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# Production Efficiency and Productivity Change in Chinese Agriculture: A Case Study of Agricultural Production in Shanxi Province

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## A Case Study of Agricultural Production in Shanxi Province

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Doctor of Philosophy Dissertation

# Production Efficiency and Productivity Change in Chinese Agriculture:

## A Case Study of Agricultural Production in Shanxi Province

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# DEDICATION

This dissertation is dedicated to my wife,

Mingming Xia.

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# Chapter 1: Introduction

## 1.1 Background and Motivations

China's development of agriculture over the course of its history has played a key role in supporting the growth of the population and economy.  Before 1978, the agricultural sector was organized according to the commune system. The largest part of the farm family incomes consisted of shares of the net team income, distributed to members according to the amount of work each had contributed to the collective effort. Beginning in the late 1970s, Chinese economic reforms accompanying the household responsibility system (HRS) moved rural China away from collective agriculture. Villages divided up collectively owned land and leased it to individual households. Farmers could produce any crops for free markets. When China started reforms in the agricultural sector, growth rate in grain and livestock accelerated (Lin, 1992; Huang, 1998). From 2000, China had introduced a series of agricultural policy reforms to expand its agricultural sector and increase farmers' income. Most significant among them are entry into the World Trade Organization (WTO) in 2001, elimination of agricultural tax in 2006, and province-level agricultural machinery subsidy in 2007. The mix of policies evolves as the Chinese agricultural sector becomes more commercialized and faces competitive pressures.

The impact of reforms on Chinese agricultural efficiency and productivity has drawn considerable interest from many economists. It has now been over 30 years after the economic reforms. More data have become available to study the impact of the reforms at both national level and regional level. This dissertation studies the production efficiency and productivity change in Shanxi province after the economic reforms using county-level panel data.

## 1.2 Research Objectives

The primary objective of this dissertation is to evaluate the performance in terms of technical efficiency and productivity of Chinese agriculture in Shanxi province at the county-level. We also evaluate a number of national and local agriculture policies[1] over the last 20 years.

Differing from most of the literature that used stochastic frontier method, this dissertation uses Data Envelopment Analysis (DEA) and contributes to the literature on efficiency and productivity of the Chinese agriculture by addressing the following research questions:

1. What is the extent of agricultural efficiency change in Shanxi province after the economic reforms?
2. Has there been any significant improvement in agricultural production efficiency over last 30 years?
3. Has there been any difference in productivity change across different regions in the province?
4. What are the factors[2] responsible for explaining the regional productivity growth?
5. What is the impact of China's entry into WTO on agricultural efficiency?
6. What is the impact of agricultural tax elimination?
7. What is the impact of a subsidy policy of agricultural machinery purchase?

[1] Two national policies are accession to WTO and elimination of the agricultural tax; one local policy is agricultural-machinery subsidy policy.

[2] The explanatory factors are income level, agricultural population percentage, share of agriculture in GDP, and road density.

## 1.3 Study Region

Shanxi is a province of the People's Republic of China, located in the North China region. The name Shanxi means "West of the Mountains", a reference to the province's location west of the Taihang Mountains. Shanxi borders Hebei to the east, Henan to the south, Shaanxi to the west, and Inner Mongolia to the north and is made up mainly of a plateau bounded partly by mountain ranges (Figure 1.1). Total land of Shanxi is 156,000 $km^2$ (60,000 square miles), ranked the 19th out of 34 provinces and districts. Since Shanxi province is around the average of China in population density, agricultural development and household income level, this is a good place to study if we want to find the average agricultural performance of the whole nation after the economic reforms.

Shanxi province has a continental monsoon climate, and is rather arid. Average January temperatures are below 0 °C[3], while average July temperatures are around 21 - 26 °C. Winters are long, dry, and cold, while summer is warm and humid. Spring is extremely dry and prone to dust storms. Shanxi is one of the sunniest parts of China; early summer heat waves are common. Annual precipitation averages around 350 to 700 millimeters (14 to 28 in), with 60% of it concentrated between June and August.

The divisions of Shanxi province are 11 prefectures, 119 counties, and 1388 townships. Population of Shanxi is 36.5 million as of year 2014. The average size of a county in Shanxi province is 1645 square kilometers (635.2 square miles)[4]. The location of Shanxi province and its 11 prefectures is shown in Figure 1.

[3] 0°C = 32ºF; 25°C = 77ºF

[4] 1 Square kilometers = 0.3861 Square miles.

As of year 2010, there is about 3,763,000 hectare of agricultural land in Shanxi province, ranked 14th out of 34 provinces and districts. Total agricultural output is more than 11,900,000 ton, ranked 19th in China. Grain and livestock outputs are 90% of total output in agricultural industry. Major food crops are wheat, sorghum, beans, and potatoes. Commercial crops are cotton, tobacco, sugar beet, flax and rapeseed.

## 1.4 Data and Variables

We collected the data from Department of Agriculture, Department of Finance and Shanxi Meteorological Bureau in the period 1981 to 2010. This data set contains detailed information of 119 counties on two principle agricultural outputs: crops and livestock (in dollar value). Agricultural labor (number), total farm land (hectare), irrigated land (hectare), total mechanical power (kilowatt), fertilizer usage (ton), agricultural electricity usage (10 thousand kilowatt), and annual average rainfall (millimeter) are seven inputs.

We constructed a data set of two outputs and seven inputs from *Shanxi Agricultural Statistical Yearbook* and *Shanxi Meteorological Bureau*[5] over the period 1981-2010. The two outputs are: (a) Crop output; (b) Livestock. The seven inputs included are: (i) Labor; (ii) Unirrigated Land; (iii) Irrigated Land; (iv) Agricultural Machinery; (v) Fertilizers, (vi) Electricity, and (vii) Rainfall[6]. We classify the 119 counties in Shanxi province into three regions in term of county's agriculture share in GDP: (a) less than 10% (groupA1); (b) 10%-20% (groupA2); (b) greater or equal to 20% (groupA3). Based on the agricultural population share, we classify all counties in to three regions: (a) less than 50% (groupB1); (b) 50%-75%

[5] Rainfall data is from *Shanxi Meteorological Bureau, 2014*. Two outputs and six inputs data are from *Shanxi Agricultural Statistical Yearbook, 2010.*
[6] The actual yearly average amount of rainfall is treated as a control input.

(groupB2); (b) greater or equal to 75% (groupB3). In 2012 China designated that counties with annual income per capita less than RMB[7] 2300 as state-level backward counties. Based on the income per capita, we classify counties into two groups: (a) advanced counties (groupC1); (b) backward counties (groupC2).  In Shanxi province, there are 30 backward counties and the rest are advanced counties.

We show the detailed information about the dataset in Table 1.1. Summary statistics for all the input–output quantities and also the annual rainfall data are reported for all counties in Table 1.2. Comparable statistics for the different regions are shown in Table 1.3.  Group A3 Counties have 22% more agricultural and 25% more livestock output than group A1 counties.  At the same time, number of workers per acre is lower in those groupA3 counties. Considering the traditional inputs (land and labor) and modern inputs (tractors, fertilizers and electricity), we find that groupA3 counties have more modern inputs and less traditional inputs on average than those groupA1 counties.

When we compare the backward counties with advanced counties (Table 1.3). We find that advanced counties have 46% more crops output and 32% more livestock output in average. Advanced counties have same average labor and land inputs. However, the average modern input usage such as mechanical power, fertilizers and electricity in advanced counties are more than doubled comparing with backward counties.  The levels of infrastructure, education and topography can explain the reasons for the big difference in modern input usage.

