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Application of the DEA on the performance evaluation of the agricultural support policy in China

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Abstract: The paper utilizes the data envelopment analysis (DEA) method based on the OECD policy classification to evaluate the performance of the agricultural support policy at the provincial and agricultural commodity levels from the respective viewpoints of agricultural input and output. The analysis at the provincial level mainly focuses on the similarities and differences in the performance of the agricultural support policies between the primary grain-producing areas and the secondary grain-producing areas; at the agricultural commodity level, 17 representative Chinese agricultural commodities are selected and their performance compared. The results are then used to proffer suggestions for the future agricultural support policy optimization in China. The paper found that 50% of the provinces were DEA-efficient, in general, during the study period due to the low overall province-level scale efficiency. The performance values of the secondary grain-producing areas were significantly lower than those of the primary grain-producing areas due to the overall low scale and technical efficiency values. These results show that the support policies for agricultural commodities in China altogether require a further improvement, mainly due to the low technical efficiency of agricultural commodities.

Keywords: allocative efficiency, data envelopment analysis, policy performance, technical efficiency

The rationality and validity of the agricultural support policy theory are rather controversial in the Western countries. In practice, however, all countries regard agricultural support as an important part of the agricultural policy. Agricultural support forms and types have been increasingly diversified, as well, under the WTO rule constraint (Zhang and Sun 2012).

The research on this topic typically focuses on the design of the measurement indicator systems that accurately measure the agricultural support level, and on building a mathematical economic model based on the general equilibrium and partial equilibrium theory. By simulating the mechanism of action for agricultural support policies, it is possible to determine the effect of implementing the said policies, and to measure the degree of the market distortion and the loss of social welfare that they would cause (El Benni and Finger 2013; Viaggi et al. 2013; Fisher and Kandiwa 2014). Many researchers have also conducted simulation analyses of the effects of the agricultural support policies (OECD 2009; Huang et al. 2011; Erokhin et al. 2014).

Since the 1990s, the researchers have focused primarily on reforming the agricultural support policies within the context of the trade liberalization (Dimitris 2003). In the recent years, scholars have given more attention to the impact of the newest round of the WTO agricultural negotiations on developing countries (Bervejillo et al. 2012). In fact, the most challenging political and economic problems facing the newest round of the WTO negotiations include persuading the member countries to cut the tariffs and the agricultural domestic support to allow the free trade of agricultural commodities.

Since the early 2000s, which have been characterized by a rapid industrial development and urbanization, China has continually explored different policies to support the agricultural development. In effect, the basic institutional framework was laid in the 2000s as the foundation and the agricultural insurance premium

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subsidies and the key production link subsidies as the complement. These policies have come to play a crucial role in increasing the food production year-by-year, ensuring the national food security and the incomes for agricultural producers. Therefore, it is of a great significance to study the performance of the agricultural support policies for the full play to their role as the capital.

On the performance evaluation of China's agricultural support policies, the previous studies were mainly focus on the single policy with the perspective of the provincial one, as it could not reflect its overall performance. On the realm of agricultural commodities, there still was at the stage of comparing the support level of agricultural commodities. In order to comprehensively analyse the performance of China's agricultural support policy, this paper evaluated the overall performance of the agricultural support policy and the performance of every agricultural support policy at the provincial and agricultural commodity levels. At the provincial level, this paper mainly focused on the similarities and differences in the performance of agricultural support policies between the primary grain-producing areas and the secondary grain-producing areas. At the agricultural commodity level, 17 representative China's agricultural commodities were selected in order to be compared in their performance.

MATERIAL AND METHODS

As the reasonable evaluation of China's agricultural support policy performance can help to reform and improve the Chinese agricultural support policy system and promote the sustainable development of its agricultural production overall. The DEA, which is a nonparametric methodology, is an important method for evaluating the relative efficiency of the decision-making units and is widely used to solve the efficiency related problems based on multi-input and multi-output production. Agricultural production is a complex system with multiple inputs and outputs, therefore, the DEA methods are likewise suitable for evaluating the efficiency of the agricultural sector.

DEA Method

The Data Envelopment Analysis (DEA) is a mathematical programming method used to assess the relative efficiencies of the decision making units (DMU) of systems with multiple inputs and multiple outputs (Chames et al. 1978).

The most basic versions of the DEA method are the CCR model, which is based on the assumption of constant returns to scale (Chames et al. 1978), and the BCC model, which is based on the assumption of variable returns to scale (Banker et al. 1984). The conventional CCR model reflects the comprehensive technical efficiency, but it cannot be used to determine whether the non-DEA-efficiency is caused by the problems with technology or scale; the BCC model can, conversely, be used to determine the pure technical efficiency. Because the comprehensive technical efficiency is equal to the product of the pure technical efficiency and scale efficiency, the pure technical efficiency value provided by BCC can be used to separate the scale efficiency from the comprehensive technical efficiency provided by the CCR. To this effect, this paper combined the CCR and BCC models to assess the performance of China's agricultural support policies by determining input and output values as they affect the DEA efficiency.

