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Estimating Capacity Utilization of Chinese State Farms

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Abstract: As the most populous country in the world, China has one of the largest agricultural systems in the world, which plays an important role in ensuring China's food security. The state farms comprise an integral part of China's agricultural system. However, there have been few studies evaluating the efficiency and capacity utilization of China's state farms. In this paper, we estimate the efficiency and capacity utilization of state farms across 27 Chinese regions by applying the data envelopment analysis method. Performance of the overall state farm system and its three sub-industries is taken into consideration simultaneously. Over the period of 2013–2017, the technical efficiency fluctuated in between 0.74 and 0.84, whereas the capacity utilization fluctuated around 0.85. The regional differences were observed. The regional differences were also observed.

Keywords: data envelopment analysis; efficiency; capacity utilization; state farms; China

1. Introduction

Agricultural production is extremely important for development of China, which has the world's largest population in the world and limited arable land area per capita [1]. With the steady development of China's economy and the continuous increase of per capita income, the demand of agricultural products has surged in China. Although China's grain production increased in 2003–2017, grain imports also increased year by year. According to the China Grain Yearbook 2014, China's grain self-sufficiency rate was less than 90%, with self-sufficiency rate of soybean being less than 20% in 2012. In order to avoid the effects of unexpected turbulences, food security and supply in China should not be dependent on imported grain.

The system of state farms in China is greatly related to the historical context. When the People's Republic of China was established in 1949, the Chinese government used the army to develop agriculture. In 1956, China established the Ministry of Agriculture and Reclamation along with a large number of state farms, which integrated the cultivated land in China. During the period of the planned economy, the income of farm workers was not directly related to their performance, which led to the low efficiency of the state farms. In 1978, the Chinese government carried out the reform of contract system, which established the linkage between employees' income and their working performance and created the competition mechanism among the state farms. In the short run, the state farms improved their outputs and efficiency due to the reform. Nevertheless, in the long run, this reform also brought China back to the traditional small-scale farming mode and induced subdued agricultural modernization of the state farms. As the development of Chinese state farm system continued, two severe problems occurred in this field, namely, the excessive complexity of functions and the decentralization of production. The Chinese government took active measures to tackle these problems. In addition to the production activities, state farms also need to provide public services, such as education, social security and medical care. Multiple complicated functions prompted the state farms to carry out the de-administration reform. The reform of concentration and industrialization was carried out to tackle the problem of fragmentation of state farm operations. The latter reform led to a significant increase in the total agricultural output, profits and taxes paid. See Gong [2] for a detailed review on the agricultural reforms in China. In spite of the development of the state farm system in China, smallholder farming remains the major contributor to fulfillment of the food security goals. As Wu et al. [3] reported, some 70% of farm area in China was occupied by holdings of less than 2 ha (as of 2010).

Despite many reforms, the development of state farms is still far from ensuring the growing domestic demand for agricultural products. The possible reason lies in the fragmentation of farms brought about by the contract system reform, which makes employees to care about the income from their own land only and thus undermines the modernization of the state farms and the promotion of new technologies. For example, China's hybrid rice technology is among the best-performing ones in the world, which can ensure annual rice yields of 17.2 t/ha. However, due to the fragmentation of the state farms and the backward technologies, China's rice yields maintain at only 1.5 t/ha, lower than that of the United States [4].

Lagging modernization and suboptimal production scale has led to oversupply of manpower in the state farms. In accordance with data from the China Statistical Yearbook 2018, the number of farmers decreased from 3.36 million to 2.72 million in the state farms during 2015–2018, while the area of cultivated land increased from 5.04 million ha to 6.46 million ha. In the new round of agricultural reform, state farm enterprises seek to promote their development under market competition. The measures of the capacity utilization (CU) can identify the gaps in resource allocation and their impact on the state farm performance in China. However, to the best of our knowledge, no previous studies analyzed the CU and efficiency of China's state farms, which would allow consideration of the effects of the input availability. The measures of efficiency and productivity change have been applied for analysis of different economic systems [5–7]. This paper estimates the efficiency and CU of state farms at the aggregate level. Specifically, 27 regions are considered over the period of 2013–2017. The results of the CU analysis suggest ways that the state farms can adjust their input structure and levels and improve their adaptation to market competition.

The integrated development of the primary, secondary and tertiary industries (i.e., crop production, manufacturing and services) is an important measure to increase farmers' income. Although the total agricultural output, profits and taxes paid increased significantly in recent years, the annual disposable income of Chinese farmers is still low: only 14,617 RMB (2125 USD) per capita in 2018 (Statistical Bulletin of Chinese Economic and Social Development 2018). Industrial integration can strengthen the relationship between the three sub-industries to improve the income of farmers. Hence, this paper also estimates the efficiency and CU of state farms in all three sub-industries to provide a detailed reference for decision-makers.

The rest of the paper is organized as follows: Section 2 reviews the previous research on the CU analysis. Section 3 presents the data envelopment analysis (DEA) models used for assessing the efficiency and CU. Empirical results are analyzed and the corresponding policy indications are proposed in Section 4. Section 5 concludes this paper.

2. Literature Review

2.1. Methodological Advancements in Non-Parametric CU Measures

In the economic literature, the notion of capacity (and its utilization) has been investigated since the study by Johansen [8]. For digression on earlier attempts to conceptualize the capacity, please consult, e.g., Ray [9]. The study by Johansen [8] initiated the strand of literature on the physical concept of capacity. Following this approach, capacity is understood as the output quantity available when the use of the variable inputs is not limited (with the usual restrictions applied for the availability of (quasi-)fixed inputs). Färe et al. [10] operationalized the concept of Johansen [8] by employing the DEA.

Färe et al. [11] developed a CU measure considering revenue maximization and the distance function. Coelli et al. [12] proposed the concept of ray CU seeking for minimization of the short-run costs. Ray et al. (2006) [9] introduced the working capital into the analysis of the CU and offered a more realistic measure. Sahoo and Tone [13] allowed for shifts in the input-mix by means of the slack-based model. Ahranjani and Matin [14] proposed CU measures for a two-stage production system modeled by the DEA.

As the original idea of capacity relates to the output production, much of the literature focused on the output-oriented measures of capacity. However, Cesaroni et al. [15] presented the input-oriented CU measures. Kerstens et al. [16] further compared the output- and input-oriented measures under assumptions of convex and non-convex technologies. Kerstens et al. [17] introduced the term "attainability" by imposing the limits on the scaling factors for the variable inputs in the measurement of capacity.

The "economic" strand of literature on CU considers the minimum level of the short- or long-run average costs when identifying the capacity level. Kalai [18] developed a DEA-based framework for identifying the minima of the short- and long-run average cost curves which determined the corresponding capacities. Cesaroni et al. [19] considered the short- and long-run capacity measures by imposing different assumptions on the disposability of inputs.

Yang et al. [20] developed the measures of capacity allowing for identification of overcapacity. They also involved undesirable outputs in the analysis. The generalized capacity indicator and its decomposition were discussed by Yang and Fukuyama [21]. These indicators are relevant to the concept of sustainability.

Thus, there have been different CU measures developed in the non-parametric framework. They differ in the sense of assumptions on disposability of inputs, inclusion of the price data, decomposition and model orientation.

2.2. Empirical Applications of the CU Measures

In this sub-section, we present the applications of the CU measures in the literature. Without being exhaustive, Table 1 summarizes the major foci of the applications. As one can note, applications of the CU measures cover a variety of economic activities. What is more, the analyses have been carried out at different levels of aggregations (from micro-data to aggregate data).

Table 1. Applications of the capacity utilization (CU) measures.

References	Issue Addressed	Methodological Approach	Variables Used
Färe et al. [10]	Coal-fired electric plants	Output-oriented capacity utilization	Micro-data O: steam and electricity energy FI: capitalVI: labor, fuel
Dupont et al. [22]	Fisheries	Output-oriented capacity utilization	Micro-data O: landings FI: capitalVI: days at sea
Vestergaard et al. [23]	Fisheries	Output-oriented capacity utilization	Micro-data O: landings FI: engine power, tonnage VI: number of trips
Kerstens et al. [24]	Fisheries	Output-oriented firm- and industry-level capacity (Johansen, 1972)	Micro-data O: landings FI: engine power, tonnage VI: labor, fishing days

Table 1. *Cont.*

References	Issue Addressed	Methodological Approach	Variables Used
Valdmanis et al. [25]	Hospitals	Output-oriented capacity utilization	Micro-data O: inpatient days, case mix FI: beds VI: labor
Karagiannis [26]	Hospitals	Output-oriented capacity utilization	Micro-data O: inpatient days, laboratory tests FI: beds VI: labor
Pascoe and Tingley [27]	Fisheries	Output-oriented capacity utilization	Micro-data O: revenue FI: capacity units, tonnage VI: days fished, days at sea
Lindebo et al. [28]	Fisheries	Output-oriented capacity utilization (Färe et al., 2010)	Micro-data O: landings FI: engine power, tonnage, length VI: days at sea
Kerstens et al. [16]	Fruit farms	Output- and input-oriented measures of capacity utilization	Micro data O: apples, other products FI: capital VI: labor, materials
Ray [9]	Production activities in US manufacturing	Cost-minimizing capacity utilization	Aggregate data O: gross output FI: capital VI: labor, energy, materials, capital
Yang and Fukuyama [21]	Production activities in China's regions	Output-oriented measures of capacity utilization and their decomposition	Aggregate data O: gross domestic product, green area, pollution (undesirable outputs) FI: built-up area VI: water use, energy use, capital, labor
Ray et al. [9]	Production activities in US manufacturing	Output-oriented capacity utilization and its decomposition	Aggregate data O: gross output FI: capital VI: labor, energy, materials, services
Sahoo and Tone [13]	Banking	Output-oriented capacity utilization based on SBM	Micro-data O: investments, performing loan assets, non-interest income FI: fixed assets VI: borrowed funds, labor
Yu et al. [29]	Airlines	Output-oriented capacity utilization and its decomposition	Micro-data O: seat-kilometers FI: fleet, network VI: labor, fuel

Note: O—Outputs, FI—Fixed Inputs, VI—Variable Inputs.

Analysis of the fishery performance appears an important topic in the context of capacity. The applications in other areas are relatively scarce, and application of Kerstens et al. [16] is based on a secondary data set. Applications outside fisheries were often based on the aggregate data. This suggests that the application of the CU measures in agriculture comprises a novel research area.

3. Methodology

In this section, we present the inputs and outputs used to define the productive technology for the state farms in China. Afterwards, the DEA-based efficiency and CU measures are introduced.

3.1. The Productive Technology of the State Farm System

The choice of the input and output variables is a key step in efficiency analysis. Table 2 presents a survey on the input and output variables used in previous research on farm efficiency. Based on the literature review, land, labor, output level and intermediate inputs can be considered as the most widely used variables.

Table 2. Variables used in previous studies on efficiency analysis of farms.

References	Input/Output Variables
Borgia et al. [30]	Inputs: energy cost, relative irrigation supply Outputs: land productivity
Chebil et al. [31]	Inputs: seeds, water, land, fertilizers, pesticides, mechanization, labor Outputs: value of output
Chemak et al. [32]	Value of fruit tree products, value of crop products, off-farm income, potential irrigated surface in hectares, rental value of potential irrigated surface, expenditure of mechanization, expenditure of fertilization, water consumption quantity, value of water consumption quantity, family labor in number of individuals
Díaz et al. [33]	Inputs: irrigated surface area in hectares, labor in annual working units, the total volume of water applied to an irrigation district Outputs: total value of agricultural production
Díaz et al. [34]	Inputs: irrigated area, labor and the total volume of water applied to an irrigation district Outputs: total value of agricultural production
Fraser and Cordina [35]	Inputs: number of cows in the milking herd adjusted for age distribution of herd, milking area—perennial pasture equivalent, irrigation water applied, supplementary feeding—grains and pellets, fertilizer, labor Outputs: total milk fat/protein
Frija et al. [36]	Inputs: land, irrigation water, labor Outputs: production quantities
Gadanakis et al. [37]	Inputs: area farmed, total agricultural costs, water use, energy cost, total labor, other agricultural costs Outputs: gross margin
Lilienfeld and Asmild [38]	Inputs: irrigation water, labor, capital, seed, fertilizer, precipitation, available water supply Outputs: wheat, corn, sorghum, soybeans, alfalfa hay, silage
Mahdhi et al. [39]	Inputs: land, water, labor, chemicals inputs, others costs Outputs: production
Naceur and Mongi [40]	Inputs: water, land, labor man, chemical inputs, chemical inputs Outputs: vegetable production
Speelman et al. [41]	Inputs: land, irrigation, labor, fertilizers, pesticides Outputs: monetary output
Wadud and White [42]	Revenue, land, labor, irrigation, fertilizer, pesticides, age, schooling, plot size
Watto [43]	Inputs: seed, seed cost, total labor hours, total labor cost, fertilizer, fertilizer cost, number of chemical applications, chemical cost, number of farm operations, machinery cost, irrigation cost, groundwater volume, cropped area Outputs: cotton yield
Yilmaz and Harmancioglu [44]	Inputs: water volume used, area irrigated Outputs: total production value

The production activities of the state farms can be modeled in terms of input and output variables. The general framework is outlined in Figure 1. The four inputs represent the resources used in the production process: labor, land, assets and investments. The gross value of production is the only output variable. The gross value of production allows aggregating multiple outputs.