[7] 1 USD= 6.5 RMB at Feb, 2016

## 1.5 Main Contributions and Findings

From the empirical analysis of Pareto-Koopmans (PK) efficiency and its component, there is clear evidence of an overall increase in input efficiencies, output efficiencies and PK efficiency over time. A broad upward trend in the different DEA efficiency measures was revealed from year 1980 to 2010. Productive utilization of the modern inputs has increased faster than the traditional inputs such as labor and land. We also find that there is considerable inter-regional variation in the levels of input- and output-specific efficiencies across counties.

This study provides valuable insights into the spatial and temporal nature of Total Factor Productivity (TFP) growth in the average performance of Shanxi province. AW-shaped productivity growth rate plot was found in this post-reform period. The Malmquist productivity increased at 1.2% per year on average. We also explain the trend of productivity growth and variation across counties.

We investigate potential implications of three important agricultural policies implemented from year 2000 to 2010, and analyze their quantitative impacts on technical efficiency. We find that subsidy on machinery has negative impact on Pareto-Koopmans, output and input efficiency. This second-stage regression analysis of the measured efficiency level can help public policy to improve efficiency and enhance resource utilization (Ray and Ghose, 2014). This study fills the gap in explaining the policy impact on agricultural productivity in a regional scale at county level.

## 1.6 Organization of the Dissertation

The main body of the dissertation is contained in Chapters 2 through 4. Chapter 2 addresses the question of what is the extent of agricultural efficiency change in Shanxi province after the economic reforms. In Chapter 2, we evaluate the production efficiency in Chinese agriculture using Data Envelopment Analysis techniques. In Chapter 3, we investigate the temporal and spatial nature of Total Factor Productivity (TFP) growth and its components. Chapter 3 measures the rate of change of productivity over time and its variation across counties using the Malmquist Productivity as the analytical framework. Chapter 4 analyzes the impact of the three agricultural policy changes mentioned above on agriculture production efficiency. Chapter 5 is the overall conclusion summarizing the main findings of the dissertation, the policy implications, limitation and some directions for future research.

# Tables and Figures

Table 1.1: Inventory of Data Sets

| Variables | Size | Period |
|---|---|---|
| Crops Output (Y1) | 119 counties | 1981-2010 |
| Livestock Output (Y2) | 119 counties | 1981-2010 |
| Labor (X1) | 119 counties | 1981-2010 |
| Farmland (X2) | 119 counties | 1981-2010 |
| Agricultural Machinery (X3) | 119 counties | 1981-2010 |
| Fertilizers (X4) | 119 counties | 1981-2010 |
| Electricity (X5) | 119 counties | 1981-2010 |
| Annual Rainfall (X6) | 119 counties | 1981-2010 |
| Total Population | 119 counties | 1981-2010 |
| Rural Population | 119 counties | 1981-2010 |
| Paved Road Length | 116 counties | 1995-2012 |
| GDP per Capita | 119 counties | 2000-2010 |
| Agricultural GDP Share | 119 counties | 2000-2010 |
| Machinery Subsidy | 119 counties | 2007-2010 |

Source: Department of Agriculture
Shanxi Meteorological Bureau

Table 1.2: Summary Statistics: All Counties and All Years

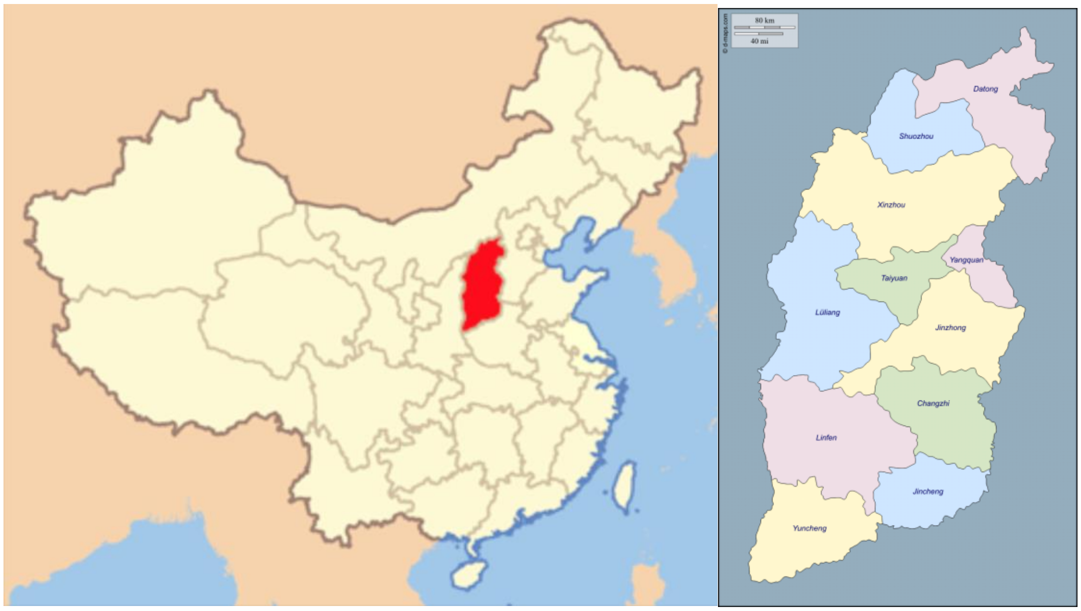
| Variable | Units | Mean | STD DEV | Min | Max |
|---|---|---|---|---|---|
| Agriculture Output | Yuan | 18842.7 | 25363.1 | 754 | 435391 |
| Livestock Output | Yuan | 7778.3 | 10509.0 | 119 | 103411 |
| Agriculture Labor | Number | 57234.5 | 38474.4 | 1947 | 375642 |
| Agricultural Machinery | Mil Kilowatt[8] | 139072.1 | 127113.2 | 1641 | 996090 |
| All Land | Hectare | 35514.4 | 17323.0 | 1786 | 108675 |
| Fertilizer | Ton | 6791.3 | 6160.4 | 14 | 77513 |
| Electricity | Kwh | 4079.1 | 5527.5 | 36 | 61182 |
| Irrigated Land | Hectare | 9371.5 | 10590.8 | 7 | 62550 |
| Non irrigated Land | Hectare | 27756.1 | 16721.7 | 100 | 106585 |
| Rainfall | mm | 4762.2 | 1228.6 | 1930 | 10598 |