As a mature efficiency evaluation method, the DEA is widely used in different kinds of fields. For example, Vlontzos et al. (2014) applied DEA approach to evaluate the energy and environmental efficiency of the primary sectors of the EU member state countries, the results show that the countries with strong environmental protection standards appear to be less energy and environmentally efficient. Zha et al. (2015) used the improved DEA model to evaluate the operational efficiency of banks in China during 2008–2012, and found that the banks in China showed both technical and scale inefficiency. Deng et al. (2016) used the slack based measure-data envelopment analysis (SBM-DEA) model to estimate the water use efficiency of 31 provinces in China during 2004–2013. The DEA also could be utilized to evaluate the agriculture efficiency on the areas with similar geographically patterns (Toma et al. 2015). Liu et al. (2015) applied the DEA to investigate the degree of efficiency and efficiency change of the prefecture-level cities in the North-East China from 2000 to 2012. Galanopoulos et al. (2011) applied the DEA in a sample of transhumance farms in Greece in order to assess the technical efficiency of the sheep and goat transhumance flocks and to determine the factors which affected their performance. Theodoridis et al. (2012) assessed the technical efficiency of the Chios sheep farms in Greece with the data envelopment analysis.

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Assuming that there are n DMUs, m inputs, and k outputs, X_i is the input of the ith DMU expressed as an m-dimensional input vector and Y_i is the output of the ith DMU expressed as a k-dimensional output vector. If the returns to scale are constant, the slack variables and the non-Archimedes infinitesimals ε are added to form the following two-stage DEA model:

$$\min \theta$$
$$s.t.\begin{cases} \sum_{i=1}^{n} \lambda_i X_i \le X_0 \theta \\ \sum_{i=1}^{n} \lambda_i Y_i \ge Y_0 \\ \sum_{i=1}^{n} \lambda_i = 1 \\ \lambda_i \ge 0 \; (i = 1,\ 2, \cdots, n) \end{cases} \tag{1}$$

$$\min\left[\theta - \varepsilon\left(e_1^T S^- + e_2^T S^+\right)\right]$$
$$s.t.\begin{cases} \sum_{i=1}^{n} \lambda_i X_i + S^- = \theta X_0 \\ \sum_{i=1}^{n} \lambda_i Y_i - S^+ = Y_0 \\ \lambda_i \ge 0 \quad (i = 1, 2, \cdots, \cdots n); \quad S^- \ge 0; \quad S^+ \ge 0 \end{cases} \tag{2}$$

where e_1, $e_2 \in R^k$, $e_1$is an m-dimensional unit vector, e_2 is a k-dimensional unit vector, and X_0 and Y_0 are the input and output vectors of DMU_0 to be evaluated. S^- and S^+ are slack variables for structural adjustment of DMU_0, and the solutions of the model are θ^*, S^{-*}, S^{+*}, and λ^*_i. When $\theta^*=1$ and $S^{-*}= S^{+*}= 0$, DMU_0 is considered DEA-efficient; in other words, the economic system that includes the DMU output Y_0 obtained on the basis of the original input X_0 has been optimized. When $\theta^*= 1$, $S^{-*}\neq 0$ or $S^{+*}\neq 0$, the DMU_0 is partially DEA-efficient; in this economic DMU system, X_0 can reduce S^{-*} while keeping the original output Y_0 unchanged or output Y_0 can be increased by S^{+*}. When $\theta^* < 1$, the system is inefficient.

As discussed above, this paper used the DEA method to evaluate the performance of China's agricultural support policies. At the provincial level, X_i is defined as the provincial implementation of the agricultural support policies, referred to the capital input such as the producer support estimate (PSE) and the general services support estimate (GSSE), and other inputs (labour, sown-area, machinery, fertilizer); where Y_i is defined as the provincial-level total grain output and producers' net incomes per capita. At the agricultural commodity level, X_i is defined as the market price support (MPS) of agricultural commodities, and Y_i is defined as the agricultural commodities' producer prices and yields. China's agricultural support policy environment is evaluated from three distinct aspects under the DEA: efficiency, returns to scale, and input redundancy.

The DEA model can be input-oriented or output-oriented. For the purposes of agricultural production, input is easier to control than output, so this paper applied an input-oriented DEA model in this study.

Study areas and data sources

Study areas

This paper analysed a total of 12 provinces/municipalities/autonomous regions: Hubei, Sichuan, Heilongjiang, Jilin, Hebei, Hunan (primary grain-producing areas), and Guizhou, Hainan, Tibet, Xinjiang, Yunnan, Chongqing (secondary grain-producing areas) (Figure 1).

Data sources

The data used in this study came mainly from the *China Statistical Yearbook*, the above 12 regions' statistical yearbooks, the *China Commerce Yearbook*, and the *Finance Yearbook of China*, *2008–2012*. Because not all data after 2012 had been published at the time this study was conducted, in order to preserve the data integrity, this paper used data from 2008–2012 for the comparative analysis. To ensure the appropriate data similarity, this paper set a two-year time period to study the agricultural support performance.

Policy classification and indicator selection

Policy classification method

China's agricultural support measures are numerous, and the data for each measure are difficult to obtain, so this paper found it necessary to first simplify the agricultural support policies via classification. At present, the international community accepts two main ways of classifying agricultural policies: the WTO classification method, which is based on the domestic agricultural support policies and their effects on the international trade, and the OECD method, which reflects the nationwide level of agricultural support in a given country by examining the specific objects of support. This paper asserts that the OECD classification more accurately and comprehensively represents the level of agricultural support and its structure within a specific country, and thus it is more

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Figure 1. 12 researched provinces' geographical locations

conducive to evaluating the national agricultural policy and better suited to our research objectives regarding the agricultural support in China.

The OECD divides the agricultural support policy environment into three categories: PSE, GSSE, and consumer support estimates (CSE) (OECD 2009).

