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The dynamic adjustment of factor inputs and its policy implications for major wheat producing areas in China

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ABSTRACT

China's major wheat producing areas play a crucial role in ensuring domestic grain production and food security more generally and it is therefore of significance, both empirically and theoretically, to investigate the current situation and future tendencies of the sector. Based on input- and output-oriented DEA models, overall technical efficiency was estimated for the sector, and both radial and slack adjustments were calculated. The course of the dynamic adjustments was identified and presented for factor inputs over the past decade. The results show that the radial adjustments have exhibited a decreasing trend, while structural, slack adjustments have practically disappeared. The course of the dynamic adjustments suggests that there has been a transformation from labor-intensive to land-intensive and capital-intensive operations which will continue to dominate China's wheat production sector. As a consequence, to optimize factor inputs and reduce radical and slack adjustments, it seems necessary that the major wheat producing areas reduce labor inputs; enhance land-intensive operations; and increase agricultural mechanization.

1. Introduction

According to China's Statistical Yearbook (CSY, 2011) wheat is the most important grain crop in northern China where it is given much. With the introduction in 2004 of either reductions in and/or exemption from agriculture taxes, and the practice of preferential policies for farmers (Liu et al., 2012), the output of wheat has grown at an annual rate of 3.5% over the 2004–2011 period. However, due to the rapidly rising prices of production materials, wheat production costs have increased while wheat production profits have become quite volatile in recent years (APCR, 1999 and 2011). With such a background, it appears imperative that a thorough investigation of the overall technical efficiency and factor input adjustments is both theoretically and empirically crucial, particularly in relation to for guaranteeing food security and increasing rural income.

Although crucial for northern China as a whole, wheat production is not evenly distributed being concentrated within several major producing regions. Nationally the total sown wheat area fell from 2001–2011, but it remains a large share in the major producing regions; Henan (21.9%), Shandong (14.8%), Hebei (9.9%), Jiangsu (8.7%) and Anhui (9.8%).[2] Moreover, when we consider output shares for the same period these are even larger; Henan (26.6%), Shandong (17.9%), Hebei (10.8%), Jiangsu (8.7%) and Anhui (10.4%). From even these basic statistics we can observe that the sown area of the five major producing regions in China account for 65.1% of the national sown area, while output accounts for 74.5%. In this study, therefore, we will focus on these five major producing regions; Henan, Shandong, Hebei, Jiangsu and Anhui.

Measures of overall technical efficiency are the major research area and as a consequence, the theoretical underpinnings have been well documented for example, using DEA[3] analysis, Yao et al. (2007) evaluated the production efficiency of China's insurance sector from 1999–2004. Using the output-oriented TFP approach, Chen et al. (2008) analyzed the productivity growth in China. Li and Zhou (2010) developed the method of output-oriented DEA to estimate the productive efficiency of the dairy product's processing sector in Heilongjiang.

Given the large population base and the importance of production, the overall technical efficiency of grain productivity in China has also attracted some attention for example, using panel data on household grain production and applying stochastic frontier production function methods, Chen et al. (2009) measured the extent of land operation dispersion and the production efficiency of farm households across 29 provinces in China. Similarly, using a stochastic frontier production

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[2] Figures relate to 2011.
[3] Data envelopment analysis.

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function, Yao et al. (2001) studied grain production efficiency across regions in China based on a panel data set of 30 provinces from 1987–1992; while Tian et al., 2000 estimated the technical efficiency and its determinants for rice, wheat and corn, respectively.

Although several studies have focused on overall technical efficiency in China, they shared a common shortcoming, that is, they only estimated the relative change in overall technical efficiency, *pure technical efficiency* and *scale efficiency*, and did not investigate the *relative* and *absolute* changes in factor inputs, which are the main reasons why technical efficiency changes. Although some studies by analyzing technical efficiency effectively conclude that factor inputs are redundant, they didn't actually consider to what extent they were (Chen et al, 2009; Tian et al., 2010; Yao et al, 2001). In fact, in this type of literature few estimate the 'slackness' of factor inputs and outputs and show how they have changed over time.

With this background, the main aims of this paper are to present estimates of the changes in overall technical efficiency and its two components and then to empirically investigate the factor input slacks and output slacks by constructing a non-parametric frontier efficiency approach based on aggregated input and output dataset for the major wheat producing provinces in China. As a result, the paper is organized as follows: in Section 2 we present details of the methods used and in Section 3 a discussion of the data. Section 4 presents the estimated results and analysis, which is followed in Section 5 with conclusions and some future policy recommendations.