[8] 1 Kilowatt = 1.34 mechanical horsepower

Table 1.3: Summary Statistics by Regions

| Variable | Mean | STD DEV | Max | Min |
|---|---|---|---|---|
| **GDP<10%** | | | | |
| Crops | 16276.04 | 19034.92 | 122439 | 907 |
| Livestock | 7448.59 | 9063.43 | 51412 | 123 |
| All land | 32158.06 | 21029.32 | 75635 | 1047.6 |
| Labor | 49885.15 | 44875.83 | 337447 | 1947 |
| Non irr land | 21938.93 | 17090.80 | 72455 | 180 |
| Irre land | 11244.91 | 11562.22 | 40390 | 200 |
| Power | 168499.80 | 117080.14 | 571345 | 8340 |
| Fertilizer | 4990.59 | 4971.36 | 28507 | 25 |
| Electricity | 6155.30 | 9881.46 | 61182 | 220 |
| Rain | 4361.81 | 1168.65 | 8844 | 2009 |
| **GDP>=20%** | | | | |
| Crops | 12556.51 | 17888.95 | 343166 | 769 |
| Livestock | 5557.69 | 7258.79 | 56919 | 129 |
| All land | 35902.95 | 20954.66 | 108675 | 1089 |
| Labor | 55629.24 | 33167.91 | 170622 | 9302 |
| Non irr land | 31063.73 | 18239.54 | 106585 | 3491 |
| Irrigated land | 6434.78 | 9500.05 | 62550 | 15 |
| Power | 118067.06 | 127376.82 | 822825 | 1641 |
| Fertilizer | 5362.16 | 4767.43 | 71185 | 497 |
| Electricity | 3194.03 | 4632.21 | 25329 | 36 |
| Rain | 4842.51 | 1183.21 | 9738 | 2267 |
| **Backward** | | | | |
| Crops | 9400.50 | 9024.19 | 58088 | 769 |
| Livestock | 5358.05 | 8161.38 | 74900 | 119 |
| All land | 33065.82 | 20476.31 | 108675 | 1089 |
| Labor | 43744.46 | 26951.86 | 153933 | 9302 |
| Non irr land | 30011.61 | 18372.76 | 106585 | 9329 |
| Irrigated land | 4654.91 | 6087.84 | 28300 | 15 |
| Power | 62655.01 | 50101.95 | 499546 | 1641 |
| Fertilizer | 4210.82 | 3326.60 | 24035 | 497 |
| Electricity | 1260.73 | 1432.11 | 14960 | 36 |
| Rain | 4644.09 | 1073.28 | 9738 | 2267 |
| **Advanced** | | | | |
| Crops | 18326.68 | 20757.50 | 343166 | 907 |
| Livestock | 7952.63 | 11322.21 | 103411 | 123 |
| All land | 32897.40 | 16909.19 | 107343 | 1047.6 |
| Labor | 59809.15 | 37270.28 | 337447 | 1947 |
| Non irr land | 22699.56 | 13516.83 | 105034 | 100 |
| Irrigated land | 11513.70 | 11476.07 | 62550 | 7 |
| Power | 154333.01 | 123030.55 | 968153 | 8340 |
| Fertilizer | 6791.35 | 5745.61 | 77513 | 25 |
| Electricity | 4638.70 | 6126.93 | 61182 | 83 |
| Rain | 4721.46 | 1254.87 | 9489 | 1930 |

Figure 1.1: 11 prefectures of Shanxi province[9]




[9] Online image from http://factsanddetails.com/china/cat15/sub103/item447.html

# Chapter 2: Production Efficiency in Chinese Agriculture:
## A Case of Agricultural Production in Shanxi Province

### 2.1 Introduction

China's development of agriculture over the course of its history has played a key role in supporting the growth of the population and economy. Today, China is the world's largest producer and consumer of agricultural products. In the year 2010, China produced 18% of the world's cereal grains, 29% of the world's meat, and 50% of the world's vegetables. With only 9% of the global sown area, today China produces about 20% of the world's food (Carter, 2011). According to the World Bank, agriculture value added (% of GDP) in China was last measured at 9.16% in 2014. From 1978, China began moving away from collective agriculture to the Household Responsibility System (HRS)[10]. Before the economic reforms, Chinese governmental policy advocated regional self-sufficiency[11] in agricultural production (Fan, 1991). Grain and livestock production barely kept pace with the population growth. When China started reforms in the agricultural sector, growth rate in grain and livestock production accelerated (Lin, 1992). Grain production such as rice, wheat, and corn increased from 247 million metric tons (mmt)[12] in 1978 to 339 mmt in 1984 and exceeded 470 mmt in 2008[13]. Output of pork, a major livestock product, rose from 11.34 mmt in 1980 to 45.5 mmt in 2008. Impact of the reforms on Chinese agricultural efficiency has attracted considerable attention from academics and policy analysts across the world.

[10] HRS, also called contract responsibility system, first adopted in agriculture in 1979 and later extended to other sectors of the economy, by which farmers are held responsible for the profits and losses.
[11] Local farmers provide agricultural output to meet local demand.
[12] 1 metric ton equals 2,240 lb.
[13] China's National Bureau of Statistics (NBS), 2008

Before the 1980s, the agricultural sector was organized according to the commune system. The largest part of the farm family incomes consisted of shares of the net income of the production team, distributed to members according to the amount of work each had contributed to the collective effort. By the end of 1984, about 98 percent of the local production teams had adopted the HRS. Farmers were no longer required to devote most of their efforts to collective production but instead generally signed contracts with the village or town to cultivate a given crop on a particular plot of land. Also, farmers were allowed to determine for themselves what kind of crops to produce. After harvest, a certain amount of the crop had to be sold to the unit at a predetermined price, and the family owned any output beyond that.

It has been over 30 years after the economic reforms by now. More data have become available making it possible to study the impact of the reforms at both national level and regional level. Many studies have addressed the impact of the reforms on agricultural efficiency in China. McMillan et al. (1989) and Stavis (1991) assessed the impact of China's Household Responsibility System on agricultural prices and individual incentives. Some other studies of Chinese agriculture include but are not limited to Lin (1992), Carter and Estrin (2001), Wu et.al (2001) and Brummer et.al (2006)[14]. Chinese agricultural productivity grew at 2 percent per year from year 1978 to 2010 (Yu, 2014). Most of the rapid change in productivity growth was noticed in period 1985–1989, then the rate of increase in total factor productivity and technical efficiency slowed down in the 1990s.

[14] Lin (1992) found that decolletivization improved total factor productivity and accounted for about half of the output growth during 1978-1984. Wu (2001) estimated that the total factor productivity grew at 2.4% annually with technical change augmenting the growth by 3.8% from 1980 to 1995. Brummer et. al.(2006), using data on farms in Zhejiang from 1986 to 2000, showed that most of the rapid change in productivity growth was realized in China's second reform period (1985–1989) and slowed down in the 1990s.

We use the nonparametric approach of Data Envelopment Analysis (DEA) to obtain Pareto-Koopmans measures of technical efficiency of each individual country of Shanxi province of China during year 1980-2010 in a multi-output, multi-input model of agricultural production. The Pareto-Koopmans efficiency measure is a complete measure in the sense that it reflects unrealized potential for increasing any output and decreasing any input that the firm has failed to exploit. Although there are some applications of Pareto-Koopmans efficiency measure in other areas such as industry, to the best of our knowledge, this is the first study measuring Pareto-Koopmans efficiency in Chinese agricultural production.

In this chapter we examine the agricultural sector of a single province, Shanxi, rather than the entire nation in order to ensure geographical homogeneity. We utilize a panel data set covering the period from 1981 to 2010 after the economic reforms with each county as the unit of analysis. This study enables us to investigate how different regions of Shanxi province have performed over this period. Because introduction of modern inputs has been a major component of modernization of Chinese agriculture, we examine the efficiency in utilization of modern inputs compared to the traditional inputs. In our empirical analysis, we disaggregate the overall efficiency measure into two distinct components representing output and input efficiencies. Use of the panel data allows us to investigate how input efficiency, output efficiency, and the overall technical efficiency have changed over the 30 years time period.

The rest of this chapter is organized as follows. In section 2, we briefly review the existing literature. In section 3, we provide an overview of the nonparametric methodology. Section 4 describes the dataset and the study region and reports the empirical findings from the efficiency analysis. Variation in the efficiency scores across counties is explained in terms

of differences in various institutional and demographic factors. A statistical analysis of the factors explaining the observed variation in technical efficiency is presented in Section 4. The main conclusion and policy implications are summarized in Section 5.