Analysis of the CU requires dividing the input variables into quasi-fixed ones and variable ones. In our case, labor, land and assets are not freely adjusted in the short run and are treated as quasi-fixed inputs. The level of investments is directly related to the business decisions, technological development and other factors specific to the state farms. Therefore, the level of investments is regarded as a variable input. Variable input is shown in the dashed boxes in Figure 1.

As was mentioned before, the activities of the state farms can be divided into the three industries (primary, secondary, tertiary). In addition to analyzing the performance of state farms using aggregate data for each variable, we also establish models for the separate industries. Thus, we partitioned three indicators, i.e., labor, investment and gross value of production, across the three sectors. Therefore, one can assess the performance of the whole state farm system or its three sectors separately as represented by the four schemes in Figure 1. Note that land and assets cannot be divided across the sectors.

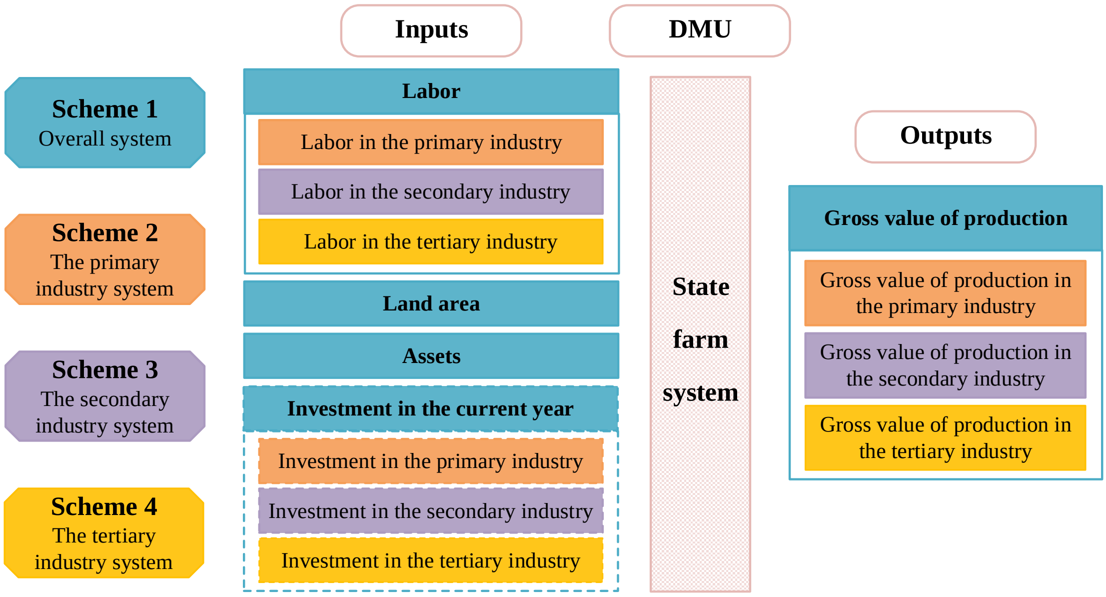


Figure 1. Input and outputs for the state farm system.

Labor refers to the average number of persons who work in the state farm and receive wages or other forms of remuneration for labor services during the period. Working employees, labor service dispatch personnel and other personnel are included in the labor input. The labor input is allocated across the three sectors. Land area denotes the total land area and water area under the jurisdiction of enterprises, institutions or government agencies engaged in the state farm system, including farmland, barren mountains, wasteland, forest land, grassland, roads and buildings, as well as rivers, lakes, reservoirs and ponds. Assets refers to all kinds of fixed assets directly at the service of the production and operation process of an enterprise, namely houses, buildings, machinery, equipment, appliances, tools, etc. Investments in the current year represent the total amount of expenditure completed during the calendar year. The value of this variable is a sum of the amount of work in monetary terms within the year, including the value of the construction and installation work actually completed, the purchase cost of equipment, tools and appliances, and other expenses actually incurred. The latter variable is also allocated across the three sectors. The gross value of production denotes the value of the total production output of agriculture, forestry, animal husbandry and fishery in monetary terms. It reflects the scale of production and includes all the outputs of the three sectors for a certain time period. Likewise, variables of three sub-industries are also adopted.

The analysis was carried at the aggregate level. Thus, we considered 27 regions. The data come from the China State Farms Statistical Yearbook. The period covered is 2013–2017. The descriptive statistics and kernel density graphs of the input and output variables are given in Table A1 and Figure A1 (Appendix A).

The average gross value of production in overall industry increased rapidly between 2013 and 2017, with a rate of annual growth of 23.29%. The average investments also went up by 21.89%. Correspondingly, the average labor, land area and assets showed no clear trends in 2013–2017. Among them, the average assets showed the most serious fluctuations reaching the highest value in 2016 and the lowest value in 2017. Much of the labor input and smallest share of investments are attributed to the first sector with the lowest (and fluctuating) output levels. The investments and gross value of production of the secondary and tertiary sectors both follow increasing trends. Investments and gross value of production in the secondary sector is much higher than the corresponding variables in the tertiary sector. However, the average investment in the primary sector showed a downward trend after 2015. The average labor input in the three sectors follow different trends. The average labor input fluctuated in 2013–2017 in the primary sector, while it follows a downward trend in the secondary sector and an upward trend in the tertiary sector.

3.2. DEA-Based CU Measures

DEA is an effective non-parametric benchmarking tool to assess the relative performance of a homogeneous group of decision-making units (DMUs). Efficient DMUs comprise the technology frontier [45,46]. DEA is able to handle multiple-inputs-multiple-outputs technologies.

In this paper, the output-oriented DEA model is utilized. In this way, we look at the potential improvement in the outputs given the efficiency frontier. Suppose there is index $j = 1, 2, \ldots, n$ for DMUs to be evaluated, and each DMU_j produces s outputs $Y_j \in R_s^+$ by consuming m inputs $X_j \in R_m^+$. Further, we suppose the input vector consists of two sub-vectors, i.e., fixed input vector $F_j \in R_p^+$ and variable input vector $V_j \in R_q^+$, so that $X_j = \left(F_j, V_j\right)$.

DEA is based on the piecewise linear technology whose boundary serves as the efficiency frontier. The reference technology set is defined as:

$$T = \left\{(X, Y) : \sum_{j=1}^{n} \lambda_j Y_j \geq Y, \sum_{j=1}^{n} \lambda_j X_j \leq X, \lambda_j \geq 0 \; \forall j\right\} \tag{1}$$

where λ_j is the intensity variable. The constraint $\sum_{j=1}^{n} \lambda_j = 1$ can be added to impose the assumption of the variable returns to scale (VRS).

To measure the maximum amount of output that can be produced, output-oriented Farrell [47] measure of technical efficiency (TE) can be used. This measure maximizes the output vector for a given input level so that the efficiency frontier is reached. The TE of DMU_0 is obtained by solving the following linear programming problem:

$$\max \theta s.t. \left\{\sum_{j=1}^{n} \lambda_j Y_j \geq \theta Y_0, \sum_{j=1}^{n} \lambda_j X_j \leq X_0, \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0 \; \forall j\right\} \tag{2}$$

where θ is the scalar representing Farrell efficiency measure. The reciprocal measure, Shephard distance function, is defined as $TE = \frac{1}{\theta}$ with $TE \in (0, 1]$. Higher values of TE indicate higher efficiency of the DMU (unity indicates full technical efficiency).

According to Johansen [8], plant capacity is measured by dividing the input variables into the fixed ones and the variable ones. After eliminating the restriction on variable inputs, the unrestricted technology set becomes:

$$\hat{T} = \left\{ (X, Y) : \sum_{j=1}^{n} \lambda_j Y_j \geq Y, \sum_{j=1}^{n} \lambda_j F_j \leq F, \lambda_j \geq 0 \; \forall j \right\} \tag{3}$$

The maximal output without restrictions on the variable inputs for DMU_0 is derived by solving the following linear programming problem:

$$\max \hat{\theta} s.t. \left\{ \sum_{j=1}^{n} \lambda_j Y_j \geq \hat{\theta} Y_0, \sum_{j=1}^{n} \lambda_j F_j \leq F_0, \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0 \; \forall j \right\} \tag{4}$$

The biased measure of the CU is defined as the reciprocal of $\hat{\theta}$, i.e.,

$$CU(biased) = \frac{1}{\hat{\theta}} \tag{5}$$

Indeed, the biased measure of the CU underestimates the true CU [10], because the technical inefficiency is present in the measurement. Therefore, we consider a more general measure of CU, which accounts for the inefficiency:

$$CU(unbiased) = \frac{\theta}{\hat{\theta}} \tag{6}$$

Hence, the unbiased CU measure compares the Farrell measures of efficiency for the restricted and unrestricted technologies. Indeed, due to the elimination of constraints on variable inputs, the $\hat{T}$ is larger than T, and $\hat{\theta}$ is no less than θ. Therefore, the values of the unbiased CU lie in the interval (0,1]. A certain DMU showing unbiased CU of unity represents performs at its full capacity.

4. Results and Policy Implications

4.1. Results

In this section, we first investigate the overall CU and efficiency for the state farms of China. The relevant measures for improving their performance are proposed according to the different categories of the farms. Afterwards, performance of the three sectors (crop production, manufacturing and services) is analyzed. The time interval of this study covers from 2013 to 2017, and we use Consumer Price Index (CPI) from the Organization for Economic Co-operation and Development (OECD) database [48] to account for inflation when using monetary indicators. Specific CPI data is listed in Table 3.

Table 3. Consumer Price Index (CPI) in 2013–2017 based on 2015.

Years	2013	2014	2015	2016	2017
CPI	96.72	98.58	100	102	103.63

Using DEA-based CU measures outlined in Section 3, we first obtained efficiency scores and unbiased CU measures for the state farms without differentiating from the dimension of sectors. The detailed results regarding the variables of interest are given in Table A2.

The efficiencies of state farms in the 27 regions estimated by Equation (2) are displayed in Figure 2. From Figure 2, Beijing, Zhejiang, Guangxi, Chongqing and Xinjiang (agriculture) operated at full efficiency in all years from 2013 to 2017. In contrast, the efficiency of Inner Mongolia, Liaoning, Fujian, Gansu and Ningxia are all lower than 0.7 in 2013–2017. Some regions had huge fluctuations in efficiency over 2013–2017 such as Shanxi, Jiangxi, Henan, Hunan and Xinjiang (livestock). Among them, the efficiency of Jiangxi, Henan and Hunan declined clearly after the year of 2013. Shanxi greatly improved its efficiency after 2014, from 0.3293 in 2014 to 1.0000 in 2015. However, Xinjiang (livestock) faced with a decline in efficiency after 2014, from 1.0000 in 2014 to 0.6403 in 2015.

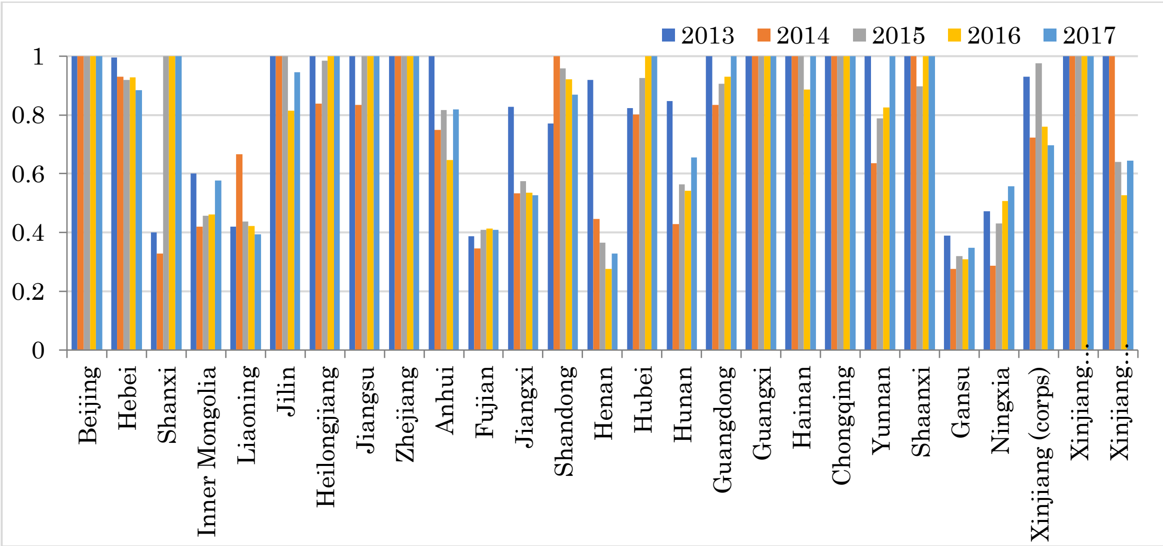


Figure 2. The efficiency estimation for the 27 regions.