Indicator selection

Table 1 summarized the inputs and outputs variables selected in the previous studies. In this paper, the selection of variables was considered from the respective viewpoints of agricultural input and output, and in the implementation process of agricultural support policy. The variables selected are not only related to the investment of the capital, but also to the input of other agricultural production factors, such as land, labour, fertilizer, agricultural machinery input. In order to evaluate the performance of every agricultural support policy, this paper selected agricultural supports as the variables of an investment of the capital, and agricultural supports were classified into two categories of the policies according to the OECD standard (the classification from the perspective of supported objects).

According to the latest OECD policy classification criteria (OECD 2009) and the research conducted

Table 1. Summary of inputs and outputs indicators selected in previous studies

Researcher	Main concept	Research object	Inputs	Outputs
Atici & Podinovski (2015)	Technical efficiency	Turkey farms	(1) Land (2) Labour (3) Crop production costs (4) Capital expenditures	(1) all individual crops produced by at least one farm in the region
Liu et al.(2015)	Efficiency	Agriculture in North-East China	(1) Capital (2) Labour (3) Land (4) Machinery (5) Fertilizer	(1) Gross value of agricultural output
Galanopoulos et al. (2011)	Technical efficiency	EU subsidies	(1) Number of animals (2) Grazing days (3) Milking days (4) Roughages and concentrates	(1) Farm's gross returns
Gao and He (2010)	Efficiency	Agriculture subsidies in China	(1) Sown-area (2) Labour (3) Amount of subsidies	(1) Total grain output (2) Per capita income of producers

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Table 2. Indicator system of agricultural support policy performance evaluation

Item	Variables	Unit	Definitions
Input indicator	PSE (X_1)	100 millions of RMB	Include: MPS Grain direct subsidy Comprehensive subsidy on agricultural inputs Improved seed variety subsidy Subsidy for the purchase of agricultural machinery Rural poverty alleviation project Return grain plots to forestry Return grazing land to grassland
	GSSE (X_2)	100 millions of RMB	Include: Agricultural comprehensive development project Sunshine Project (training for rural labour transfer) Measuring soil fertilizer subsidies Rural infrastructure construction Modern agricultural demonstration project Food security reserve Large county incentive policies
	Labour (X_3)	Persons	Number of agricultural workers
	Sown-area (X_4)	Hectares	Sown area of crops
	Machinery (X_5)	Kilowatts	Total power of agricultural machinery
	Fertilizer (X_6)	Tons	The sum of N, P, K fertilizer and compound fertilizer
Output indicator	Per capita income of producers (Y_1)	RMB	They are two important agricultural support policy objectives in China
	Total grain output (Y_2)	Tons	

MPS includes the minimum purchase price of wheat (third-class), early indica rice (third-class), late indica rice (third-class), and japonica rice (third-class), as well as temporary purchase and storage policies for maize, rapeseed, and sugar, and subsidy policies for cotton and soybean (Beginning in 2014, the stock holding program for cotton and soybean were abandoned and switched to a trial subsidy program based on the target price system).

recently by the domestic and overseas scholars (Zong and Li 2006; Gao and He 2010; Galanopoulos et al. 2011; Atici and Podinovski 2015; Liu et al. 2015), the indicator system which this paper set up is as shown in Table 2. Overall, this paper use six inputs (PSE, GSSE, labour, sown-area, machinery, fertilizer) in our DEA models. These reflect the data available to us and are consistent with the literature. The PSE and GSSE are the total indicators of policy after the classification, which are composed of the major agricultural support policies in China, and defined as an investment of the capital. Labour is measured as the number of workers employed in the primary industry. Sown-area is the land input in the process of agricultural production which reflects the actual utilization of the cultivated land in each province. Machinery represents the level of farming mechanization which is measured by the total power of farm machinery in each province. Fertilizer refers to the sum of pure weights of potash, nitrogen, phosphate and the complex fertilizer.

The target location of agricultural support policy directly affects the effectiveness of the policy as reflected in the output indicator. According to the No. 1 Central Document (2004–2015), the most recent agricultural subsidy system in China has a two-fold goal: ensuring the food security for China, and making sure the producers' incomes increase as necessary. The effect of the agricultural support policies is reflected in the per capita income of producers and the total grain output, so we selected the per capita income of producers and the total grain output as the variables of output indicators.

Agriculture commodity coverage and data processing

Agricultural commodity coverage

The OECD uses the inference method to calculate the MPS. According to the OECD requirements, the representative agricultural commodities needed to meet two conditions: that the total output value of all agricultural commodities accounts for more than 70% of the total value of the farm output, and that the output value of a single agricultural commodity

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Table 3. Calculated types of agricultural commodities contained in MPS

Types of agricultural commodities	Yields (10 kiloton)	Producer prices (RMB/t)	value of output (billion RMB)	Proportion (%)
Wheat	12 102.36	2 166.20	2 621.61	3.54
Paddy	20 423.59	4 060.88	8 293.78	11.19
Maize	20 561.41	2 222.60	4 569.98	6.16
Soybean	1 301.09	4 727.80	615.13	0.83
Rapeseed	1 400.73	4 939.40	691.88	0.93
Peanut	1 669.16	10 976.86	1 832.21	2.47
Apple	3 849.07	4 259.40	1 639.47	2.21
Citrus	3 167.80	2 129.47	674.57	0.91
Sugarcane	12 311.39	3 906.67	4 809.65	6.49
Flue-cured tobacco	312.62	21 831.20	682.49	0.92
Cotton	683.60	18 242.20	1 247.04	1.68
Milk	3 743.60	3 528.60	1 320.97	1.78
Beef	662.26	44 581.82	2 952.48	3.98
Pork	5 342.70	20 924.17	11 179.15	15.08
Mutton	400.99	51 538.85	2 066.66	2.79
Poultry	1 981.30	17 092.62	3 386.56	4.57
Eggs	2 861.17	8 013.40	2 292.77	3.09

Agricultural commodity yields provided by the China Statistical Yearbook 2013, and producer prices of commodities from the China Agricultural Products Cost-benefit Assembly 2013

accounts for more than 1% of the total value of the farm output (Wilfrid 2002).