## 2.2 Literature Review

There are numerous studies in the existing literature that measure efficiency in Chinese agriculture after the economic reforms. Early studies by McMillan et al. (1989), Stavis (1991) examined the impact of China's HRS and market reform policies. During the year 1978 to 2010, average productivity grew at 2% per year (Yu, 2014). Most of the rapid change in efficiency growth was realized in China's second reform period during 1985–1989. In the third reform phase 1990 to1993 factor productivity still increase at the rate of 4% per annum. By the fourth period 1994 to 1998, it had fallen to 0.9% per annum (Brummer, Glauben and Lu, 2006). Lambert and Parker (1998) studied the technical efficiency and multifactor productivity indices using Chinese Provincial data for 1979-1995 period. They found a significant variation in efficiency and productivity change between different years and different provinces. They concluded that productivity is sensitive to relative grain prices, to natural disasters and proximity of the provinces to coastal areas.

Three important points need to be noted about the existing studies in Chinese agriculture efficiency. First, most of these studies were based on province level data covering the country. Second, none of these studies individually nor all of them collectively can be regarded as a long-term analysis of production efficiency in agriculture at a county level. Third, most of the studies used some explicit parametric specification of the production function as the analytical format.

Some studies used stochastic frontier analysis (SFA) as the analytical methodology (e.g., Fan, 1991; Lambert and Parker, 1998; Fan, 2000; Tian and Wan 2000; Zhang and Fan, 2001; Brummer, Glauben and Lu, 2006; Chen, Huffman and Rozelle, 2009[15]). Cho et al., 2008, studied the output growth in Chinese agriculture. Zhang and Fan (2001) used a generalized maximum entropy approach to empirically estimate crop-specific production technologies in Chinese agriculture. A multi-output technology for Chinese agriculture was estimated and input allocations for each province were recovered simultaneously. The estimated multi-output production technology and input allocations imply that China may have greater grain production potentials. Using provincial-level production data, Fan and Pardey (1997) found that investment in agricultural research accounted for 20 percent of productivity growth. Zhang and Carter (1997) found that 38% of the production growth was due to economy reforms and 8% due to good weather condition during 1980-1985.

There are few papers focusing on Chinese agricultural efficiency and growth using county-level or firm-level data from different provinces all over China (Wailes et. al., 1996). Duvivier (2013) assessed whether proximity to cities enhance the technical efficiency of nearby rural counties through a Production Frontier Model. Using 910 counties that belong to 19 provinces for the period of 2005–2009, he found that urban proximity significantly enhances efficiency in the Eastern region, while its effect was lower and less significant for the Central region and not significant at all for the Western region. Brummer, Glauben and Lu (2006) used SFA to estimate a multi-input multi-output distance function to analyze observed productivity growth under the policy reforms. Using farm-level data in Zhejiang province for

[15] The authors fit stochastic frontier production functions to data of Chinese farms grouped into four regions—North, Northeast, East, and Southwest—over year 1995–1999. They argued that standardized technical efficiency scores are estimated for the farms and are shown to have the same structure across regions.

1986 to 2000, they decomposed the total factor productivity change to distinguish between allocative effects, scale effects, technological change, and technical efficiency change. The results showed that most of the rapid change in productivity growth was realized in China's second reform period (1985–1989). This strong increase in factor productivity and technical efficiency slowed down in the 1990s.

Data Envelopment Analysis (DEA) methodology is widely used in evaluating the performance of agricultural sector for many countries. These studies include Jeon and Kim (2000) for Korea, Ray and Ghose (2014)[16] for India, and Gerdessen and Pascucci (2013)[17] for European countries. Several studies have also examined Chinese agricultural production with DEA and spatial analysis. (e.g., Wu, Liu and Davis 2005, and Chen and Huffman 2006). Jia, Zhang and Tang (2011) empirically investigated the time variance and provincial diversity of agricultural production efficiency of China's pastoral areas from 2000 to 2008 by using DEA models. They pointed out that provincial pastoral areas had grown evidently, and the variance in efficiency of agricultural productivity was mainly caused by technical efficiency.

Our study contributes to the existing literature in several ways. We evaluate the performance in terms of technical efficiency of Chinese agriculture at the county-level. We use DEA models to estimate the input-oriented efficiency, output-oriented efficiency, and Pareto-Koopmans efficiency in agriculture sector from year 1981 to 2010. The DEA scores are utilized to compare the agricultural performance of sub-regions and to find the difference in the efficiency change over time.

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[16] Nonparametric method of DEA is used to obtain Pareto- Koopmans measures of technical efficiency of individual states over the years 1970–71 through 2000–01.

[17] Authors used DEA to partition 252 European agricultural regions into a subset of DEA-efficient regions and a subset of non-efficient regions.

## 2.3 The Nonparametric Methodology

### 2.3.1 The Technical Efficiency

Technical efficiency is the effectiveness with which a given set of inputs is used to produce an output. A producer is technically efficient if an increase in an output requires a reduction in at least one other output or an increase in at least one input, and if a reduction in any input requires an increase in at least one other input or a reduction in at least one output (Koopmans, 1951). Technical efficiency can be measured by two main approaches:

(1) The input approach if one is considering the ability to avoid waste by using as little input as output production allows, i.e. we evaluate the ability to minimize input use while keeping outputs fixed; (2) The output approach if one is considering the ability to avoid waste by producing as much output as input usage allows, i.e. we evaluate the ability to maximize outputs keeping inputs fixed.

Now, consider an industry producing bundles of m outputs (y) from bundles of n inputs (x). The production technology is defined by the production possibility set :

$$\mathrm{T} = \{(\mathrm{x}, \mathrm{y}) : \mathrm{y} \in R_{+}^{m} \text{ can be producted from } \mathrm{x} \in R_{+}^{n}\}$$

An input-output bundle $(\mathrm{x}^0, \mathrm{y}^0)$ is feasible if $(\mathrm{x}^0, \mathrm{y}^0) \in \mathrm{T}$.

In welfare analysis in general, Pareto efficiency is a state of allocation of resources in which it is impossible to make any one individual better off without making at least one individual worse off. In DEA, a unit is Pareto-efficient when an attempt to improve on any of its inputs or outputs will adversely affect some other inputs or outputs. We use the concepts of weakly efficient and strongly efficient to better explain Pareto-Koopmans efficiency in DEA.

Weakly efficient in input-orientation means that it is not possible to reduce all inputs simultaneously from the bundle $(x^0, y^0)$ without reducing any output. Similarly, output-oriented weak efficiency is not compatible with simultaneous increase in all outputs. Thus, both input- and output-oriented weak efficiencies are radial, and they do not imply Pareto efficiency (Ray, 2004). However, in contrast with weakly efficient, a bundle $(x^0, y^0)$ is strongly input-oriented efficient when a reduction in *any* component of the input bundle would render the output bundle infeasible. Similarly, a bundle $(x^0, y^0)$ is strongly output-oriented efficient when an increase in *any* component of the output bundle would render the input bundle infeasible.

Thus, strong input- and output-efficiency are both necessary and are together sufficient for Pareto-Koopmans efficiency (Ray, 2004). In the following sections, we will introduce the Pareto-Koopmans measurement of technical efficiency.