The unbiased CU is plotted in Figure 3. According to the unbiased CU (Figure 3), the regions can be grouped in terms of the state farm performance. Specifically, there are four well-performing areas, where capacity is utilized to a full extent, and the CU in 23 regions should be improved in at least one year. The two worst performing areas that fail to get their capacity fully utilized are Shanxi and Jilin. Both of these provinces achieved high efficiency levels, yet lagged behind the rest of regions in regards to CU. This means that the inadequate supply of variable resources led to the low capacity utilization within these two areas. The values of CU for Shanxi, Gansu, Anhui, Zhejiang and Ningxia show a significant downward trend. Conversely, the values of CU values for Liaoning, Henan and Shaanxi show an upward trend. Looking at the average levels of the CU and efficiency, Figure 4 indicates that overall efficiency fluctuated slightly between 2013 and 2017, whereas the overall unbiased CU showed a downward trend as it decreases from 0.89 to 0.86 in 2014–2017.

The four best-performing regions that perform at both full efficiency and full CU are observed throughout 2013–2017, including Beijing, Shandong, Jiangxi and Guangxi. The rest of the regions fall within any of the three groups: (1) efficient and not operating at full capacity, (2) inefficient and operating at full capacity and (3) inefficient and not operating at full capacity. Although the first category of non-optimal state farm regions achieves full technical efficiency, the capacity utilization needs to be improved. This indicates that land or other fixed inputs are underutilized there. The examples of this situation include Zhejiang and Jiangsu in 2013. The supply of the variable resources and elimination of backward equipment are the key measures to improve CU in such regions. As regards the state farms in regions belonging to the second category, e.g., Jiangxi, the full unbiased CU indicates that the proportion of fixed inputs to variable inputs is reasonable. The state farms in these areas need to improve their technical efficiency by enhancing managerial skills to fully utilize the fixed inputs. The regions in the third category not only need to improve technical efficiency, but also need to change the proportion of fixed and variable inputs. Figure 5 shows the changes in the number of regions within each category. Note that most of the regions operates inefficiently and underutilizes their fixed inputs. The number of state farms in the latter category increases in 2013–2016 and decreases in 2016–2017, indicating that state farms in most regions gradually improves their efficiency or unbiased CU after 2016.

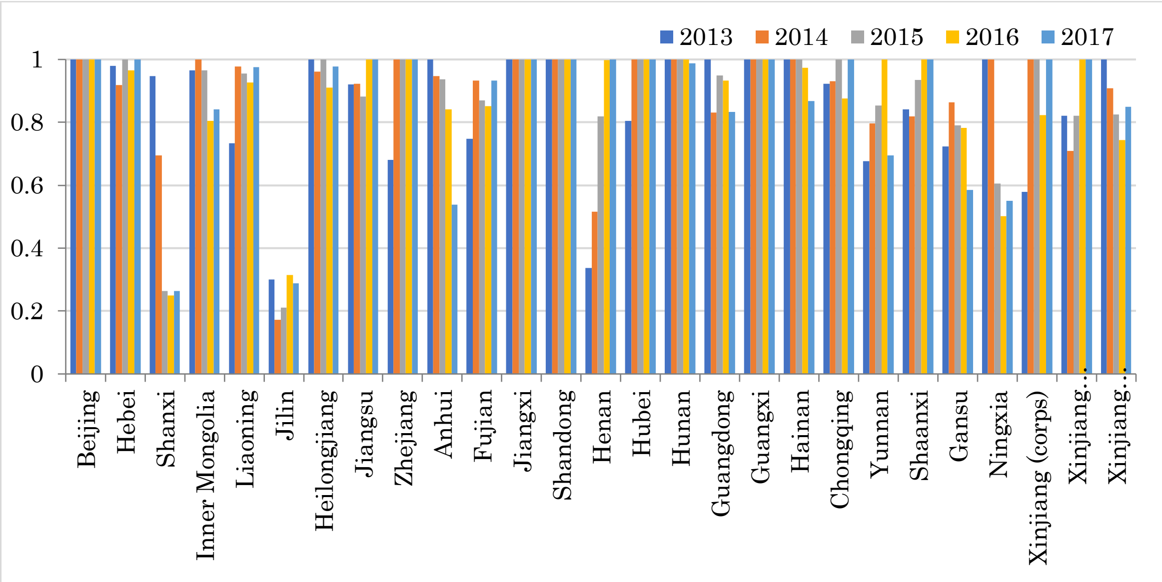


Figure 3. The overall unbiased CU for the 27 regions.

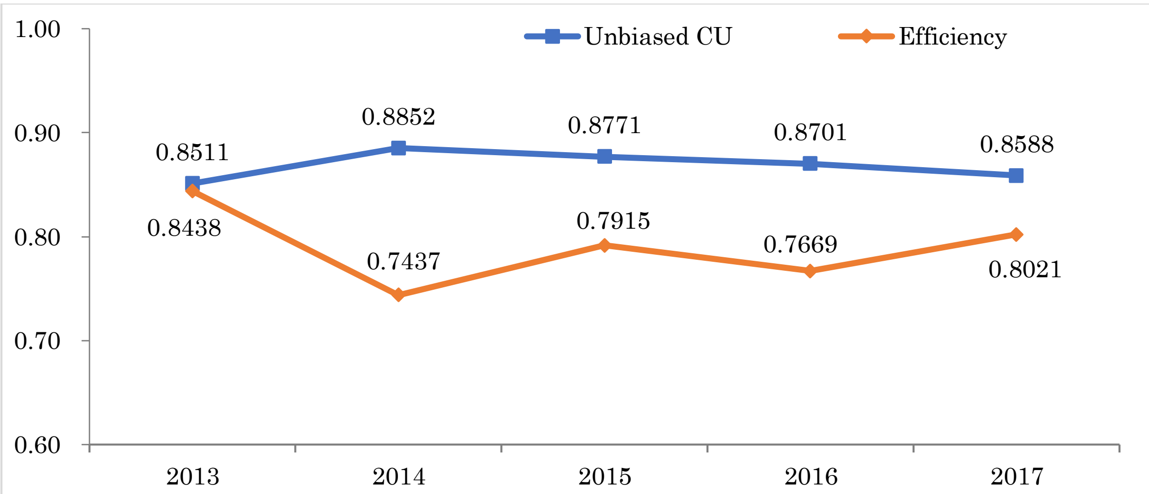


Figure 4. Average unbiased CU for the 27 regions in 2013–2017.

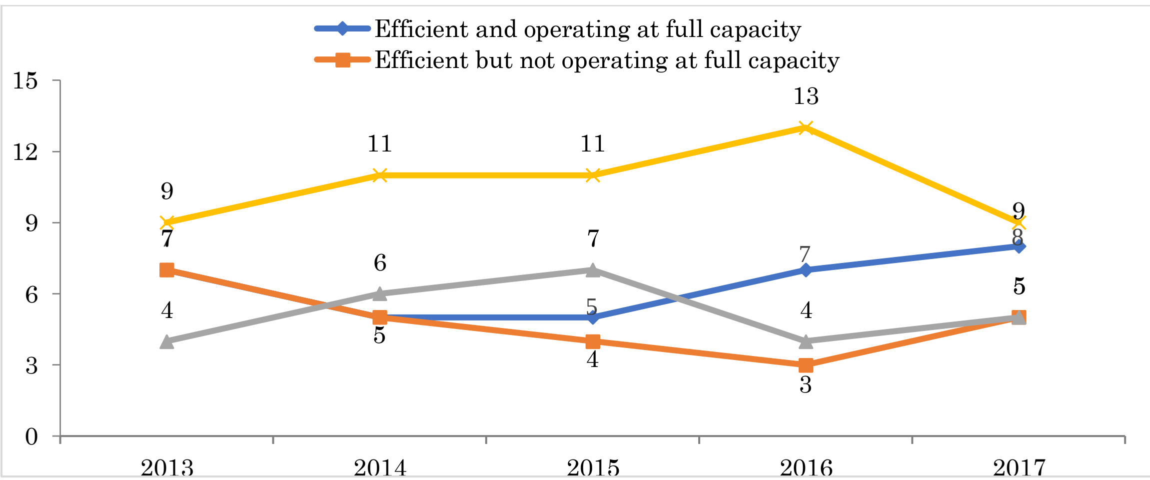
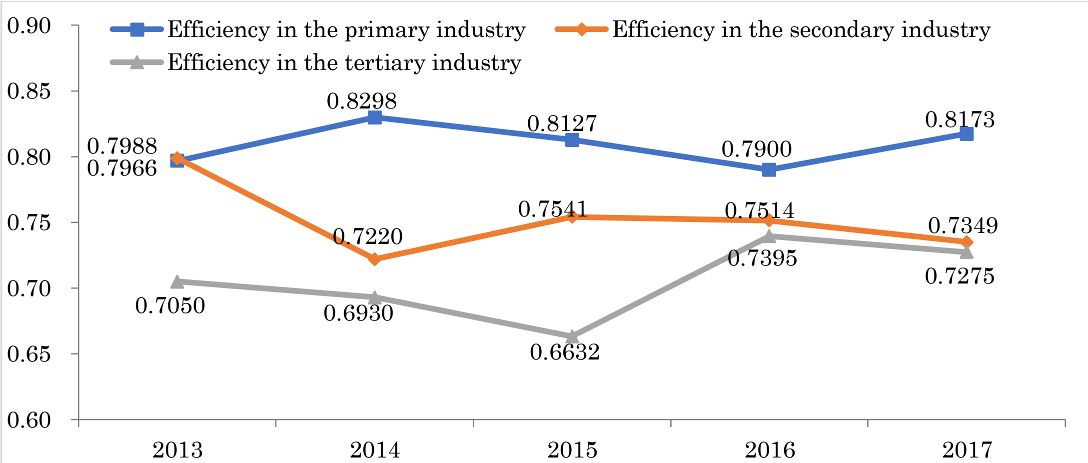
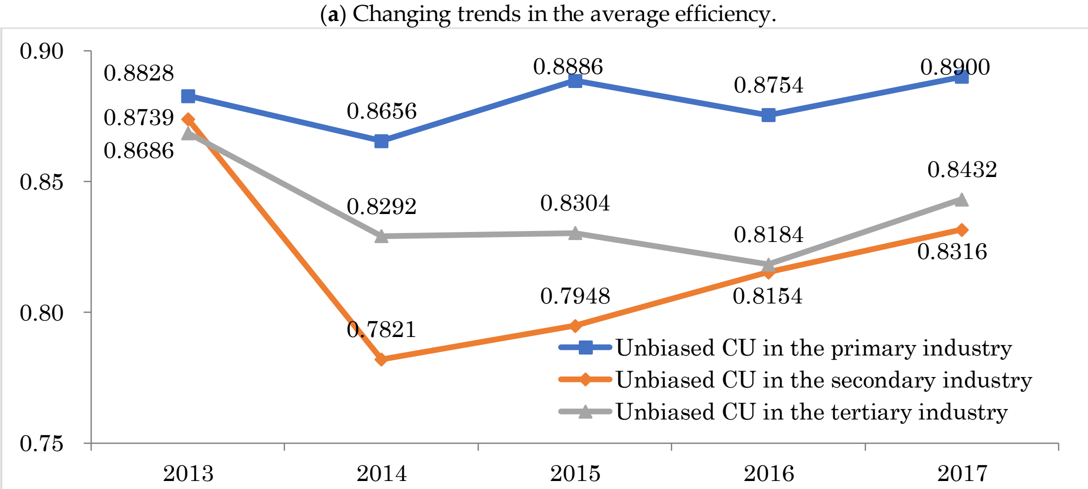


Figure 5. Distribution of the regions across different levels of efficiency and CU (2013–2017).

To gain further insights into the operation of the state farms in China and the potential gains in productivity and efficiency, we further look at the three sub-systems represented by the primary, secondary and tertiary sectors. This is done by breaking down the variables of labor, investment in the current year and gross value of production and reiterating the DEA-based calculations. Specific input-output logic models of the three sectors are also presented in Figure 1. The changing trends of average efficiency and unbiased CU are presented in Figure 6.



(**a**) Changing trends in the average efficiency.