In order to reduce any calculation errors in the support level by increasing the coverage of agricultural commodities, this paper took 2012 data which was more comprehensive and readily available to calculate the MPS; in this dataset, the output value of a single agricultural commodity accounts for more than 0.5% of the total value of the farm output, and the total output value of the selected 17 agricultural commodities accounted for 68.62% of the total value of the farm output. Table 3 lists the agricultural commodities this paper selected for this purpose in detail.

MPS computational processing

The MPS was calculated as follows:

$$\text{MPS} = \sum_{j=1}^{m} sMPS_j \tag{3}$$

$sMPS$ = (domestic price – border price) × yield × commodity rate

where m is the number of the type of the selected agricultural commodities (in this paper, m = 17), and $sMPS_j$ represents the transfer of market price for the jth agricultural commodity.

The domestic price is the producer price defined based on the *China Agricultural Products Cost-benefit Assembly.* An appropriate treatment was made by referring to processing methods used by other domestic scholars: the producer prices of poultry commodities were replaced by the price of broiler chickens, the producer prices of eggs were the simple average of the cost of the scatter-feeding breeding chickens at the small, medium, and large scales, and the producer prices of milk were the simple average of the cost of the scatter-feeding breeder cows at the small, medium, and large scales. The producer prices of certain commodities were also adjusted according to the commodity characteristics in order to better suit an international scale – these included the paddy, wheat, unshelled peanuts, sugarcane, scatter-fed cows, scatter-fed pigs, farm-raised sheep, and chickens. Producer prices were adjusted for the rice, wheat, peanuts, sugar, beef, pork, mutton, and poultry at adjustment coefficients of 68%, 75%, 82%, 12%, 54%, 65%, 55%, and 75%, respectively (Zong and Li 2006; Zhu and Cheng 2011).

The commodity rates of grain and fruit were set based on the *China Agricultural Products Cost-benefit Assembly*. The commodity rate of livestock commodities was set to 1, as it is not included in the *China* Agricultural Products Cost-benefit Assembly (Zhu and Cheng 2011). Border prices came from the China *Commerce Yearbook*, and because the commodity border price unit is the US dollar, this paper applied the official exchange rate to convert the values to the

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RMB. This paper defined transportation expenses to set the border prices (including loading, unloading, processing, and marketing related to the import and export of agricultural commodities) as the cost of exporting rice, cotton, peanuts, flue-cured tobacco, fruit, sugar, and meat adjusted by 10%, 8%, 15%, 30%, 40%, 30%, and 20%, respectively (Wang 2011).

Normalization processing

The DEA methodology requires that the input and output indices are positive; the MPS this paper calculated had a negative value, so this paper normalized the data as follows (Liu 2014):

$$Max\ (z_1, z_2 \dots z_n) = a$$
$$Min\ (z_1, z_2 \dots z_n) = b \qquad (4)$$
$$Z' = \frac{(Z-b)}{(a-b)} \times 0.9 + 0.1$$

where $z_1, z_2, \dots, z_n$ respectively express the market price support for each agricultural commodity in a certain year. So, a is the maximum value of the market price support among the current group of agricultural commodities and b is the minimum value of the market price support among the same group of agricultural commodities. Z represents the market price support for each of the processed agricultural commodities and Z' represents the data obtained after processing. In effect, the normalization processing narrows down the dates in the indicator into similar proportions after processing the data to ensure positive values. Because the DEA method obtains the relative efficiency, the normalized output indicator translates the DMU frontier while maintaining the system's original overall shape. The relationship among the decision units is not changed, so normalizing the inputs does not impact the results of the agricultural commodity support performance analysis.

RESULTS AND DISCUSSION

Current agricultural support status in China

China has begun only recently to enact policies that support the agricultural development. Prior to the most recent period of reforms in the country, the government overwhelmingly prioritized the industrial development – the agricultural surplus during this period was funnelled back into industry, creating an agricultural support system that was effectually negative. The Chinese government gradually realized the importance of the agriculture industry after the reform and border-opening policies took a toll on the country's food security. The *No. 1 Central Document* published yearly from 1982 to 1986 focused on the agriculture industry as a whole, as well as on the rural communities and producers, making specific arrangements for the rural reform and agricultural development. Remarkably, the per capita net income of producers increased from 133.57 RMB in 1986 to 423.76 RMB in 1987, in other words, an increase of 24.14% in one year.