2. Methodology

2.1. Overall technical efficiency (TE)

Assume that the overall technical efficiency of the decision making unit (DMU) is affected by two factors: one, whether the potential for production technology is fully developed; the other, whether the input scales of production factors are reasonable. In practice, in the constant returns to scale (CRS), DEA (data envelopment analysis) model, technical efficiency, (which is referred to as *overall* technical efficiency), is decomposed into two components, pure technical efficiency and scale efficiency. In the variable returns to scale (VRS) DEA model, the technical efficiency score is the DMU's pure technical efficiency. To illustrate this, take a one-input example and one-output example (Fig. 1).

In Fig. 1, OR represents the production technique frontier under the consumption of CRS, while the production technique frontier is G, C, D, F, H under the assumption of VRS. Points G, P, D, F and H represent respectively the input and output combinations of different DMUs. Under the assumption of CRS, only DMU D is technically efficient and its overall technical efficiency (TE_{CRS}) is equal to 1; while under the assumption of VRS, DMUs G, D, F and H represent technical efficiency and the pure technical efficiencies (TE_{VRS}) are equal to 1. For DMU P, under the assumption of CRS DEA model, point B is the projection of point P,

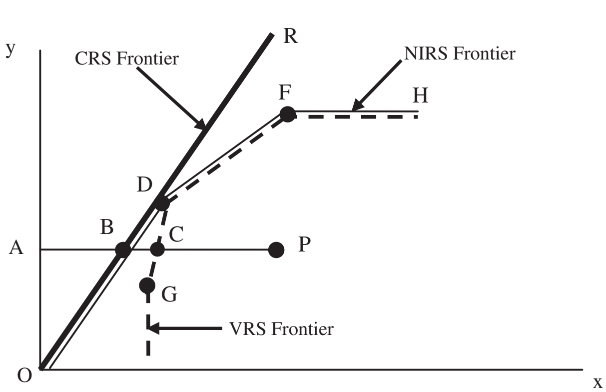

Fig. 1. The various production frontiers of constant return to scale (CRS), variable return to scale (VRS) and non-increasing return to scale (NIRS).

whose technical efficiency (here overall technical efficiency) can be expressed as:

$$TE_{CRS} = AB/AP.$$

However, under the assumption of VRS DEA model, point C is the projection of point P, whose technical efficiency (here is pure technical efficiency) is defined as:

$$TE_{VRS} = AC/AP.$$

The difference between TE_{CRS} and TE_{VRS} is caused by scale efficiency (*SE*). Hence, scale efficiency can be expressed as:

$$SE = AB/AC.$$

Therefore, we can conclude from the three formulas above that: overall technical efficiency (TE_{CRS}) is equal to pure technical efficiency (TE_{VRS}) multiplied by scale efficiency (*SE*), that is:

$$TE_{CRS} = TE_{VRS} \times SE.$$

Furthermore, if pure technical efficiency (TE_{VRS}) is equal to 1, the DMU is taken as fully technically efficient. However, if pure technical efficiency is not equal to 1, then the DMU is taken as technically inefficient. Similarly, if the scale efficiency is equal to 1, the DMU is taken as scale efficient, which indicates that the production of DMU lies in the constant returns to scale portion; otherwise, the DMU is called scale inefficient. However, the value of scale efficiency does not enable us to identify whether a DMU is operating in the area of increasing or diminishing returns to scale. Therefore, it is necessary to calculate the technical efficiency of the non-increasing returns to scale. According to Banker (1984), the non-increasing returns to scale DEA model linear programming can be expressed as:

$$\min\left[\theta-\varepsilon\left(e_1^T IS + e_2^T OS\right)\right]$$
$$s.t\begin{cases} \sum_{j-1}^{K}\lambda_j x_j + IS = \theta X_0 \\ \sum_{j-1}^{K}\lambda_j y_j - OS = Y_0 \\ \sum_{j-1}^{K}\lambda_j \le 1 \\ \lambda_j \ge 0 \quad j = 1, 2, \cdots, K \\ IS \ge 0, OS \ge 0 \end{cases}.$$

As can be seen from Fig. 1, O, B, D, F, H represents the production technique frontier under the assumption of non-increasing returns to scale. The part below the point D is coincident with the CRS production technique frontier. Above that, it overlaps with the VRS production technique frontier (for the convenience of marking, the lines, they don't coincide totally, but are very close). If we take the technical efficiency of non-increasing returns to scale as TE_{NIRS}, the technical efficiencies of the three types of returns to scale meet the following relationship:

$$TE_{VRS} \ge TE_{NIRS} \ge TE_{CRS}.$$

Usually, the following method can be applied: The scale efficiency score is less than 1, if $TE_{NIRS} = TE_{CRS}$ and then increasing returns to scale exist for that DMU; If $TE_{NIRS} > TE_{CRS}$, then decreasing returns to scale apply to that DMU.

2.2. Radial and slack adjustments

Farrell (1957) proposed the definition of technical efficiency based on the input-oriented DEA model. In particular, *technical efficiency* is