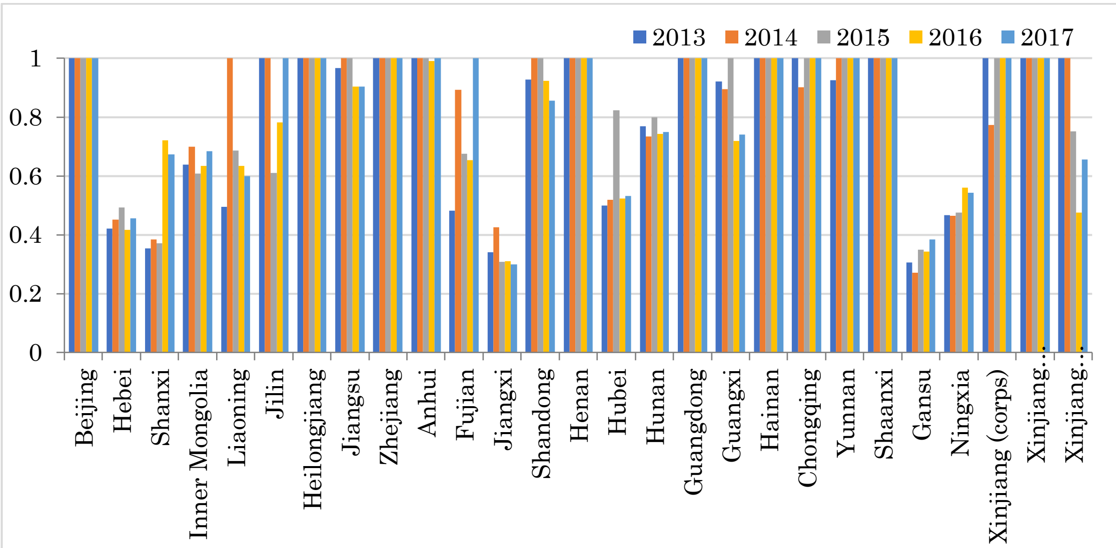


(**b**) Changing trends in the average unbiased CU.

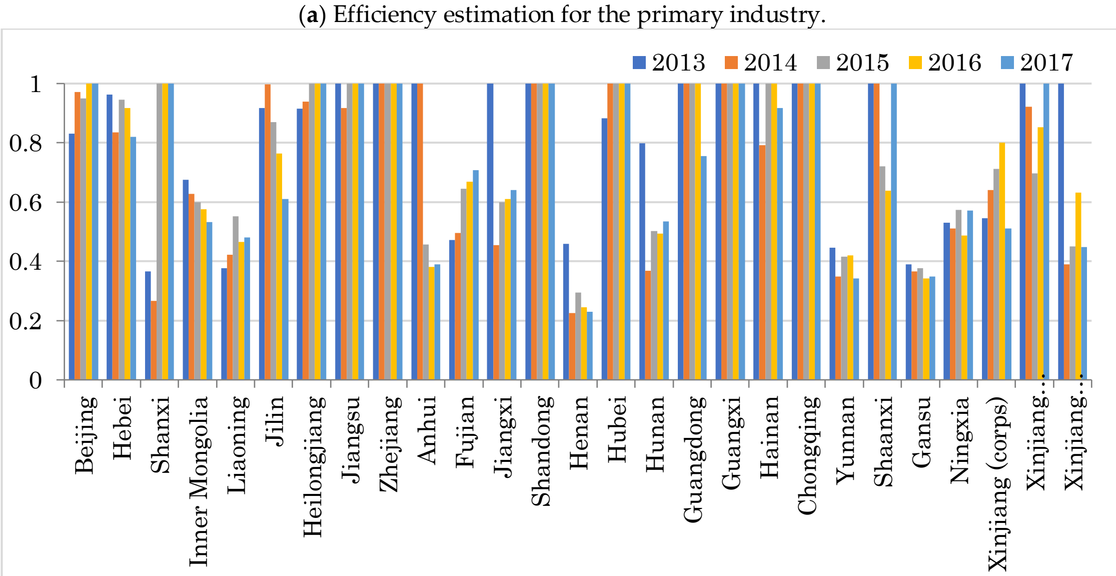
Figure 6. Changing trends in average efficiency and unbiased CU (2013–2017).

Figure 6 suggests that the performance of the primary sector is better than that of the secondary and tertiary sectors, as indicated by higher average efficiency and average unbiased CU. The average efficiency in the tertiary sector is the lowest one, which indicates that the state farms need to concentrate on improving the efficiency of the tertiary sector (services). Compared with the primary industry and the secondary industry, lower levels of the unbiased CU are observed in the tertiary industry. This indicates that the proportion of variable inputs and fixed inputs in the tertiary industry is unreasonable. To increase the CU and fully exploit labor, land and assets in the tertiary industry, there are two ways to choose for the state farms. One is to further increase the investments in the variable inputs in the tertiary industry in order to make full use of the existing fixed inputs, or to eliminate the backward fixed inputs. Technical inefficiency is also related to inappropriate handling of the inputs.

The efficiency of state farms in the 27 regions in the three sub-industries is shown in Figure 7. In the primary industry (Figure 8a), Beijing, Heilongjiang, Zhejiang, Guangdong, Hainan, Shannxi and Xinjiang (agriculture) performed at the highest efficiency in all years from 2013 to 2017. Jiangxi and Gansu as the regions with the worst efficiency need to improve their efficiency by introducing advanced technologies, enhancing their management ability or other methods. In Figure 8b, Zhejiang, Shandong, Guangxi and Chongqing are the most efficient regions in the secondary industry. Regions with efficiency less than 0.5 in the secondary industry in 2013–2017 are Henan, Yunnan and Gansu. For the tertiary industry, Liaoning, Shandong, Fujian and Ningxia operated at efficiency lower than 0.5 in all years from 2013–2017. They need to improve their efficiency and take the regions with unity efficiency as benchmark such as Beijing, Hebei, Heilongjiang, Chongqing and Xinjiang (agriculture). One region often operated with different efficiency in different sub-industries. For example, the efficiency of Hebei in the secondary and the tertiary industries are much higher than in the primary industries. This may be due to the different divisions of labor for each region. However, state farms in Inner Mongolia and Ningxia operated with the efficiency less than 0.7 in all three sub-industries in 2013–2017. Before improving efficiency, they need to first define the characteristics and advantages of their own development.

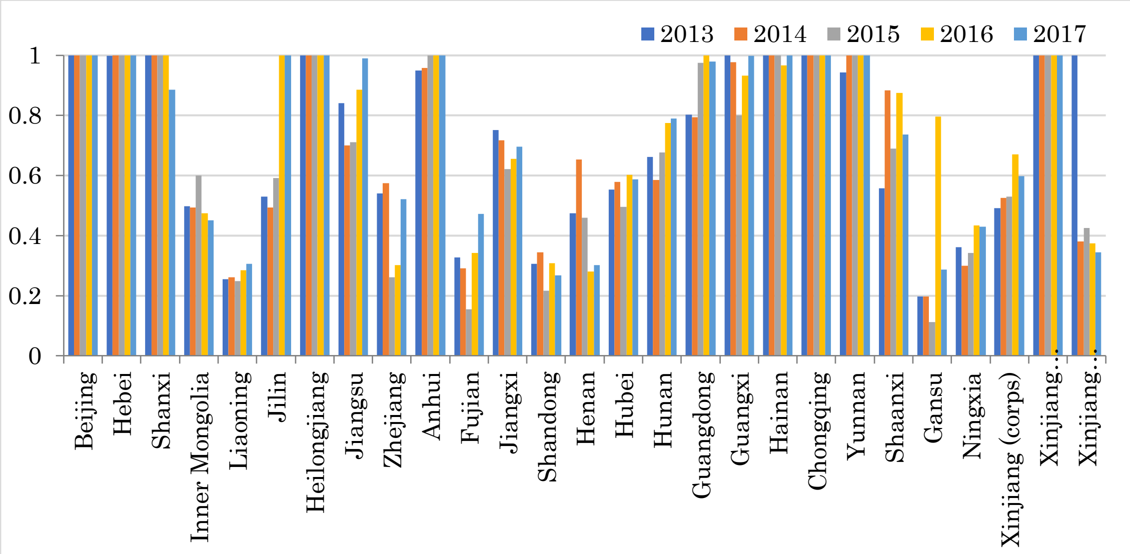


(**a**) Efficiency estimation for the primary industry.



(**b**) Efficiency estimation for the secondary industry.

Figure 7. *Cont.*

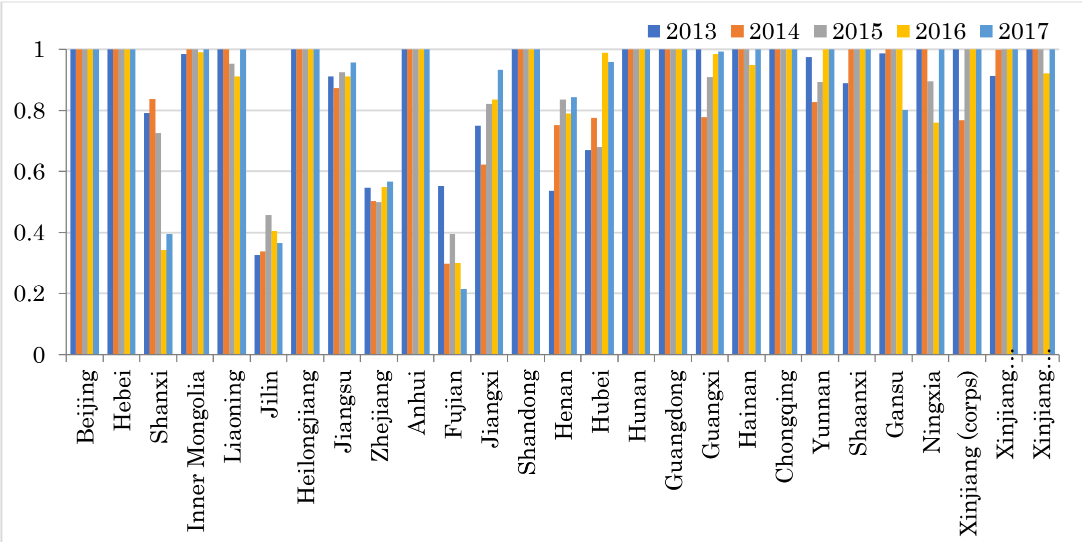


(**c**) Efficiency estimation for the tertiary industry.

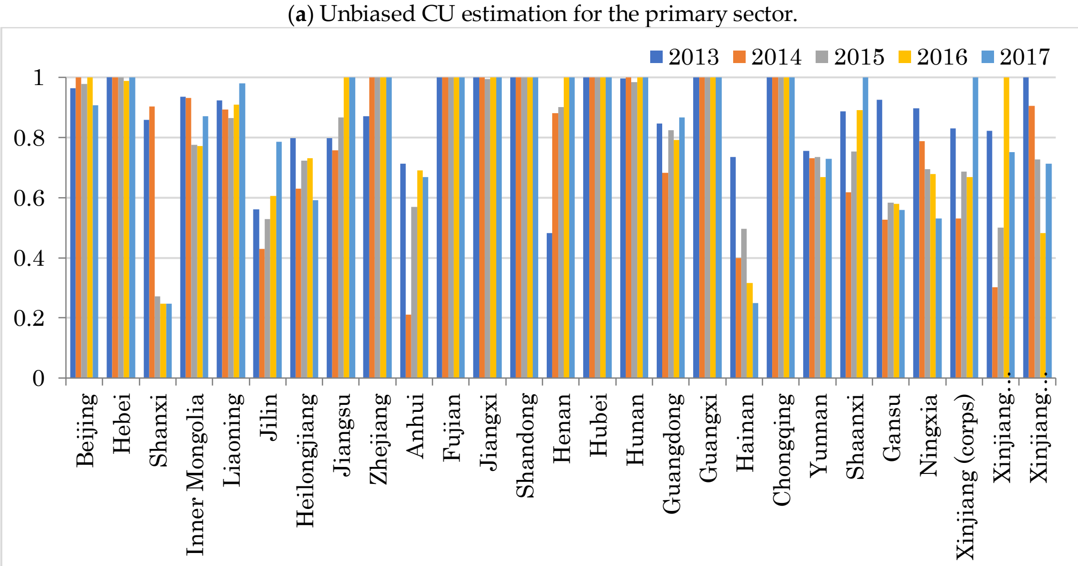
Figure 7. Efficiency estimation across the three sectors.

Figure 8 employs the column diagram to present the CU results for the three sectors during the examined period, and Tables A3–A5 present the specific unbiased CU and technical efficiency values. In the case of the primary sector (Figure 8a), there are eight regions where the unbiased CU equals unity, namely, Beijing, Hebei, Heilongjiang, Anhui, Shandong, Hunan, Guangdong and Chongqing. These areas can be seen as the best-performing ones in the sense of the fixed input exploitation in the primary sector. The state farms in Shanxi, Jilin, Zhejiang and Fujian have the lowest unbiased CU (0.47 on average), which indicates that these four provinces urgently need to adjust the proportion of their fixed and variable inputs by increasing supply of the variable inputs or reducing excessive fixed inputs such as land, labor and assets in the primary industry. As suggested by Figure 8b, there exist only five regions with full CU, including Jiangxi, Shandong, Hubei, Guangxi and Chongqing. The four areas with lowest unbiased CU scores are Shanxi, Jilin, Anhui and Hainan. Zhejiang and Fujian have low CU in the primary sector but high CU in the secondary sector, indicating that these two regions tend to lack variable resources for the crop production. For the tertiary sector (Figure 8c), Beijing, Hebei, Jiangxi, Shandong, Chongqing and Yunnan fully utilized their capacity in all five years. This is also the case of the primary industry; Shanxi, Jilin, Zhejiang and Fujian have the lowest unbiased CU in the tertiary industry. Indeed, Shandong is the region with the highest unbiased CU across all three sub-industries and overall system. Therefore, this province can be considered as an example for the management of the variable and fixed inputs. The unbiased CU for Shanxi and Jilin is low across all the three sub-industries, making the adjustment of the input structure more urgent in these areas.