In 2004, the Chinese government again began to focus on agriculture, rural areas, and producers in the *No. 1 Central Document*, then continued to do so for 12 consecutive years. Basically, agriculture has been given the priority status during the most recent Chinese socialist modernization period, accompanied by the introduction of a series of policies to support and benefit agriculture. China abolished the agricultural tax in 2006, ending an era characterized by agriculture serving the government. Agricultural support policies gradually increased, diversified, and underwent an extensive research to enrich and improve their effects, ultimately forming the basic institutional framework. The government's annual capital investment in agriculture has continually increased and the support policies have intensified. The government spending on agriculture totalled 12 286.6 billion RMB in 2012, an increase of 1788.9 billion RMB over the previous year (17.05%). The agricultural insurance premium subsidies in 2012 amounted to 171.91 billion RMB, an increase of 35.22% over the previous year. The total amount of the "four subsidies" reached 1653 billion RMB, at an increase of 17.57% over the previous year, including subsidies for purchasing general agricultural supplies (107.8 billion RMB, 25.35% growth), grain direct subsidies (maintained at 15.1 billion RMB,) subsidies for purchasing agricultural machinery (200 billion RMB, 14.29% growth), and subsidies for growing superior grain cultivars (224 billion RMB, 1.82% growth).

Agricultural commodity support level

Agricultural commodity support levels can be measured by producer single commodity transfers (%PSCT), or the total subsidies of a single agricultural commodity accounting for the proportion of the total output value of the commodity. Due to the data availability constraints, this paper used the MPS of a single agricultural commodity to replace the total

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subsidies of a single agricultural commodity, which expresses the government level of support for the circulation of agricultural commodities in China. See the following:

$$\%PSCT_j = \frac{sMPS_j}{T_{sj}} = \frac{\left(P_j^o - P_j^*\right)\times Q_j \times R}{P_j^o \times Q_j} = \frac{\left(P_j^o - P_j^*\right)\times R}{P_j^o} \quad (5)$$

where $\%PSCT_j$ is the jth agricultural commodity's %PSCT, the revenue accounting for the share of the total output value of the j^{th} agricultural commodity and a reflection of increased profits due to MPS. $sMPS_j$, as mentioned above, is the jth agricultural commodity's MPS, and T_{sj} is the total output value of the jth agricultural commodity. P_j^o is the domestic price of the jth agricultural commodity, and P_j^* is the border price of the jth agricultural commodity. R is the commodity rate of the jth agricultural commodity, and Q_j is the yield of the jth agricultural commodity.

This paper divided our 17 types of agricultural commodities into three larger categories: grain crops, economic crops and livestock commodities. Grain crops include wheat, rice, maize, and soybeans. Economic crops include rapeseed, peanut, apple, citrus, sugarcane, flue-cured tobacco, and cotton (subdivided into oil crops, sugar crops, fibre crops, and fruit crops). Livestock commodities include milk, beef, pork, mutton, poultry, and eggs. Table 4 lists the %PSCT values of all 17 agricultural commodities.

As shown in Table 4, in the circulation of agricultural commodities, the Chinese government provided the highest level of support to the grain crops during the study period followed by the livestock commodities, then the economic crops. There were sizeable disparities in support level among different agricultural commodities, and the support for wheat, rice, soybeans, and milk increased overall, while the support for rapeseed, pork, and mutton decreased and the support for maize, peanut, apple, citrus, sugar, flue-cured tobacco, cotton, beef, poultry, and eggs fluctuated. In 2008, the %PSCTs of most of the grain crops and economic crops were negative due to the impact of the economic crisis, during which the time crop prices rose sharply in the international market.

On the whole, the support level of grain crops and livestock commodities in China continually increased over the course of the study period. The level of support for the grain crops was higher than that of the livestock commodities, but the support level of the livestock commodities rose faster. This observation can be understood best based on the fact that food security has been the primary focus of the agricul-

Table 4. %PSCT of Chinese agricultural commodities in 2008, 2010, 2012 (%)

Types of agricultural commodities		2008	2010	2012	Average
Grain crops	Wheat	2.48	38.32	44.68	28.49
	Rice	−44.78	−1.56	9.80	−12.18
	Maize	−22.45	22.31	16.48	5.45
	Soybean	1.34	26.72	27.07	18.38
	Average	−15.85	21.45	24.50	
Economic crops	Rapeseed	24.10	19.40	15.01	19.50
	Peanut	−33.03	−0.16	−2.80	−12.00
	Apple	−17.18	36.26	12.45	10.51
	Citrus	−66.94	10.59	−58.13	−38.16
	Sugar	−0.02	3.19	2.97	2.05
	Flue-cured tobacco	−1.58	−56.31	7.00	−16.96
	Cotton	−7.35	46.33	21.87	20.28
	Average	−14.57	8.47	−0.23	
Livestock commodities	Milk	−24.36	16.80	34.45	8.96
	Beef	8.82	5.90	27.03	13.92
	Pork	12.82	11.75	3.20	9.26
	Mutton	32.00	14.87	11.97	19.61
	Poultry	8.38	21.63	13.79	14.60
	Eggs	4.72	10.67	8.19	7.86
	Average	7.06	13.60	16.44	

The author calculated the above based on data from the China Commerce Yearbook, the China National Statistics Yearbook, and the China Agricultural Products Cost-benefit Assembly.

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tural support policy in China for some time; this is evidenced where the minimum purchase price of wheat (third-class), early indica rice (third-class), late indica rice (third-class), and japonica rice (third-class), as well as the temporary purchase and storage policies for maize and the target price support for soybeans, all received an intense level of the government support. China's continued economic development has provided an enhanced quality of life in general, which has been accompanied by the consumption structure changes including the increased demand for livestock commodities, which has prompted the central government to enact policies targeted toward supporting the animal husbandry and livestock commodities (especially milk, the support level of which rose very rapidly).

