, Rao DSP, O'Donnell CJ, Battese GE (2005). An Introduction to Efficiency and Productivity Analysis, 2nd edition, New York: Springer Publishers, 349 pp.
- Fan S (1991). Effects Of technological change and institutional reform on production growth in Chinese agriculture. Am. J. Agric. Econ., 73: 266-275.
- Fan S (1997). Production and productivity growth in Chinese agriculture: new measurement and evidence. Food Policy, 22: 213-228.
- Han ZRF, Feng Y (1991). Agricultural Prices in New China.Beijing:Water Conservancy and Electricity Publishing House(in Chiese).
- Jin S, Huang JK, Hu R, Rozelle F (2002).The creation and spread of technology and total factor productivity in China's agriculture. Am. J. Agric. Econ., 84(4): 916-930.
- Kumbhakar SC, Knox Lovell CA (2003). Stochastic Frontier Analysis. New York:Cambridge University Press.
- Lin JY (1992). Rural reforms and agricultural growth in China. Am. Econ. Rev., 82(1): 34-51.
- Mao W, Koo WW (1997).Productivity growth,technological progress,and efficiency change in Chinese agriculture after rural economic reforms: A DEA approach. J. Dev. Econ., 71: 395-415.
- McMillan J, Whalley J, Zhu L (1989). The impact of China's economic reforms on agricultural productivity growth. J. Political Econ., 97: 781-801.
- Meeusen WJ, van den Broeck (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. Int. Econ. Rev., 18: 435-444.
- National Development and Reform Commission (1984). Price Department, various years. Agricultural Production Cost and Revenue Materials Compilation. Beijing: China Statistics Press.
- National Bureau of Statistics of China, various years (2008). Statistical Yearbook of China, Beijing: China Statistics Press.
- Tian WM, Wan GH (2000). Technical Efficiency and Its Determinants in China's Grain Production. J. Prod. Anal., 13(2): 159-174.
- Yao SJ, Liu Z (1998). Determinants of Grain Production and Technical Efficiency in China. J. Agric. Econ., 49(2): 171-184.