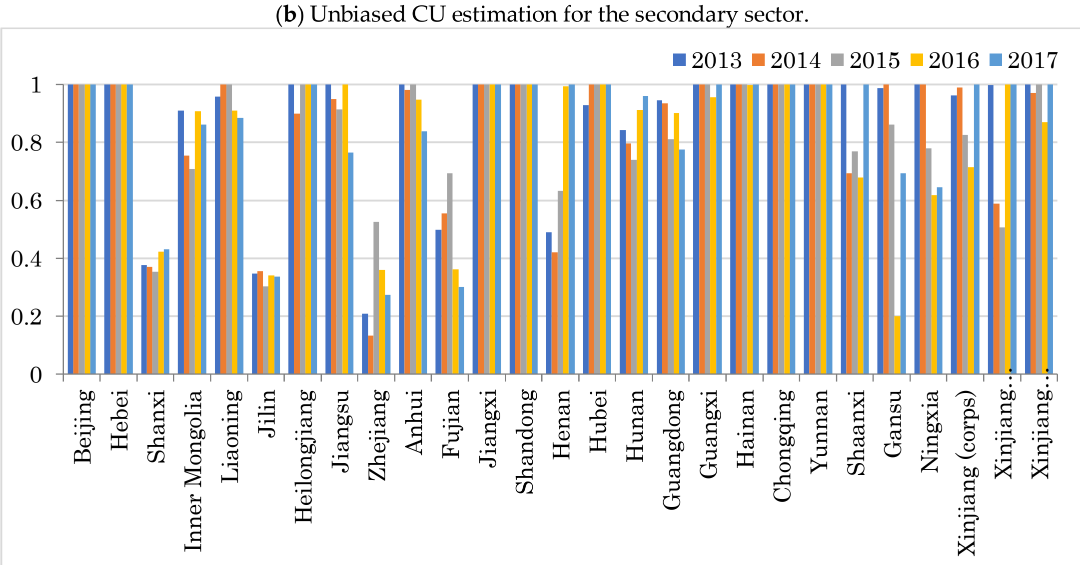
To further explore the relationship between the ratio of fixed input to variable input and the value of unbiased CU, we employed the Pearson correlation coefficient for linear correlation measurements. The results are shown in Table 4.



(**a**) Unbiased CU estimation for the primary sector.



(**b**) Unbiased CU estimation for the secondary sector.



(**c**) Unbiased CU estimation for the tertiary industry.

Figure 8. Unbiased CU estimation across the three sectors.

Table 4. Correlation between the value of CU and the ratio of fixed input to variable input.

Year	The Ratio of Fixed Input and Variable Input	The Overall Unbiased CU	Unbiased CU for the Primary Sector	Unbiased CU for the Secondary Sector	Unbiased CU for the Tertiary Sector
2013	Labor/Investment	−0.653 **	−0.714 **	−0.439 *	−0.687 **
	Land area/Investment	0.044	−0.009	0.044	−0.436 *
	Assets/Investment	−0.733 **	−0.624 **	−0.562**	−0.767 **
2014	Labor/Investment	−0.846 **	−0.678 **	−0.600 **	−0.749 **
	Land area/Investment	−0.178	−0.143	−0.114	−0.722 **
	Assets/Investment	−0.766 **	−0.879 **	−0.418 *	−0.689 **
2015	Labor/Investment	−0.811 **	−0.751 **	−0.673 **	−0.710 **
	Land area/Investment	−0.157	−0.044	−0.125	−0.560 **
	Assets/Investment	−0.831 **	−0.855 **	−0.650 **	−0.665 **
2016	Labor/Investment	−0.794 **	−0.773 **	−0.786 **	−0.497 **
	Land area/Investment	−0.204	−0.113	−0.315	−0.602 **
	Assets/Investment	−0.842 **	−0.798 **	−0.878 **	−0.589 **
2017	Labor/Investment	−0.779 **	−0.832 **	−0.514 **	−0.645 **
	Land area/Investment	−0.082	−0.273	−0.556 **	−0.443 *
	Assets/Investment	−0.829 **	−0.766 **	−0.516 **	−0.679 **

Note: * and ** indicate significant correlation at the 0.05 level and 0.01 level.

Two rules can be found from Table 4. First, the ratio of assets to investment and the ratio of labor and investment are significantly negatively related to the value of CU, which indicates that the increase in investment or the decrease in labor and asset will enhance the CU in state farms. The change of land area of each state farm cannot significantly affect the value of unbiased CU linearly from the perspective of the overall, the primary industry and the secondary industry. Second, the ratio of land area to investment is significantly negatively related to the value of CU in the tertiary industry, which means that the increase in land area or the decrease in investment will result in a decrease of unbiased CU of each state farms in the tertiary industry.

The significant correlation between the ratio of fixed inputs to variable inputs and the value of unbiased CU explains that proper proportion between fixed inputs and variable inputs can increase the CU. In order to better propose policy recommendations, we further calculated the average input ratio of DMUs with the unbiased CU equaling to one in each industry, as shown in Table 5.

Table 5. The average input ratio for fully utilized DMUs.

Overall		The Primary Industry		The Secondary Industry		The Tertiary Industry		
The ratio of labor to investment	The ratio of asset to investment	The ratio of labor to investment	The ratio of asset to investment	The ratio of labor to investment	The ratio of asset to investment	The ratio of labor to investment	The ratio of land area to investment	The ratio of asset to investment
0.3349	0.5761	1.1253	3.2987	0.1941	2.1387	0.1614	18.8899	3.3365

Since the ratio of land area to investment and the value of overall CU and CU in the primary and the secondary industry have no significant correlation, only the average of the ratio of land area to investment in the tertiary industry is listed in Table 5. From Table 5, it can be seen that the ratio of labor to investment in the primary industry is higher than in other industries, which indicates that the labor needs to be matched with less investment. In comparison, DMUs need less labor to match more investment in the second and third industries. For DMUs with unity unbiased CU, the ratio of asset to investment in the secondary industry is the lowest among three industries, which means that DMUs that make fully utilize of their fixed inputs generally invested more in the secondary industry, compared with the investment of other two industries.

The emergence of the same four regions with the lowest levels of the unbiased CU in the primary industry and the tertiary industry indicate that the CU of the primary and tertiary industries may be related. In order to verify this link, the Pearson correlation coefficient is employed. Table 6 provides the results.

Table 6. Correlation among CU scores for different sectors.

	Unbiased CU in the Primary Sector	Unbiased CU in the Secondary Sector	Unbiased CU in the Tertiary Sector
Unbiased CU in the primary sector	1.000		
Unbiased CU in the secondary sector	0.087	1.000	
Unbiased CU in the tertiary sector	0.713 **	0.246 **	1.000

Note: ** indicates significant correlation at the 0.01 level.

The results show that the unbiased CU in the tertiary sector is related to the primary and the secondary sectors. The linkage between CU in the primary and tertiary sectors is stronger if compared to that between the primary and secondary sectors. This suggests that capacity utilization of the primary and secondary sectors is not directly related. As for the other linkages, they indicate that coordinated development of sectors may be needed.

Based on the analysis of empirical results above, three findings can be summarized as follows: First, from the perspective of efficiency, the overall efficiency of Inner Mongolia, Liaoning, Fujian, Gansu and Ningxia need to be improved. Among them, the poor performance of Inner Mongolia and Ningxia in all three sub-industries requires them to clarify their development direction. From the perspective of CU, Shanxi and Jilin are the worst in terms of the CU, not only in the overall performance, but also in the sense of three sectors. Second, from the point of view of performance in sub-industries, the efficiency of tertiary industry needs to be improved, as compared to the two other sub-industries. Moreover, state farms need to improve the CU in the secondary industry. Finally, the unbiased CU in the tertiary industry is significantly related to the other two sub-industries. Regions with high CU in the tertiary industry often perform in a high CU in the primary industry and the secondary industry.

4.2. Policy Implications

The state farms with low efficiency levels operating in Inner Mongolia and Ningxia not only need to improve their output by introducing advanced technologies and improving management capabilities, but also need to clear their appropriate development routes. State farms showing low efficiency in one or two sub-industries could cooperate with the regional governments to improve the distribution of the labor force across the sub-industries. For state farms in Shanxi and Jilin with low CU, they need to adjust the proportion of labor, land and assets as fixed inputs and investments as a variable input. In the short term, state farms in Shanxi and Jilin can increase their investment to further enhance their gross value of production as the output and improve their CU. In the long run, state farms in Shanxi and Jilin can decrease the fixed inputs (i.e., labor, asset and land area) to improve their CU. The benchmark ratio of the fixed inputs to the variable input is given in Table 5.

In the context of the integrative development of the primary, the secondary and the tertiary industries, state farms should improve the efficiency of the tertiary industry by further developing tourism infrastructure and agricultural productive services. When developing the tertiary industry, the state farms should pay attention to the talent management as development of the tertiary industry requires high quality labor input. The low level of CU in the secondary industry indicates that the ratio of the fixed inputs and the variable input in many state farms are not at optimal level. Thus, the ratio of labor to investment and the ratio of asset to investment in Table 5 can be used as a reference. Given the results in Table 5, it should be noted that state farms should invest more in the secondary industry than in the primary industry and the tertiary industry to achieve the full CU.

Regions with high levels of the CU in the tertiary industry tend to perform at a high level of CU in the primary and the secondary industries. The full utilization of labor, asset and area land in the primary and the secondary industries contributes to the development of the tertiary industry.

Therefore, in the improvement of the CU in the tertiary industry, state farms should also pay attention to the use of labor, asset and area land in the primary and secondary industries. Significant correlation also indicates that the existing policies for integrative development of the primary, the secondary and the tertiary industries are necessary for the state farms.

5. Conclusions

Agricultural production is fundamental for China, a country with the world's largest population. After conducting a number of reforms, China's state farms face the problems of decentralization and multiple functions. The improvement of efficiency and capacity utilization in Chinese state farms is important for resource conservation and food security. This paper looked into technical efficiency and CU of state farms in China at the regional level. The DEA-based CU models were applied to quantify the trends in the efficiency and CU for the 27 regions over 2013–2017. The three sectors (crop production, manufacturing and services) were investigated.

The results showed there had been variation in efficiency and CU across different regions and sectors. We found that the overall unbiased CU showed a downward trend during 2014–2017, and Shandong was the only province with full CU in all three sectors during the examined period. However, the technical efficiency of Shandong needs to be improved. In general, the productivity of Chinese state farms can be improved by altering the use of the existing inputs and supplying new ones. From the sector perspective, the technical efficiency of the tertiary sector and the CU of the secondary sector require the most attention. The correlation between CU and the ratio of fixed inputs to variable inputs was also analyzed. The policy recommendations associated with operating conditions defined in terms of CU and efficiency scores were outlined.

Author Contributions: Conceptualization, Guo-liang Yang; Data curation, Zhuo-wan Liu and Yao-yao Song; Formal analysis, Zhuo-wan Liu and Tomas Balezentis; Funding acquisition, Guo-liang Yang; Methodology, Yao-yao Song; Resources, Guo-liang Yang; Writing—original draft, Zhuo-wan Liu; Writing—review & editing, Tomas Balezentis and Guo-liang Yang.

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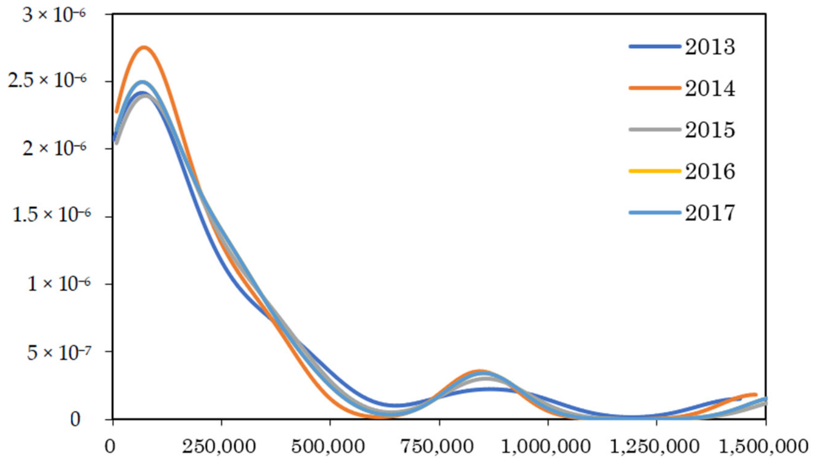
Conflicts of Interest: The authors declare no conflict of interest.