The overall support level for the economic crops was not especially high, as mentioned above. The support for rapeseed declined, but it remained relatively high, and much higher than the average level of support for the economic crops. The support for cotton changed considerably over the course of the study period, though it also stayed higher overall than that given to the other crops, reaching its maximum in 2010, where its % PSCT was 46.33%. The support given to sugar was relatively low overall, but it changed from negative to positive during the study period. Unsurprisingly, crops given higher levels of agricultural support usually also have specific price policies (e.g., the temporary purchase and storage policies for cotton, rapeseed, and sugar).

In 2008, 2010, and 2012, the average level of support for wheat showed % PSCT of 28.49%, representing the highest support level of any of the agricultural commodities this paper examined. Wheat was followed by cotton (20.28%), mutton (19.61%), rapeseed (19.50%), soybean (18.38%), poultry (14.60%), beef (13.92%), eggs (7.86%), and maize (5.45%). The support levels of these agricultural commodities were higher than those of other OECD countries for wheat (3.43%), lamb (4.61%), soybean (11.27%), beef (5.75%), eggs (3.23%), and maize (12.93%) (OECD 2013). China's support for rice (–12.18%) was negative, while the other OECD countries support rice at the levels as high as 58.50%. There have been minimum purchase price policies set for rice since 2005, but because the increases in the international market rice prices outpaced the national policy, the domestic market prices fell below the international levels. In 2008, when this phenomenon was especially problematic, the China's level of support for rice dropped to –44.78%; the level then began to gradually increase, however, and reached a positive value of 9.8% in 2012.

Province-domain results

This paper used the DEA analysis software to respectively analyse the agricultural support performance of the 12 provinces (municipalities, autonomous regions) using data from 2008, 2010, and 2012. Table 5 lists the comprehensive technical efficiency, pure technical efficiency, scale efficiency, and returns to scale values.

Only Heilongjiang, Jilin, Hebei, Hubei, Hunan, Tibet and Hainan, five of which are primary grain-producing areas, reached the comprehensive valid DEA (recall that "efficiency" is marked by a value of 1) in 2008. Only eight provinces, Heilongjiang, Jilin, Hebei, Hubei, Hunan, Sichuan, Tibet and Hainan, achieved the valid DEA in 2010. In 2012, only Heilongjiang, Jilin, Hubei, Hunan, Chongqing, Tibet and Hainan reached the valid DEA. Over the entire study period, the number of the valid DEA provinces generally decreased, and the average comprehensive technical efficiency of the primary grain-producing areas was greater than that of the secondary grain-producing areas.

In 2008, 2010, and 2012, the pure technical efficiency of Heilongjiang, Jilin, Hebei, Hubei, Hunan, Tibet and Hainan reached a value of 1 (Valid DEA). Five of these are the primary grain-producing areas. Sichuan reached a value of 1 in 2010. Chongqing reached a value of 1 in 2012. In fact, out of all primary grain-producing areas, Sichuan was the only province that did not show the pure technical efficiency equal to 1. In the secondary grain-producing areas, only Tibet and Hainan's pure technical efficiency always reached 1 and the values of the other provinces' pure technical efficiency were lower. To this effect, the average value of pure technical efficiency of the primary grain-producing areas, similarly, is greater than that of the secondary grain-producing areas.

Seven areas reached the scale efficiency in 2008: Heilongjiang, Jilin, Hebei, Hubei, Hunan, Tibet and Hainan. In 2010, eight areas reached the scale efficiency: Heilongjiang, Jilin, Hebei, Hubei, Hunan, Sichuan, Tibet and Hainan. Seven areas reached the scale efficiency in 2012: Heilongjiang, Jilin, Hubei, Hunan, Chongqing, Tibet and Hainan. On the whole, the average value of the scale efficiency of the primary grain-producing areas, comparatively, is greater than that of the secondary grain-producing areas during the study period.

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Table 5. Twelve provinces (municipalities, autonomous regions) agricultural support policy performance values in 2008, 2010, and 2012

Provinces (municipalities, autonomous regions)		crste			vrste			scale			Returns to scale		
		2008	2010	2012	2008	2010	2012	2008	2010	2012	2008	2010	2012
P	Heilongjiang	1	1	1	1	1	1	1	1	1	–	–	–
	Jilin	1	1	1	1	1	1	1	1	1	–	–	–
	Hebei	1	1	0.969	1	1	1	1	1	0.969	–	–	drs
	Hubei	1	1	1	1	1	1	1	1	1	–	–	–
	Hunan	1	1	1	1	1	1	1	1	1	–	–	–
	Sichuan	0.887	1	0.933	0.897	1	0.958	0.989	1	0.974	irs	–	irs
	average	0.981	1.000	0.984	0.983	1.000	0.993	0.998	1.000	0.991			
S	Chongqing	0.959	0.977	1	0.991	0.988	1	0.968	0.989	1	irs	irs	–
	Guizhou	0.674	0.639	0.619	0.718	0.699	0.712	0.939	0.915	0.869	irs	irs	irs
	Yunnan	0.541	0.953	0.617	0.572	0.995	0.645	0.946	0.959	0.957	irs	irs	irs
	Xinjiang	0.643	0.658	0.617	0.691	0.673	0.648	0.931	0.977	0.952	irs	irs	irs
	Tibet	1	1	1	1	1	1	1	1	1	–	–	–
	Hainan	1	1	1	1	1	1	1	1	1	–	–	–
	average	0.803	0.871	0.809	0.829	0.893	0.834	0.964	0.973	0.963			

crste = Comprehensive technical efficiency from the CCR model; vrste = Pure technical efficiency from the BCC model; scale = Scale efficiency = crste/vrste

"P" marks primary grain-producing areas, "S" marks secondary grain-producing areas

Though several provinces were of the valid DEA, the other provinces pure technology efficiency and scale efficiency require a further improvement. The low scale efficiency was, in fact, the reason that Hebei failed to reach the valid DEA. Sichuan (a primary grain-producing area), and Guizhou, Xinjiang, Yunnan, and Chongqing (secondary grain-producing areas) all failed to reach the valid DEA, mainly due to the low pure technical efficiency.