### 2.3.2 Data Envelopment Analysis

In empirical research one may apply either a parametric or a non-parametric method. The parametric approach involves an explicit specification of the production function, which is then estimated by appropriate econometric techniques. As a result, the parametric approach is vulnerable to functional form misspecification. By contrast, the non-parametric approach avoids specifying any explicit functional form and makes a number of fairly general assumptions about the production technology. In this approach, one use mathematical programming methods to obtain a point-wise estimate of the production function. In this study, we apply the non-parametric DEA method to study the efficiency and efficiency change of Chinese agricultural sector.

The non-parametric method of DEA introduced by Charnes, Cooper, and Rhodes (CCR) (1978) and further generalized by Banker, Charnes, and Cooper (BCC) (1984) requires no parametric specification of the production frontier. DEA relies on a number of fairly general assumptions about the nature of the underlying production technology. There are four basic assumptions in DEA about the production technology: (i) All observed input-output combinations are feasible; (ii) The production possibility set is convex; (iii) Inputs are freely disposable; (iv) Outputs are freely disposable.

The DEA models construct a frontier to derive a benchmark output quantity with which the output of a firm or an institution can be compared for efficiency measurement. In the multiple-output multiple-input case, with the assumptions of convexity of the production possibility set and along with free disposability of both outputs and inputs, the production possibility set can be constructed as the following (Ray, 2004):

$$T^V = \left\{(x, y):\ x \geq \sum_{j=1}^{N} \lambda_j\, x^j;\ y \leq \sum_{j=1}^{N} \lambda_j\, y^j;\ \sum_{j=1}^{N} \lambda_j = 1;\ \lambda_j \geq 0\,; (j = 1,2, \dots, N)\right\}$$

**Equation 1**

Where $(x^j, y^j)$ is the observed input and output bundle of an individual county $j$ in a sample of $N$ counties in the dataset. The technology defined by equation 1 is described as variable returns to scale (VRS). Under the assumption of constant return to scale (CRS), we need to remove the constraint $\sum_{j=1}^{N} \lambda_j = 1$ in equation 1. The corresponding Production possibility set is

$$T^C = \left\{(x, y):\ x \geq \sum_{j=1}^{N} \lambda_j\, x^j;\ y \leq \sum_{j=1}^{N} \lambda_j\, y^j;\ \lambda_j \geq 0\,; (j = 1,2, \dots, N)\right\}$$

**Equation 2**

We then define the *input requirement set* (for all $y \in T$) as:

$$V(y) = \left\{ \mathrm{x} \in R_{+_0}^{m_0} \; (\mathrm{x}, \mathrm{y}) \in \mathrm{T} \right\}.$$

**Equation 3**

An input requirement set *V(y)* consists of all input vectors that can produce the output vector $\mathrm{y} \in R_{+}^{m}$. The corresponding input requirement for any output level $y_j$ that corresponds to $T$ in equation 3 is

$$V(y) = \left\{ (x)\colon\; x \geq \sum_{j=1}^{N} \lambda_j \, x^j;\; y \leq \sum_{j=1}^{N} \lambda_j \, y^j;\; \sum_{j=1}^{N} \lambda_j = 1;\;\; \lambda_{\mathrm{j}} \geq 0\,; (\mathrm{j} = 1,2, \ldots, \mathrm{N}) \right\}$$

**Equation 4**

For any production possibility set, we can define the input requirement set *V(y)* for any specific output bundle y.

### 2.3.3 Radial Measures of Technical Efficiency

The radial DEA measure is based on the radial distance function defined by Shephard (1953) and formulated by Farrell (1957). In DEA, radial technical efficiency measurement was first introduced by CCR and later modified by BCC. Radial models rely on a radial or proportional measure as a DMU's efficiency score assuming proportional change of inputs/outputs. It measures how much the observed input levels can be jointly contracted when we measure in the input space, or how much the observed output levels can be jointly expanded when we measure in the output space. Under the variable returns to scale

assumption (VRS), the input-oriented radial technical efficiency of a DMU with an observed input–output bundle ($x^0$, $y^0$) can be obtained by the following model (BCC, 1984):

$$\min \theta$$
$$\text{s.t.} \sum_{1}^{N} \lambda_j\, y^j \geq y^0\,;$$
$$\sum_{1}^{N} \lambda_j\, x^j \leq \theta x^0\,;$$
$$\sum_{1}^{N} \lambda_j = 1\,;$$
$$\lambda_j \geq 0\ (j = 1,2, \dots, N)$$

**Equation 5**

If $\theta^*$ is the minimum value of $\theta$ such that $(\theta x_i, y_i)$ lies within the technology set, the input-oriented VRS radial DEA technical efficiency of county *i* can be defined as: $TE = \theta^*$.

Similarly, the output-oriented radial technical efficiency under VRS is measured as

$$\max \varphi$$
$$\text{s.t.} \sum_{1}^{N} \lambda_j\, y^j \geq \varphi y^0\,;$$
$$\sum_{1}^{N} \lambda_j\, x^j \leq x^0\,;$$
$$\sum_{1}^{N} \lambda_j = 1\,;$$
$$\lambda_j \geq 0\ (j = 1,2, \dots, N)$$

**Equation 6**

If $\varphi^*$ is the maximum value of $\varphi$ such that $(x_i, \varphi y_i)$ lies within the technology set, the input-oriented VRS radial DEA technical efficiency of county *i* can be defined as: $TE = 1/\varphi^*$.

When we assume CRS, the restriction $\sum_{1}^{N} \lambda_j = 1$ is removed from equations above. Neither the input- nor the output-oriented radial measure of technical efficiency is affected by the presence (or magnitude) of slacks in any of the individual input or output constraints. One major problem with a radial measure of technical efficiency is that it does not reflect all identifiable potential for increasing outputs and reducing inputs (Ray, 2004). Any optimal solution of a radial model expands all outputs or contracts all inputs by the same proportion. To circumvent this, in non-radial models one allows the individual outputs to increase or the inputs to decrease at different rates.

### 2.3.4 Non-radial Measures of Technical Efficiency

In the DEA framework, non-radial DEA models have been well developed in the past. Such studies include Färe and Lovell (1978), Thanassoulis and Dyson (1992), and Zhu (1996). Recently, Chen (2003) applied the weighted non-radial DEA model to Chinese industrial productivity analysis.

Non-radial DEA models allow the individual outputs to increase or the inputs to decrease at different rates. Non-radial models measure efficiency with slacks of each input/output individually and independently, and integrate them into an efficiency measure. Färe and Lovell (1978) introduced the non-radial measure of technical efficiency called the Russell measure. The input oriented Russell measure is:

$$\min \frac{1}{N}\sum_{i} \theta_i$$

$$\text{s.t.} \sum_{j}^{N} \lambda_j\, y_r^j \geq y_r^0; \quad (r = 1,2 \ldots m);$$

$$\sum_{j}^{N} \lambda_j\, x_i^j \leq \theta_i x_i^0\, ; (i = 1,2 \ldots n);$$

$$\sum_{j}^{N} \lambda_j = 1\, ;$$

$$\lambda_j \geq 0; \; (j = 1,2, \ldots, N)$$

$$\theta_i \leq 1; (i = 1,2 \ldots m)$$

**Equation 7**

When input slacks do exist at the optimal solution of a radial DEA model, the non-radial Russell measure falls below the conventional measure obtained from an input-oriented BCC model (Equation 7), because the radial projection is always a feasible solution. That is, the non-radial Russell measure of technical efficiency never exceeds the corresponding radial measure. The output-oriented technical efficiency is obtained as the inverse of the the objective function of the following DEA model:

$$\max \frac{1}{m}\sum_{r} \varphi_r$$

$$\text{s.t.} \sum_{j}^{N} \lambda_j\, y_r^j \geq \varphi_r y_r^0; \quad (r = 1,2 \ldots m);$$

$$\sum_{j}^{N} \lambda_j\, x_i^j \leq x_i^0\, ; (i = 1,2 \ldots m);$$

$$\sum_{j}^{N} \lambda_j = 1\, ;$$

$$\lambda_j \geq 0; \; (j = 1,2, \ldots, N)$$

$$\varphi_r \geq 1; \; (r = 1,2 \ldots m);$$

**Equation 8**

Charnes et al. (1978) argued that the adjustment for the slacks in inputs and outputs

were required to make the radial efficient projection of an inefficient input–output bundle becomes Pareto-Koopmans efficient. Unless all slacks are zero, any unit is not Pareto-Koopmans efficient even if its (radial) technical efficiency is found to be equal to unity (Ray, 2004). A non-radial Pareto-Koopmans measure of technical efficiency of the input–output pair ($x^0$, $y^0$) can be computed as:

$$\tau = \min \frac{\frac{1}{n}\sum_i \theta_i}{\frac{1}{m}\sum_r \varphi_r}$$

$$\text{s.t.} \ \sum_j^N \lambda_j \, y_r^j \geq \varphi_r y_r^0; \ \ (r = 1,2 \ldots m);$$

$$\sum_j^N \lambda_j \, x_i^j \leq \theta_i x_i^0 \ ; (i = 1,2, \ldots, n);$$

$$\sum_j^N \lambda_j = 1 \ ;$$

$$\lambda_j \geq 0; \ \ (j = 1,2, \ldots, N)$$

$$\varphi_r \geq 1; \ \ (r = 1,2 \ldots m);$$

$$\theta_i \leq 1; (i = 1,2 \ldots m);$$

**Equation 9**

Note that the efficient input-output projection $(x^*, y^*)$ satisfies

$$x_i^* = \sum_j^N \lambda_j^* \, x_j \leq \theta_i x^0$$

and

$$y_r^* = \sum_j^N \lambda_j^* \, y_j \geq \varphi_r y^0$$

Then, $(x^0, y^0)$ is Pareto-Koopmans efficient if and only if $\varphi_r^* = 1$ for each output r and $\theta_i^* = 1$ for each input *i* implying $\tau = 1$ (Ray, 2004).

The objective function in equation 9 can be interpreted as:

$$\boldsymbol{\tau}(\mathbf{x}^{\mathbf{0}}, \mathbf{y}^{\mathbf{0}}) = \boldsymbol{\tau}_{\mathbf{x}} * \boldsymbol{\tau}_{\mathbf{y}}\ .$$ **Equation 10**

Here,

$$\boldsymbol{\tau}_x = \frac{\mathbf{1}}{\mathbf{N}} \sum\nolimits_{\mathbf{i}} \boldsymbol{\theta}_{\mathbf{i}}$$ **Equation 11**

is the input-oriented component, and

$$\boldsymbol{\tau}_y = \frac{\mathbf{1}}{\frac{\mathbf{1}}{m} \sum_r \boldsymbol{\varphi}_r}$$ **Equation 12**

is the output-oriented component. The objective function in equation 9 is non-linear. Both Pastor et al. (1999) and Tone (2001) transformed this linear fractional functional programming problem into a linear program (LP) problem by normalizing the denominator to unity. It is also shown in Ray (2004) that we may replace the objective function by a linear approximation

$$\tau = f(\theta, \varphi) \approx f(\theta^0, \varphi^0) + \sum_i (\theta_i - \theta_i^0) \left(\frac{\partial f}{\partial \theta_i}\right)_0 + \sum_r (\varphi_r - \varphi_r^0) \left(\frac{\partial f}{\partial \theta_r}\right)_0$$

**Equation 13**

Note that

$$\frac{\partial f}{\partial \theta_i} = \frac{\frac{1}{n}}{\frac{1}{m} \sum_r \varphi_r}$$

**Equation 14**

and

$$\frac{\partial f}{\partial \varphi_r} = \frac{\frac{1}{\mathrm{n}} \sum_{\mathrm{i}} \theta_{\mathrm{i}}}{\frac{1}{m} (\sum_r \varphi_r)^2}$$

**Equation 15**

Thus, if $\varphi_{\mathrm{r}}^0 = 1$ for each output r and $\theta_{\mathrm{i}}^0 = 1$ for each input *i*,

$$\tau \approx 1 + \frac{1}{\mathrm{n}}\sum_{\mathrm{i}} \theta_{\mathrm{i}} - \frac{1}{m}\sum_{r} \varphi_r \,.$$

**Equation 16**

Therefore, we may solve the LP problem by

$$min\ \tilde{\tau} \approx \frac{1}{\mathrm{n}}\sum_{\mathrm{i}} \theta_{\mathrm{i}} - \frac{1}{m}\sum_{r} \varphi_r$$

$$\text{s.t.} \ \sum_{j}^{N} \lambda_j \, y_r^j \geq \varphi_r y_r^0; \ \ (r = 1,2 \ldots m);$$

$$\sum_{j}^{N} \lambda_j \, x_i^j \leq \theta_i x_i^0 \,; (i = 1,2, \ldots, n);$$

$$\sum_{j}^{N} \lambda_j = 1 \,;$$

$$\lambda_{\mathrm{j}} \geq 0; \ (\mathrm{j} = 1,2, \ldots, \mathrm{N})$$

$$\varphi_r \geq 1; \ (r = 1,2 \ldots m);$$

$$\theta_i \leq 1; (i = 1,2 \ldots m);$$

**Equation 17**

Once we obtain the optimal $(\theta^*, \varphi^*)$ from this problem, we evaluate

$$\tau^* = \frac{\frac{1}{n}\sum_i \theta_i^*}{\frac{1}{m}\sum_r \varphi_r^*}$$

**Equation 18**

as a measure of the Pareto-Koopmans efficiency of $(x^0, y^0)$ (Ray, 2004). In addition, equation 18 provides information about the potential for reducing individual inputs and increasing individual outputs. $(x^0, y^0)$ is Pareto–Koopmans efficient when $\varphi_r = 1$ for each output r and $\theta_i = 1$ for each input *i*.

## 2.4 The Empirical Analysis

### 2.4.1 Overall Efficiency and Its Components

We examine the input efficiency, output efficiency and overall technical efficiency in the Chinese agricultural sector from year 1981 to 2010 with non-radial measures using data of individual counties from Shanxi province. The reported values of input and output quantities are county-level aggregates. Using aggregate quantities of inputs and outputs implicitly assumes an additive technology[18], which, in term, implies CRS.

The estimated county-wise average levels of overall productive efficiency and its two principal components, input and output efficiencies, are presented in Table 2.1. More detailed breakup of the input and output efficiencies are reported in Tables 2.2 and Table 2.3. The average input technical efficiency (ITE) over the entire sample period was 0.788, which means it would be possible to reduce the average level of inputs by about 21.2%. Output technical efficiency (OTE), averaged over all years and all counties, was 0.826 implying that on average output was about 82.6% of the maximal attainable level. The corresponding average level of Pareto Koopmans (PK) efficiency was 72.1%. Comparing with the benchmark bundle, it suggests that the agricultural sector in Shanxi province could increase its output by 18.4%, and at the same time reduces its input by 21.2%.