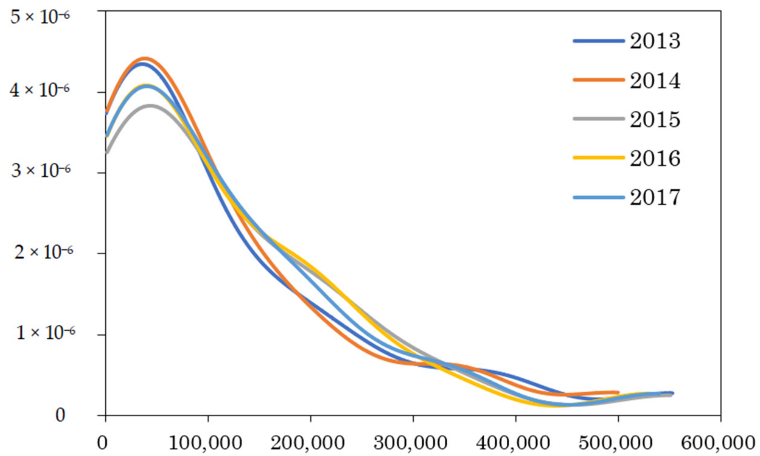
Appendix A

Table A1. Descriptive statistics of inputs and outputs.

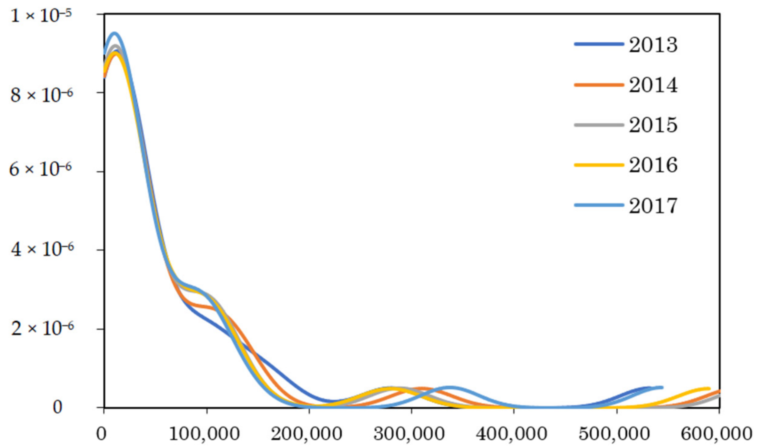
Year	Statistic	Labor, persons				Land Area, Hectares	Assets, Ten thousand RMB of 2015	Investments, Ten thousand RMB of 2015				Gross Value of Production, hundred million RMB of 2015			
		Overall	Primary Industry	Secondary Industry	Tertiary Industry			Overall	Primary Industry	Secondary Industry	Tertiary Industry	Overall	Primary Industry	Secondary Industry	Tertiary Industry
2013	Max	1,439,431	552,646	532,669	511,766	11,397,017	9,335,394	15,611,037	896,986	7,112,074	7,601,977	15,301,902	6,054,454	6,441,274	4,363,110
	Min	1815	1075	596	144	3143	5299	12,178	1098	1466	117	45,792	12,331	12,344	4418
	Mean	238,331	115,682	64,568	58,081	1,299,607	954,674	1,517,555	155,740	772,015	589,800	2,208,938	662,773	977,263	568,902
	Median	91,932	54,565	12,586	15,138	225,652	234,384	212,602	38,437	36,420	71,215	515,291	233,525	216,612	82,194
	St. Dev.	336,006	138,712	114,093	105,916	2,747,059	2,021,960	3,197,904	246,117	1,603,963	1,481,136	3,831,209	1,375,569	1,629,982	1,063,647
2014	Max	1,477,638	499,361	616,680	516,376	11,574,804	13,585,859	17,867,003	1,257,200	7,995,608	8,614,196	17,637,292	5,514,896	7,880,562	5,527,025
	Min	9682	1305	559	1599	3873	3988	7644	931	821	18	47,893	13,680	9466	2362
	Mean	234,380	107,544	66,498	60,338	1,306,256	1,066,089	1,700,558	180,289	837,415	682,854	2,340,369	645,620	1,054,733	640,016
	Median	119,757	54,837	12,333	16,428	226,704	213,555	259,860	56,873	52,658	102,872	573,973	245,382	177,027	119,641
	St. Dev.	331,743	125,715	128,921	107,485	2,776,463	2,676,145	3,709,723	290,185	1,838,040	1,687,020	4,094,532	1,265,357	1,890,599	1,239,944
2015	Max	1,572,125	551,192	629,162	634,748	13,256,646	13,688,618	17,813,458	2,038,678	7,776,245	8,547,057	19,345,905	5,545,732	8,838,761	6,229,948
	Min	9334	1387	464	0	3128	3195	5134	401	500	171	42,298	13,402	5660	2751
	Mean	247,823	117,841	64,188	65,795	1,369,279	1,032,564	1,783,456	239,886	815,823	727,747	2,478,708	645,684	1,130,993	702,031
	Median	119,964	62,466	11,686	16,298	227,663	221,824	269,573	54,298	53,464	89,167	561,634	244,451	169,814	196,620
	St. Dev.	348,561	129,834	129,092	127,703	3,017,786	2,657,835	3,821,392	475,333	1,868,164	1,709,829	4,434,596	1,274,979	2,115,147	1,381,731
2016	Max	1,542,322	531,037	589,706	666,952	13,556,673	16,935,135	16,874,576	1,754,237	6,606,520	8,761,565	20,924,811	5,087,202	9,466,450	6,871,362
	Min	9053	1387	351	1338	2942	2259	1825	644	916	185	42,624	12,873	4834	2552
	Mean	245,365	115,112	61,694	68,559	1,379,987	1,156,158	1,733,878	180,694	840,465	712,718	2,587,513	643,457	1,182,771	761,285
	Median	119,706	63,817	10,817	26,426	223,439	265,333	268,765	48,694	51,660	100,390	663,876	241,123	164,199	236,543
	St. Dev.	343,012	125,547	121,991	134,053	3,064,376	3,260,023	3,756,239	354,386	1,795,638	1,766,428	4,718,477	1,245,035	2,261,645	1,525,449
2017	Max	1,572,247	540,286	544,097	702,304	1,3419,728	8,040,584	18,972,797	1,938,240	7,448,277	10,044,482	22,571,387	5,191,579	9,905,454	7,780,002
	Min	9092	1381	367	1382	2942	2441	2856	729	7	35	45,902	13,418	13,186	3653
	Mean	246,418	114,310	61,428	70,680	1,367,632	821,583	1,849,786	181,592	912,046	756,147	2,723,391	669,002	1,238,504	815,885
	Median	122,741	64,745	11,288	28,755	228,364	256,037	264,868	48,857	77,298	63,457	672,788	245,145	171,030	240,755
	St. Dev.	352,402	128,513	119,135	140,438	3,040,519	1,662,629	4,164,512	385,712	1,988,235	1,993,215	5,024,407	1,295,095	2,390,565	1,687,345