The returns to scale remained unchanged during the study period for six provinces, Heilongjiang, Jilin, Hubei, Hunan, Tibet and Hainan – in other words, these provinces completely maintained the valid DEA. The invalid DEA provinces in several primary grain-producing areas maintained growing returns to scale, while the secondary grain-producing areas generally showed declining returns to scale.

As shown in Table 6, because the input redundancy was computed based on the invalid pure technical efficiency of the DMUs, the input redundancy value of the primary grain-producing areas was zero (except Sichuan in 2008). Other provinces (except Tibet,

Table 6. Province (municipalities, autonomous regions) PSE and GSSE redundancy in 2008, 2010, 2012 (100 million RMB)

Provinces (municipalities, autonomous regions)		PSE			GSSE		
		2008	2010	2012	2008	2010	2012
Primary grain-producing areas	Heilongjiang	0	0	0	0	0	0
	Jilin	0	0	0	0	0	0
	Hebei	0	0	0	0	0	0
	Hubei	0	0	0	0	0	0
	Hunan	0	0	0	0	0	0
	Sichuan	0	0	13.358	0	0	0
Secondary grain-producing area	Chongqing	0	16.74	0	23.338	0	0
	Guizhou	0	0	0	0	8.492	11.132
	Yunnan	0	0	0	0	12.819	0
	Xinjiang	0	177.841	125.825	0	0	0
	Tibet	0	0	0	0	0	0
	Hainan	0	0	0	0	0	0

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Hainan), in the secondary grain-producing areas showed varying degrees of redundancy, and the six primary grain-producing areas showed generally high levels of the pure technical efficiency. There were more provinces with the PSE input redundancy than provinces with the GSSE input redundancy, and the redundancy values were fairly negligible regardless of whether they fell into the GSSE or PSE categories.

Agricultural commodity results

This paper used the market price support of single agricultural commodities as the input indicator to calculate the performance of agricultural support policies for all commodities, and the producer prices and yields of the commodities then served as the output indicator. The market price support values were normalized, as discussed above, before the performance values of the 17 commodities this paper identified in 2008, 2010, and 2012 were plugged into the DEAP 2.1 for analysis. Results are shown in Table 7.

As shown in Table 7, the performance of support policies at the agricultural commodity level was generally unfavourable. There were very few commodities which achieved the valid DEA – only about two per year – implying that the general level of support for commodities requires a further improvement. On the whole, the comprehensive technical efficiency of grain crops was higher than that of the economic crops or livestock commodities, suggesting that the China's policies set for the grain crops are more effective than those for the economic crops or livestock commodities. The performance values of wheat, maize, peanuts, oranges, sugar, and milk all improved over the study period, the rice and beef's performance values decreased, and those of soybeans, rapeseed, apples, flue-cured tobacco, cotton, pork, mutton, poultry, and eggs constantly fluctuated.

The low pure technical efficiency was the primary cause of the low comprehensive agricultural commodity efficiency. The pure technical efficiency values of wheat, maize, soybeans, rapeseed, peanut, apple, citrus, sugar, and eggs were small in general but they increased over the study period. In other words, the pure technical efficiency of grain and economic crops appears to be increasing.

Table 7. Agricultural commodity support performance

Types of agricultural commodities		crste			vrste			scale			Returns to scale		
		2008	2010	2012	2008	2010	2012	2008	2010	2012	2008	2010	2012
G	wheat	0.081	0.121	0.382	0.138	0.165	0.401	0.59	0.732	0.953	irs	irs	drs
	rice	1	1	0.813	1	1	1	1	1	0.813	–	–	drs
	maize	0.15	0.208	0.855	0.174	0.22	1	0.865	0.948	0.855	irs	irs	drs
	soybean	0.139	0.1	0.179	0.171	0.275	0.283	0.811	0.365	0.631	irs	irs	irs
	average	0.343	0.357	0.557	0.371	0.415	0.671	0.817	0.761	0.813			
E	rapeseed	0.183	0.11	0.207	0.212	0.305	0.314	0.86	0.36	0.659	irs	irs	irs
	peanut	0.248	0.264	0.474	0.281	0.398	0.56	0.882	0.664	0.845	irs	irs	irs
	apple	0.088	0.086	0.308	0.146	0.164	0.319	0.604	0.525	0.964	irs		
	citrus	0.051	0.127	1	0.15	0.338	1	0.342	0.377	1	irs	irs	–
	sugar	0.104	0.324	0.952	0.14	0.408	1	0.743	0.794	0.952	irs	irs	drs
	flue-cured tobacco	0.51	1	0.572	0.532	1	0.699	0.959	1	0.818	irs	–	irs
	cotton	0.396	0.219	0.372	0.422	0.341	0.456	0.939	0.642	0.816	irs	drs	irs
	average	0.226	0.304	0.555	0.269	0.422	0.621	0.761	0.623	0.865			
L	milk	0.107	0.125	0.216	0.152	0.287	0.223	0.707	0.435	0.969	irs	irs	drs
	beef	0.885	0.549	0.526	0.891	0.904	0.53	0.993	0.608	0.992	irs	drs	irs
	pork	0.507	0.153	0.607	0.512	0.195	0.645	0.99	0.782	0.941	irs		
	mutton	1	0.563	1	1	1	1	1	0.563	1	–		
	poultry	0.525	0.168	0.341	0.541	0.203	0.356	0.97	0.827	0.958	irs		
	eggs	0.226	0.168	0.333	0.252	0.26	0.333	0.895	0.647	0.999	irs		
	average	0.542	0.288	0.504	0.558	0.475	0.515	0.926	0.644	0.977			