At the regional level, the overall input efficiency is higher in backward counties (0.805) than advanced counties (0.781). However, backward counties have lower score in output efficiency (0.816) than advanced counties (0.83). This shows that backward counties utilize the inputs more efficiently, but are less efficient in realizing outputs (Table 2.1). On

[18] For $y_1 = f(x_1)\ and\ y_2 = f(x_2)$, additive means $f(x_1 + x_2) = f(x_1) + f(x_2) = y_1 + y_2$. Setting $x_1 = x_2, y_1 = y_2 = y$, we get $f\ (2x\quad) = f(2x)$.

average, counties with higher agricultural share in local GDP have higher efficiency scores in both inputs (0.821) and outputs (0.933) (Table 2.2). Counties with higher agricultural population share also have higher input (0.821) and output orientation (0.993) efficiency on average (Table 2.3). The results of overall efficiency score shows that backward counties have higher P-K value than advanced counties. Counties with high agricultural GDP share and counties with high agricultural population share have higher P-K value (Table 2.3). Since backward counties are less developed, they have higher agricultural output share and farming employment.

The decomposition of the output efficiency into two components for agricultural products and livestock products is shown in Table 2.4, Table 2.5 and Table 2.6. The average output efficiency is 82.6%. Specifically, a county can increase its crops output by 8.4% and livestock output by 10%. Livestock output still have more room to increase than crops. There is little room for increasing crops outputs simply through improved efficiency. Comparing across different groups, we find that high agricultural GDP share have both high crops output efficiency (0.936), and input efficiency (0.926). However, backward counties have higher livestock efficiency (0.943) than advanced counties (0.882), but lower crops outputs efficiency score (0.888) than advanced counties (0.942). In addition, comparing with counties with different agricultural population share, we find the crops output efficiencies of the groups are same. Counties with lower agriculture population share have higher efficiency score in livestock (0.945). In Shanxi province, backward counties are usually counties in mountain areas and the main agricultural production is livestock products. This explains why backward counties have higher livestock efficiency.

We divide the agricultural inputs into two broad categories: modern and traditional.

The modern inputs are: (i) fertilizers, (ii) agricultural machinery, and (iii) electricity. The other inputs: (a) labor, (b) irrigated land, and (c) non-irrigated land are treated as traditional inputs. For any individual input, the input-specific technical efficiency of sub-regions shows what proportion of the actual quantity of that input used would be required if the state operated at the selected Pareto-Koopmans efficient point on the frontier. Table 2.7 records each individual components of input technical efficiency. This provides us with detailed information about the efficiency of input utilization for each county. In respect of individual inputs, inefficiency is most pronounced for labor (0.742) and electricity (0.749). Irrigated land (0.883) and fertilizers (0.833) are the most utilized efficiently inputs in Shanxi province. The average input efficiency of modern inputs is 0.784 implying a rate of under-utilization as high as 21.6%. Traditional input efficiency (0.792) is higher than modern inputs efficiency (0.784).

At the regional level, backward counties show higher levels of input efficiency (0.835) of modern inputs than advanced counties (0.762), but lower traditional input efficiency (0.774) (Table 2.7). This may be explained by the fact that backward counties have less modern input usage than advanced counties. Due to the machinery subsidy policy, advanced counties used more machinery than the needs in agricultural production. For the counties with higher agricultural GDP share, they have higher modern input efficiency (0.846), such as machinery (0.886) and electricity (0.848). Traditional input efficiency is same (Table 2.8). Labor use is more efficient (0.786) in counties with highest agricultural GDP share, but irrigated land use efficiencies (0.850) are higher in less share counties. Overall, the P-K score is lowest in counties groupA1, but highest in counties groupA3. When we compare the efficiency scores of counties across different agricultural population share (Table 2.9), we find lower share counties have highest efficiency scores in labor (0.9), fertilizer (0.958) and

electricity (0.854). Overall, the Pareto Koopmans efficiency of counties with lower population shares has much higher scores (0.847) than other two regions. Counties with lower population share are usually more developed counties in terms of income. Therefore, the labor use is more efficient due to the higher agricultural labor cost. In addition, the farmer's average education level is higher in developed counties. Those farms have more knowledge and experience in operating modern inputs. These may explain the higher efficiency scores of fertilizer and electricity.

### 2.4.2 Trends of the Overall Efficiency and Its Components

In this study, one question that we address is how input, output and overall efficiency have changed over time. We want to find whether there is any pattern in any component efficiency. In this section, we first focus on yearly average levels of efficiency. The findings in this respect are reported in Table 2.10 and Table 2.11, which show the province's average efficiency scores change over years from 1983 to 2010. Table 2.12 shows the P-K score for different regions over the study time period.

We show the trend of output and input efficiency scores change in Figure 2.1. Overall, there is an increase in both input and output efficiencies from 1983 to 2010. Input efficiency has increased at a higher rate than output efficiency. When we look at the growth of efficiency in different time periods, we find that the efficiency scores increased in 1980s and 2000s. However, there is no clear change in the 1990s.

The economic reforms provided strong economic incentives for farmers to use modern technology and inputs (especially, fertilizers and machinery) to improve production

efficiency. As we see in Figure 2.2, traditional and modern input efficiency are both increasing over the last 30 years. The average score of traditional input efficiency is higher than modern input efficiency. However, modern input efficiency is increasing faster than traditional efficiency. In late 2000s, the difference between those two scores is much smaller than in 1980s. This is quite consistent with a phase of gradual learning by farmers about how best to use the modern inputs such as machinery and fertilizers.

The efficiency scores reported in Table 2.11 and Table 2.12 provide a productive performance audit for all the component efficiency over years. We particularly look at livestock output and some inputs (especially, labor and agricultural mechanical power). From figure 2.3, we find that the pattern of agriculture output efficiency change is not clear. However, the livestock output is increasing especially from late 1990s. Since the agricultural labor in Shanxi province is keeping decreasing over the last 30 years, we expect that labor input efficiency would have been increasing with the increasing outputs. Figure 2.4 shows the labor input efficiency increased from 0.6 (1983) to 0.8 (2010). This increase shows a great improvement of labor productivity in Shanxi agriculture over the last 30 years.

We show the Pareto-Koopmans efficiency score changing trend over the study time period in Figure 2.5. This score provides the overall performance of each year in Chinese agriculture. The value starts at average of 0.65 in 1980s, and increased to 0.75 in 1990s. Then, in 2000s, the values increased to 0.8 in average. There are some fluctuations between years, but the increasing trend is clear to see. In 1980s, the P-K scores increased from 0.6 to 0.78. However, in 1990s, there was a decrease of P-K scores from 0.78 to 0.70. When entered 2000s, although there was a growth of the average score, the volatility is high especially from year 2005 to 2010.

Regional differences of P-K efficiency changes over time are shown in Figure 2.6, Figure 2.7 and Figure 2.8. Figure 2.6 shows important differences in P-K efficiency change for counties with different income level. These two groups have similar increase patterns. The scores increase in 1980s, keep the same in 1990s and increase again in 2010s. It is interesting to notice that backward countries have slightly higher P-K efficiency score than advanced counties in most years during from 1983-2010 (Figure 2.6). It is partly because with the faster increase of modern inputs in advanced counties than backward countries. The diminishing marginal productivity matters here. Backward counties have lower modern input efficiency especially in machinery and electricity.