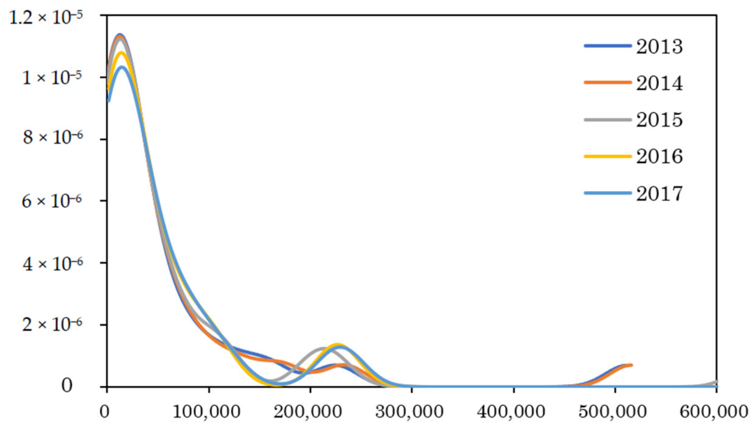
(a) Labor



(b) Labor in the primary industry

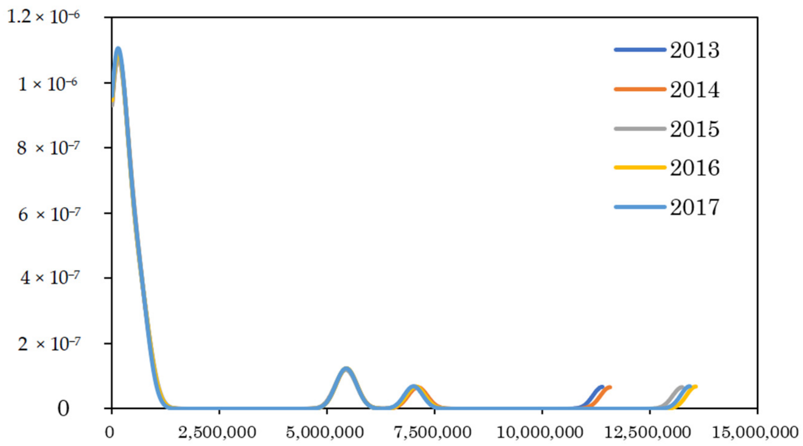


(c) Labor in the secondary industry

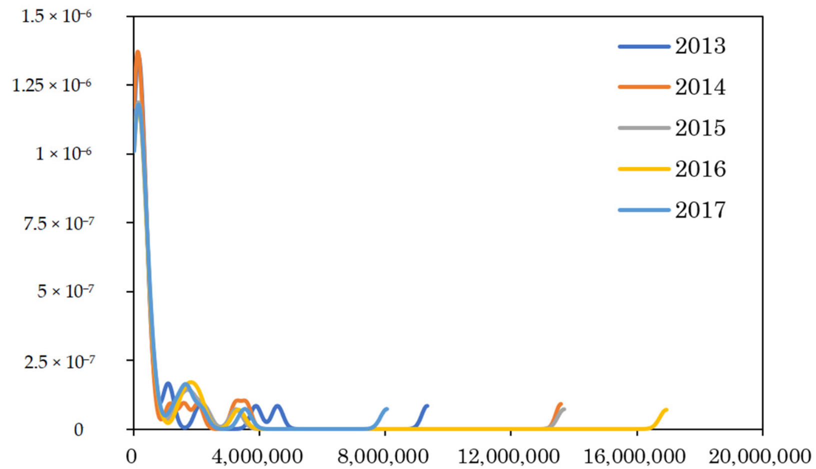


(d) Labor in the tertiary industry

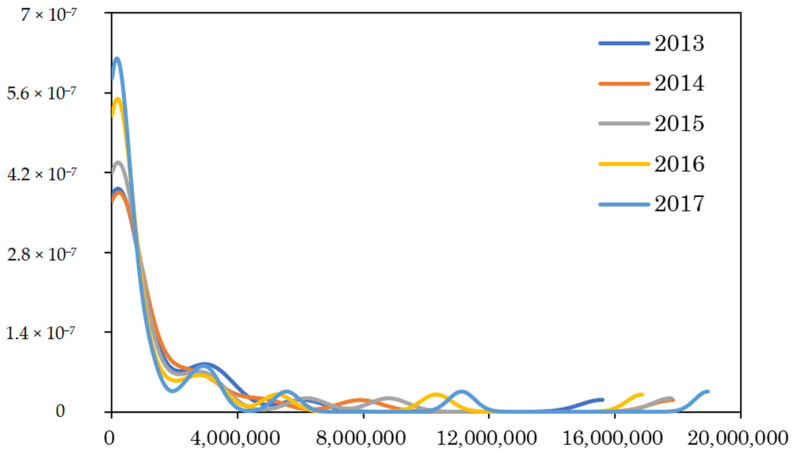
Figure A1. *Cont.*



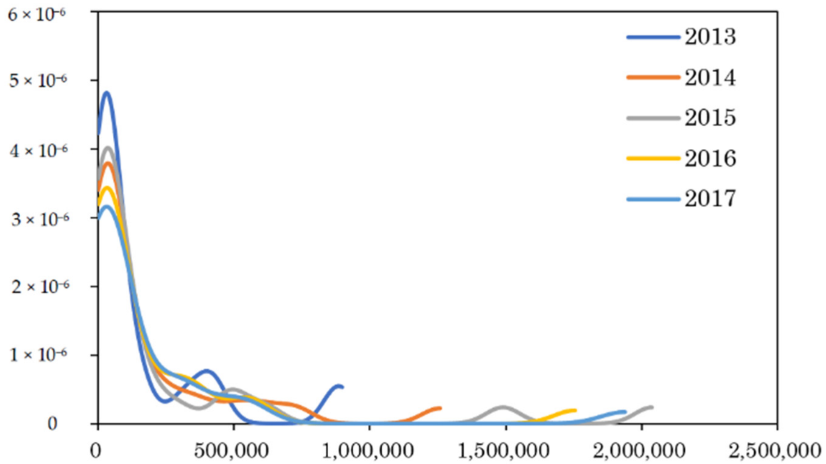
(e) Land area



(f) Assets

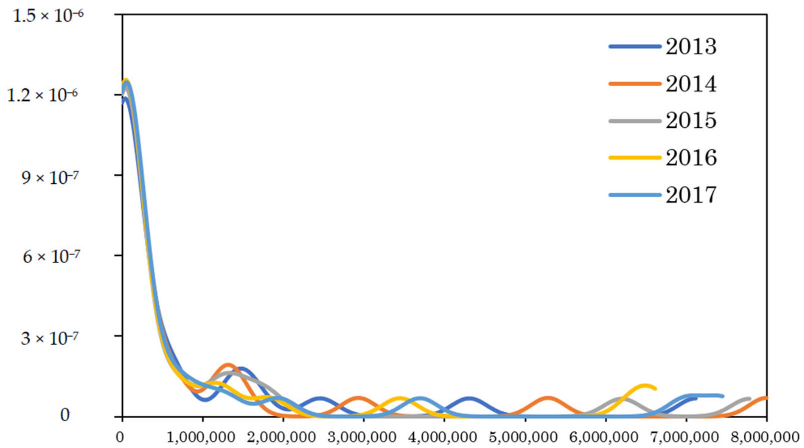


(g) Investment in the current year

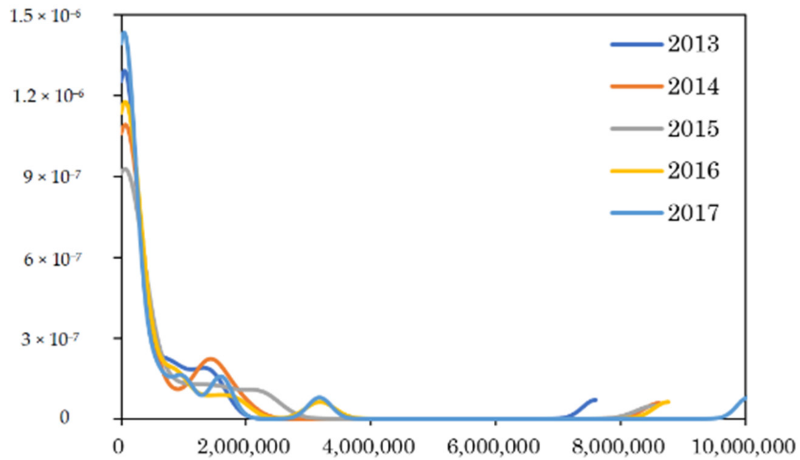


(h) Investment in the primary industry

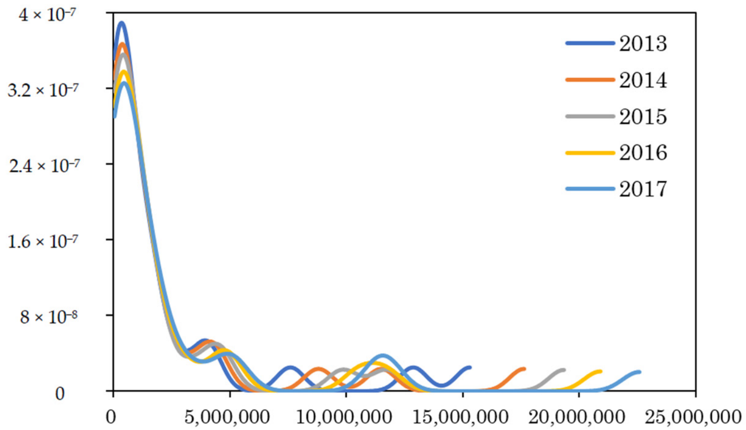
Figure A1. *Cont.*



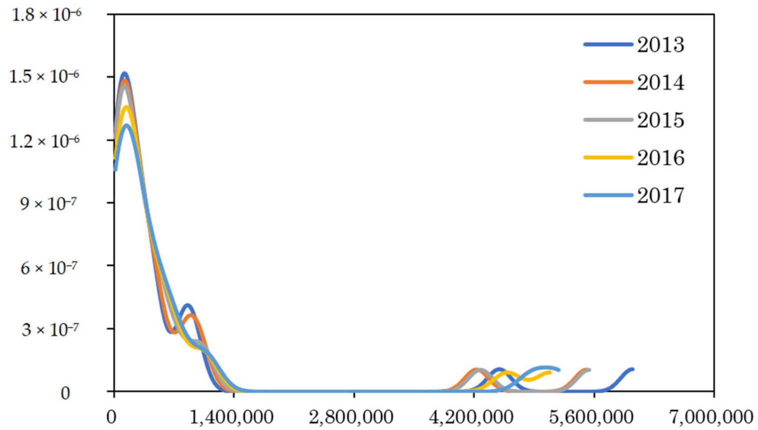
(i) Investment in the secondary industry



(j) Investment in the tertiary industry

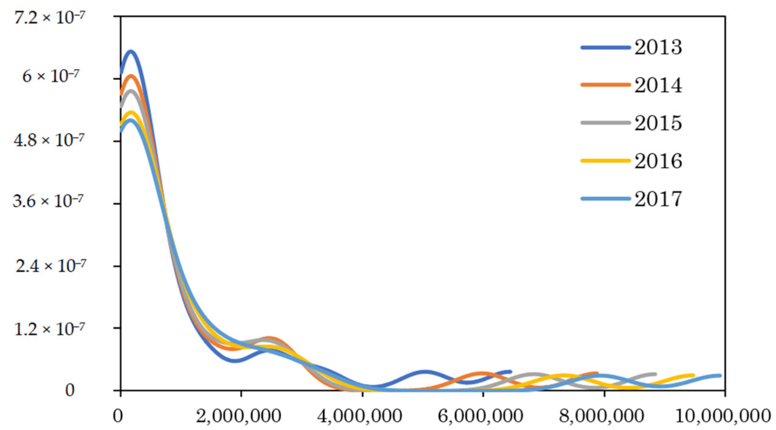


(k) Gross value of production

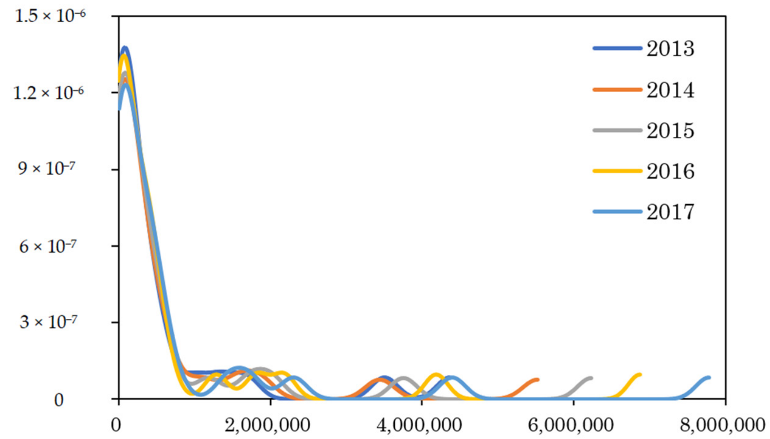


(l) Grosss value of production in the primary industry

Figure A1. *Cont.*



(m) Gross value of production in the secondary industry



(n) Gross value of production in the tertiary industry

Figure A1. Kernel density graphs of inputs and outputs.

Table A2. Overall efficiency, biased CU and unbiased CU of 27 sample state farm areas.

State Farm Areas	**2013**			**2014**			**2015**			**2016**			**2017**		
	$1/\theta$	$1/\hat{\theta}$	$\theta/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$	$\theta/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$	$\theta/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$	$\theta/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$	$\theta/\hat{\theta}$
Beijing	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Hebei	0.9958	0.9747	0.9788	0.9294	0.8533	0.9181	0.9185	0.9185	1.0000	0.9274	0.8950	0.9651	0.8854	0.8854	1.0000
Shanxi	0.4005	0.3793	0.9471	0.3293	0.2289	0.6949	1.0000	0.2631	0.2631	1.0000	0.2491	0.2491	1.0000	0.2642	0.2642
Inner Mongolia	0.6003	0.5795	0.9654	0.4200	0.4200	1.0000	0.4572	0.4412	0.9651	0.4612	0.3713	0.8052	0.5779	0.4862	0.8412
Liaoning	0.4195	0.3076	0.7333	0.6671	0.6528	0.9786	0.4378	0.4182	0.9553	0.4230	0.3923	0.9274	0.3945	0.3847	0.9753
Jilin	1.0000	0.3001	0.3001	1.0000	0.1713	0.1713	1.0000	0.2109	0.2109	0.8147	0.2558	0.3140	0.9459	0.2733	0.2889
Heilongjiang	1.0000	1.0000	1.0000	0.8391	0.8072	0.9620	0.9842	0.9842	1.0000	1.0000	0.9098	0.9098	1.0000	0.9773	0.9773
Jiangsu	1.0000	0.9198	0.9198	0.8350	0.7706	0.9229	1.0000	0.8817	0.8817	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Zhejiang	1.0000	0.6800	0.6800	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Anhui	1.0000	1.0000	1.0000	0.7489	0.7088	0.9466	0.8157	0.7651	0.9379	0.6460	0.5431	0.8407	0.8197	0.4409	0.5379
Fujian	0.3865	0.2892	0.7482	0.3451	0.3218	0.9324	0.4083	0.3551	0.8698	0.4132	0.3520	0.8518	0.4087	0.3810	0.9322
Jiangxi	0.8275	0.8275	1.0000	0.5336	0.5336	1.0000	0.5757	0.5757	1.0000	0.5353	0.5353	1.0000	0.5275	0.5275	1.0000
Shandong	0.7706	0.7706	1.0000	1.0000	1.0000	1.0000	0.9583	0.9583	1.0000	0.9222	0.9222	1.0000	0.8682	0.8682	1.0000
Henan	0.9198	0.3102	0.3373	0.4472	0.2305	0.5155	0.3659	0.2995	0.8185	0.2754	0.2746	0.9970	0.3275	0.3275	1.0000
Hubei	0.8231	0.6627	0.8052	0.8016	0.8016	1.0000	0.9254	0.9254	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Hunan	0.8468	0.8468	1.0000	0.4289	0.4289	1.0000	0.5648	0.5648	1.0000	0.5424	0.5424	1.0000	0.6548	0.6467	0.9877
Guangdong	1.0000	1.0000	1.0000	0.8332	0.6926	0.8313	0.9062	0.8609	0.9500	0.9303	0.8675	0.9325	1.0000	0.8333	0.8333
Guangxi	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Hainan	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.8875	0.8647	0.9743	1.0000	0.8686	0.8686
Chongqing	1.0000	0.9237	0.9237	1.0000	0.9311	0.9311	1.0000	1.0000	1.0000	1.0000	0.8754	0.8754	1.0000	1.0000	1.0000
Yunnan	1.0000	0.6763	0.6763	0.6361	0.5065	0.7963	0.7878	0.6721	0.8531	0.8252	0.8252	1.0000	1.0000	0.6950	0.6950
Shaanxi	1.0000	0.8419	0.8419	1.0000	0.8195	0.8195	0.8967	0.8392	0.9358	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Gansu	0.3900	0.2823	0.7237	0.2751	0.2374	0.8628	0.3196	0.2525	0.7899	0.3079	0.2409	0.7822	0.3471	0.2033	0.5858
Ningxia	0.4722	0.4722	1.0000	0.2876	0.2876	1.0000	0.4312	0.2608	0.6047	0.5075	0.2544	0.5014	0.5582	0.3076	0.5510
Xinjiang (crops)	0.9293	0.5372	0.5781	0.7221	0.7221	1.0000	0.9757	0.9757	1.0000	0.7601	0.6254	0.8228	0.6974	0.6974	1.0000
Xinjiang (agriculture)	1.0000	0.8216	0.8216	1.0000	0.7099	0.7099	1.0000	0.8207	0.8207	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Xinjiang (livestock)	1.0000	1.0000	1.0000	1.0000	0.9083	0.9083	0.6403	0.5281	0.8247	0.5259	0.3913	0.7441	0.6444	0.5477	0.8498
Average	0.8438	0.7186	0.8511	0.7437	0.6572	0.8852	0.7915	0.6952	0.8771	0.7669	0.6736	0.8701	0.8021	0.6895	0.8588

Table A3. Efficiency, biased CU and unbiased CU of 27 sample state farm areas in the primary industry.