crste = Comprehensive technical efficiency from the CCR model; vrste = Pure technical efficiency from the BCC model; scale = Scale efficiency = crste/vrste

"G" = grain crops, "E" = economic crops, "L" = livestock commodities

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The returns to scale of soybean, rapeseed, and peanut decreased over the study period, while the returns to scale of wheat, rice, maize, apples, sugar, milk, and poultry gradually decreased at first and then began to increase. On the whole, the returns to scale of the grain crops and livestock commodities appear to be increasing, and the returns to scale of the economic crops appear to be decreasing.

CONCLUSIONS

The evaluation of the effect of China's agricultural support policy provided us with the following results:

(1) This paper used the % PSCT of agricultural commodities to evaluate the efficiency level of agricultural support policies in the agricultural commodity circulation. The results showed that the level of support for grain crops in China is the highest, followed by the livestock commodities, then the economic crops. On the whole, the support level of grain crops and livestock commodities in China is on the rise, and the level of support for grain crops is higher than that of the livestock commodities, but the livestock commodities have been supported at a quicker rate. The support level of agricultural commodities in China is higher overall than that of the other OECD countries.

(2) This paper utilized the OECD policy classification, the BCC and CCR models to analyse the DEA efficiency of 12 DMUs: Hubei, Sichuan, Heilongjiang, Jilin, Hebei, and Hunan (primary grain-producing areas) and Guizhou, Hainan, Tibet, Xinjiang, Yunnan, and Chongqing (secondary grain-producing areas), in 2008, 2010, and 2012. This paper found that only 50% of the provinces in China that reached the valid DEA over the course of the study period, because the scale efficiency at the province level became invalid. The performance values of the secondary grain-producing areas were significantly lower than those of the primary grain-producing areas. The low scale efficiency was the reason that the primary grain-producing areas did not reach the valid DEA, but the secondary grain-producing areas failed to reach the valid DEA due to the low pure technical efficiency.

(3) This paper also selected 17 types of agricultural commodities representative of China and formed a corresponding input indicator comprised of the market price support which was normalized as necessary, and the output indicator comprised of producer prices and yields. The DEAP 2.1 software analysis results showed that the performance of grain crops in China was higher than that of the economic crops or livestock commodities during the study period. Agricultural support policies, to this effect, do not sufficiently enhance the commodity values; the low performance of agricultural commodities is characterized by the low pure technical efficiency of the commodities.

Policy recommendations

Agricultural support policies should be tailored to in the individual regions in order to ensure the maximum effectiveness. Various regions show a varying comprehensive technical efficiency, pure technical efficiency, and scale efficiency, especially between the primary and secondary grain-producing areas. Of course, the production conditions and the level of production technology differ within different regions, which is responsible for some of the disparities this paper observed. The imbalanced levels of the economic development at the regional scale, however, especially differences between the primary grain-producing areas and the secondary grain-producing areas, which calls for different modes of support to ensure the fair distribution of social welfare. The agricultural support efficiency in the secondary grain-producing areas was low due mostly to the technical inefficiency, i.e., the input funds were ineffective, so these areas would benefit more from adjustments made to the regional policy structures. The agricultural support efficiency in the primary grain-producing areas was generally low, mainly due to the scale inefficiency, so the policies enacted in the primary grain-producing areas should be designed to equalize the scale of the agricultural support and the scale of the agricultural production. The returns to scale of the primary grain-producing areas improved but only incrementally during the study period, so the agricultural support scale in the primary grain-producing areas should be expanded – this can be done by encouraging the circulation of agricultural land and/or expanding the scale of the agricultural production in order to improve the regional production-scale economies. The central government would also do well to increase the stimulus intensity of the agricultural support policies in the primary grain-producing areas, to encourage producers to increase the agricultural production inputs, and to expand the scale of the agricultural support, thus allowing the agricultural support scale and the scale of agricultural production to correspond

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more closely and improving the overall efficiency of agricultural support in China.

The policy support for agricultural commodities should be biased in favour of the production process. China's support for agricultural commodities in the circulation of agricultural commodities is quite high, but the effects of the said support are generally not ideal. The support for the agricultural commodities in circulation also distorts the market price of the commodities, though by contrast, support for the production process of agricultural commodities (especially the technical support), minimizes the degree of the market price distortion and ensures that the ultimate beneficiaries are the producers.

The functional objective of agricultural support policy should be improving the agricultural production efficiency. There were fewer valid DEA provinces at the end of the study period than there were at the beginning, during which time some provinces' performance transformed from the valid DEA to the invalid DEA. Producers' incomes and the grain output have continually increased and the rural social security system is currently successful, so the functional objective of the agricultural support policy in China must shift from increasing the producers' incomes to improving the agricultural production efficiency.

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