State Farm Areas	**2013**			**2014**			**2015**			**2016**			**2017**		
	$1/\theta$	$1/\hat{\theta}$	$\theta/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$	$\theta/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$	$\theta/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$
Beijing	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Hebei	0.4219	0.4219	1.0000	0.4517	0.4517	1.0000	0.4920	0.4920	1.0000	0.4172	0.4172	1.0000	0.4553	0.4553	1.0000
Shanxi	0.3530	0.2797	0.7923	0.3832	0.3211	0.8377	0.3702	0.2691	0.7269	0.7204	0.2464	0.3421	0.6727	0.2667	0.3965
Inner Mongolia	0.6393	0.6292	0.9843	0.6985	0.6985	1.0000	0.6067	0.6067	1.0000	0.6336	0.6276	0.9906	0.6829	0.6829	1.0000
Liaoning	0.4941	0.4941	1.0000	1.0000	1.0000	1.0000	0.6851	0.6534	0.9536	0.6327	0.5760	0.9103	0.5995	0.5995	1.0000
Jilin	1.0000	0.3259	0.3259	1.0000	0.3374	0.3374	0.6099	0.2785	0.4566	0.7813	0.3164	0.4049	1.0000	0.3666	0.3666
Heilongjiang	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Jiangsu	0.9666	0.8803	0.9106	1.0000	0.8728	0.8728	1.0000	0.9247	0.9247	0.9041	0.8234	0.9108	0.9025	0.8635	0.9568
Zhejiang	1.0000	0.5461	0.5461	1.0000	0.5025	0.5025	1.0000	0.4993	0.4993	1.0000	0.5491	0.5491	1.0000	0.5672	0.5672
Anhui	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9905	0.9905	1.0000	1.0000	1.0000	1.0000
Fujian	0.4816	0.2660	0.5524	0.8922	0.2669	0.2991	0.6743	0.2668	0.3956	0.6541	0.1963	0.3001	1.0000	0.2148	0.2148
Jiangxi	0.3413	0.2562	0.7508	0.4244	0.2641	0.6222	0.3075	0.2526	0.8214	0.3102	0.2590	0.8350	0.2985	0.2785	0.9329
Shandong	0.9267	0.9267	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9235	0.9235	1.0000	0.8550	0.8550	1.0000
Henan	1.0000	0.5377	0.5377	1.0000	0.7519	0.7519	1.0000	0.8356	0.8356	1.0000	0.7896	0.7896	1.0000	0.8435	0.8435
Hubei	0.4981	0.3340	0.6706	0.5184	0.4024	0.7762	0.8232	0.5607	0.6811	0.5224	0.5168	0.9894	0.5318	0.5096	0.9582
Hunan	0.7682	0.7682	1.0000	0.7329	0.7329	1.0000	0.7987	0.7987	1.0000	0.7436	0.7436	1.0000	0.7485	0.7485	1.0000
Guangdong	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Guangxi	0.9215	0.9215	1.0000	0.8942	0.6952	0.7774	1.0000	0.9087	0.9087	0.7194	0.7077	0.9838	0.7407	0.7348	0.9920
Hainan	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9499	0.9499	1.0000	1.0000	1.0000
Chongqing	1.0000	1.0000	1.0000	0.9015	0.9015	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Yunnan	0.9253	0.9016	0.9743	1.0000	0.8266	0.8266	1.0000	0.8937	0.8937	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Shaanxi	1.0000	0.8896	0.8896	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Gansu	0.3053	0.3014	0.9871	0.2704	0.2704	1.0000	0.3483	0.3483	1.0000	0.3421	0.3421	1.0000	0.3842	0.3083	0.8024
Ningxia	0.4661	0.4661	1.0000	0.4646	0.4646	1.0000	0.4752	0.4250	0.8944	0.5601	0.4259	0.7603	0.5416	0.5416	1.0000
Xinjiang (corps)	1.0000	1.0000	1.0000	0.7732	0.5939	0.7681	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Xinjiang (agriculture)	1.0000	0.9133	0.9133	1.0000	0.9989	0.9989	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Xinjiang (livestock)	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.7520	0.7520	1.0000	0.4755	0.4379	0.9209	0.6548	0.6548	1.0000
Average	0.7966	0.7059	0.8828	0.8298	0.7168	0.8656	0.8127	0.7321	0.8886	0.7900	0.6977	0.8754	0.8173	0.7219	0.8900

Table A4. Efficiency, biased CU and unbiased CU of 27 sample state farm areas in the secondary industry.

State Farm Areas	**2013**			**2014**			**2015**			**2016**			**2017**		
	$1/\theta$	$1/\hat{\theta}$	$\theta/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$	$\theta/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$	$\theta/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$
Beijing	0.8317	0.8015	0.9636	0.9712	0.9712	1.0000	0.9501	0.9295	0.9783	1.0000	1.0000	1.0000	1.0000	0.9075	0.9075
Hebei	0.9625	0.9624	0.9999	0.8349	0.8349	1.0000	0.9459	0.9459	1.0000	0.9175	0.9059	0.9873	0.8204	0.8204	1.0000
Shanxi	0.3658	0.3138	0.8579	0.2665	0.2404	0.9023	1.0000	0.2715	0.2715	1.0000	0.2466	0.2466	1.0000	0.2464	0.2464
Inner Mongolia	0.6761	0.6320	0.9347	0.6266	0.5837	0.9315	0.5998	0.4651	0.7754	0.5758	0.4447	0.7723	0.5327	0.4637	0.8705
Liaoning	0.3777	0.3488	0.9234	0.4220	0.3769	0.8932	0.5515	0.4767	0.8642	0.4645	0.4226	0.9098	0.4807	0.4715	0.9809
Jilin	0.9176	0.5149	0.5611	0.9978	0.4289	0.4298	0.8707	0.4610	0.5295	0.7643	0.4623	0.6049	0.6103	0.4793	0.7854
Heilongjiang	0.9145	0.7306	0.7989	0.9398	0.5911	0.6290	1.0000	0.7228	0.7228	1.0000	0.7302	0.7302	1.0000	0.5923	0.5923
Jiangsu	1.0000	0.7979	0.7979	0.9179	0.6947	0.7569	1.0000	0.8660	0.8660	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Zhejiang	1.0000	0.8703	0.8703	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Anhui	1.0000	0.7121	0.7121	1.0000	0.2100	0.2100	0.4562	0.2598	0.5695	0.3804	0.2631	0.6915	0.3893	0.2604	0.6690
Fujian	0.4713	0.4713	1.0000	0.4965	0.4965	1.0000	0.6455	0.6455	1.0000	0.6684	0.6684	1.0000	0.7078	0.7078	1.0000
Jiangxi	1.0000	1.0000	1.0000	0.4538	0.4538	1.0000	0.5985	0.5954	0.9948	0.6093	0.6093	1.0000	0.6414	0.6414	1.0000
Shandong	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Henan	0.4588	0.2214	0.4826	0.2261	0.1992	0.8809	0.2942	0.2650	0.9010	0.2440	0.2440	1.0000	0.2302	0.2302	1.0000
Hubei	0.8828	0.8828	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Hunan	0.7988	0.7961	0.9966	0.3691	0.3691	1.0000	0.5023	0.4939	0.9833	0.4946	0.4946	1.0000	0.5340	0.5340	1.0000
Guangdong	1.0000	0.8464	0.8464	1.0000	0.6819	0.6819	1.0000	0.8244	0.8244	1.0000	0.7918	0.7918	0.7562	0.6557	0.8671
Guangxi	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Hainan	1.0000	0.7346	0.7346	0.7930	0.3158	0.3982	1.0000	0.4971	0.4971	1.0000	0.3152	0.3152	0.9179	0.2296	0.2501
Chongqing	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Yunnan	0.4468	0.3377	0.7559	0.3490	0.2553	0.7315	0.4168	0.3068	0.7361	0.4193	0.2803	0.6685	0.3421	0.2498	0.7301
Shaanxi	1.0000	0.8871	0.8871	1.0000	0.6187	0.6187	0.7205	0.5425	0.7530	0.6387	0.5685	0.8901	1.0000	1.0000	1.0000
Gansu	0.3895	0.3607	0.9261	0.3656	0.1925	0.5266	0.3767	0.2197	0.5833	0.3415	0.1977	0.5790	0.3487	0.1952	0.5598
Ningxia	0.5294	0.4746	0.8965	0.5107	0.4023	0.7878	0.5734	0.3984	0.6948	0.4867	0.3303	0.6787	0.5721	0.3040	0.5314
Xinjiang (crops)	0.5453	0.4522	0.8294	0.6408	0.3400	0.5306	0.7115	0.4891	0.6873	0.7997	0.5344	0.6682	0.5099	0.5099	1.0000
Xinjiang (agriculture)	1.0000	0.8213	0.8213	0.9226	0.2780	0.3013	0.6972	0.3491	0.5007	0.8516	0.8516	1.0000	1.0000	0.7512	0.7512
Xinjiang (livestock)	1.0000	1.0000	1.0000	0.3900	0.3530	0.9052	0.4512	0.3283	0.7277	0.6310	0.3038	0.4815	0.4485	0.3193	0.7120
Average	0.7988	0.7026	0.8739	0.7220	0.5514	0.7821	0.7541	0.6057	0.7948	0.7514	0.6172	0.8154	0.7349	0.6137	0.8316

Table A5. Efficiency, biased CU and unbiased CU of 27 sample state farm areas in the tertiary industry.

State Farm Areas	**2013**			**2014**			**2015**			**2016**			**2017**		
	$1/\theta$	$1/\hat{\theta}$	$\theta/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$	$\theta/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$	$\theta/\hat{\theta}$	$1/\theta$	$1/\hat{\theta}$
Beijing	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Hebei	0.9977	0.9977	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Shanxi	1.0000	0.3756	0.3756	1.0000	0.3698	0.3698	1.0000	0.3526	0.3526	1.0000	0.4231	0.4231	0.8858	0.3819	0.4311
Inner Mongolia	0.4969	0.4525	0.9108	0.4929	0.3715	0.7537	0.5991	0.4248	0.7090	0.4741	0.4300	0.9070	0.4508	0.3887	0.8623
Liaoning	0.2553	0.2444	0.9575	0.2610	0.2610	1.0000	0.2476	0.2476	1.0000	0.2854	0.2598	0.9101	0.3069	0.2714	0.8843
Jilin	0.5299	0.1836	0.3465	0.4932	0.1749	0.3546	0.5915	0.1794	0.3032	1.0000	0.3415	0.3415	1.0000	0.3373	0.3373
Heilongjiang	1.0000	1.0000	1.0000	1.0000	0.8989	0.8989	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Jiangsu	0.8408	0.8408	1.0000	0.7002	0.6647	0.9493	0.7107	0.6492	0.9135	0.8866	0.8866	1.0000	0.9898	0.7569	0.7647
Zhejiang	0.5413	0.1126	0.2080	0.5738	0.0763	0.1330	0.2613	0.1375	0.5261	0.3023	0.1090	0.3604	0.5206	0.1420	0.2728
Anhui	0.9489	0.9489	1.0000	0.9582	0.9401	0.9811	1.0000	1.0000	1.0000	1.0000	0.9469	0.9469	1.0000	0.8374	0.8374
Fujian	0.3267	0.1629	0.4985	0.2915	0.1619	0.5552	0.1552	0.1075	0.6928	0.3427	0.1242	0.3623	0.4712	0.1419	0.3011
Jiangxi	0.7518	0.7518	1.0000	0.7175	0.7175	1.0000	0.6206	0.6206	1.0000	0.6564	0.6564	1.0000	0.6957	0.6957	1.0000
Shandong	0.3057	0.3057	1.0000	0.3450	0.3450	1.0000	0.2160	0.2160	1.0000	0.3073	0.3073	1.0000	0.2674	0.2674	1.0000
Henan	0.4736	0.2318	0.4894	0.6528	0.2742	0.4200	0.4588	0.2899	0.6318	0.2813	0.2798	0.9946	0.3026	0.3026	1.0000
Hubei	0.5539	0.5150	0.9298	0.5793	0.5793	1.0000	0.4948	0.4948	1.0000	0.6023	0.6023	1.0000	0.5879	0.5879	1.0000
Hunan	0.6622	0.5586	0.8435	0.5857	0.4659	0.7954	0.6768	0.5003	0.7391	0.7755	0.7075	0.9124	0.7888	0.7580	0.9610
Guangdong	0.8025	0.7589	0.9456	0.7944	0.7427	0.9350	0.9750	0.7899	0.8101	1.0000	0.9024	0.9024	0.9792	0.7592	0.7753
Guangxi	1.0000	1.0000	1.0000	0.9773	0.9773	1.0000	0.8003	0.8018	1.0018	0.9330	0.8915	0.9555	0.9989	0.9989	1.0000
Hainan	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9669	0.9655	0.9985	1.0000	1.0000	1.0000
Chongqing	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Yunnan	0.9425	0.9425	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Shaanxi	0.5581	0.5581	1.0000	0.8831	0.6119	0.6929	0.6895	0.5300	0.7687	0.8760	0.5950	0.6792	0.7369	0.7369	1.0000
Gansu	0.1966	0.1942	0.9877	0.1977	0.1977	1.0000	0.1110	0.0956	0.8616	0.7972	0.1590	0.1995	0.2869	0.1989	0.6933
Ningxia	0.3608	0.3608	1.0000	0.3003	0.3003	1.0000	0.3432	0.2674	0.7791	0.4345	0.2688	0.6185	0.4306	0.2781	0.6458
Xinjiang (crops)	0.4908	0.4718	0.9614	0.5260	0.5210	0.9906	0.5297	0.4379	0.8267	0.6701	0.4791	0.7150	0.5975	0.5975	1.0000
Xinjiang (agriculture)	1.0000	0.9975	0.9975	1.0000	0.5879	0.5879	1.0000	0.5062	0.5062	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Xinjiang (livestock)	1.0000	1.0000	1.0000	0.3802	0.3688	0.9701	0.4257	0.4257	1.0000	0.3740	0.3251	0.8695	0.3441	0.3441	1.0000
Average	0.7050	0.6284	0.8686	0.6930	0.5781	0.8292	0.6632	0.5583	0.8305	0.7395	0.6171	0.8184	0.7275	0.6216	0.8432

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