We compare the P-K efficiency change of the different kinds of sub-regions over time (Figure 2.7 and Figure 2.8). The efficiency score of groupB1 and groupB2 counties have similar pattern over the study period, but the P-K score of groupB3 counties increased with a lower rate that increased in 1980s and then decreased in 1990s. This means that the rate of increase in P-K scores over time is faster in low agricultural population share counties than others. This is partly because counties with lower agricultural population ratio gained more over the period of China's industrialization. Especially, the higher increase rate of modern input efficiency and labor efficiency contributed the most to the overall efficiency growth.

Figure 2.8 shows that groupA2 counties had lower than groupA1 counties in 1980s. However in middle 90s, groupA2 counties passed over and kept higher scores than groupA1 counties later on. Basically, higher agricultural GDP share counties have higher increase rate of overall efficiency. It is because the overinvestment on agriculture in more developed counties (usually with a smaller shares in GDP) has resulted in slower efficiency increasing.

Over time, especially after 1990s, the traditional input such as agricultural labor began decreasing which made the traditional input efficiency increasing constantly. At the same time, after the reforms, the more productive farmers increasing relied in modern inputs like machinery and fertilizers. In any event, it seems to be the case that Chinese agriculture is likely to retain the current traditional inputs use and keep increasing modern inputs in the future.  On the other hand, the breakthrough in the agricultural technology is another factor that make the overall efficiency in an upward trend over last 30 years.

## 2.5 Conclusion

In this chapter, we examine the technical efficiency in the Chinese agricultural sector from year 1981 to 2010 with non-radial measures using data of individual counties from Shanxi province. We estimate the input efficiency, output efficiency, and Pareto-Koopmans efficiency in each of the 119 counties. From the empirical analysis, there is clear evidence of an overall increase in input efficiencies, output efficiencies and P-K efficiency over time. A broad upward trend in the different DEA efficiency measures was revealed by the yearly averages from year 1980 to 2010.  For the component of outputs, livestock output still has more room to increase. There is little room for increasing agricultural production simply through improved efficiency. At the same time, we observe a secular decline in the quantities of traditional inputs like land and labor over time. These suggest that these inputs could limit increasing output without another technological breakthrough.

The use of modern input such as fertilizers, agricultural machinery, and electricity power has increased phenomenally over years. Productive utilization of the modern inputs has

increased faster than the traditional inputs such as labor and land. Moreover, there is considerable variation across regions. Because the use of these modern inputs is an integral part of the modern technology, potential benefits of the technological change remain unrealized to a large extent.

We also compare the agricultural performance of the different kinds of sub-regions and compare the difference in the efficiency change over time. There is considerable inter-regional variation in the levels of input- and output-specific efficiencies across counties. This is particularly true for modern inputs and livestock output. Apart from agro-climatic factors there may be differences in the state of development of physical infrastructures that account for such variation in input, output and overall efficiency.

At this point, we need to note some limitations of the data used and to acknowledge that the results should be interpreted with some caution. In the first place, we are using county-level aggregated data. Not only are the input–output data aggregates over a county, the data are also aggregated over crops and, hence, across different varieties of any crop (like traditional and high yielding varieties of rice or wheat). Similarly, inputs (like fertilizers) are also aggregated. Despite this limitation, our 2-output multi-input framework is more disaggregated than what is found in the relevant literature. Another important point to notice is that county-level efficiency measures computed for each year are based on the input–output data for that particular year only. By definition, an improvement in overall productive efficiency can be achieved by enhancing either input or output efficiency. Our findings can help to better understand the performance in Chinese agriculture.

## Tables and Figures

Table 2.1: Output, Input, and Overall Efficiencies by Region

| Group | Name | OTE | ITE | PK |
|---|---|---|---|---|
| C1 | Backward | 0.816 | 0.805 | 0.740 |
| C2 | Advanced | 0.830 | 0.781 | 0.714 |
| All | All | 0.826 | 0.788 | 0.721 |

Table 2.2: Aggregated Output and Input Efficiency (by Counties' agricultural GDP share)

| Group | GDP Share | OTE | ITE | PK |
|---|---|---|---|---|
| A1 | <10% | 0.913 | 0.771 | 0.703 |
| A2 | 10%-20% | 0.918 | 0.800 | 0.726 |
| A3 | >20% | 0.933 | 0.821 | 0.768 |
| All | All | 0.918 | 0.788 | 0.721 |

Table 2.3: Aggregated Output and Input Efficiency (by Counties' agricultural population share)

| Group | Ag. Population Share | OTE | ITE | PK |
|---|---|---|---|---|
| B1 | <50% | 0.913 | 0.771 | 0.703 |
| B2 | 50%-75% | 0.918 | 0.800 | 0.726 |
| B3 | >75% | 0.933 | 0.821 | 0.768 |
| All | All | 0.918 | 0.788 | 0.721 |

Table 2.4: Output Efficiencies by Region

| Group | Name | Agriculture | Livestock | Output |
|---|---|---|---|---|
| C1 | Backward | 0.888 | 0.943 | 0.816 |
| C2 | Advanced | 0.942 | 0.882 | 0.830 |
| All | All | 0.926 | 0.900 | 0.826 |

Table 2.5: Output Efficiencies by Counties’ Agricultural GDP Share

| Group | GDP Share | Crops | Livestock | Output |
|---|---|---|---|---|
| A1 | <10% | 0.919 | 0.900 | 0.913 |
| A2 | 10%-20% | 0.935 | 0.878 | 0.918 |
| A3 | >20% | 0.936 | 0.926 | 0.933 |
| All | All | 0.926 | 0.900 | 0.918 |

Table 2.6: Output Efficiencies by Counties’ Agricultural Population Share

| Group | Ag. Population Share | Crops | Livestock | Output |
|---|---|---|---|---|
| B1 | <50% | 0.926 | 0.945 | 0.932 |
| B2 | 50%-75% | 0.920 | 0.901 | 0.915 |
| B3 | >75% | 0.928 | 0.895 | 0.918 |
| All | All | 0.926 | 0.900 | 0.918 |

Table 2.7: Input Efficiencies by Region

| Group | Name | Labor | No irrigated Land | Irrigated Land | Machinery | Fertilizers | Electricity | Traditional | Modern |
|---|---|---|---|---|---|---|---|---|---|
| C1 | Backward | 0.733 | 0.761 | 0.829 | 0.833 | 0.856 | 0.816 | 0.774 | 0.835 |
| C2 | Advanced | 0.746 | 0.815 | 0.835 | 0.742 | 0.824 | 0.722 | 0.799 | 0.762 |
| All | All | 0.742 | 0.799 | 0.833 | 0.768 | 0.833 | 0.749 | 0.792 | 0.784 |

Table 2.8: Inputs Efficiency Counties' Agricultural GDP Percentages

| Group | GDP Share | Labor | No irrigated Land | Irrigated Land | Machinery | Fertilizers | Electricity | PK | Traditional | Modern |
|---|---|---|---|---|---|---|---|---|---|---|
| A1 | <10% | 0.732 | 0.794 | 0.850 | 0.712 | 0.836 | 0.702 | 0.703 | 0.792 | 0.750 |
| A2 | 10%-20% | 0.730 | 0.800 | 0.827 | 0.809 | 0.850 | 0.783 | 0.726 | 0.786 | 0.814 |
| A3 | >20% | 0.786 | 0.813 | 0.792 | 0.886 | 0.803 | 0.848 | 0.768 | 0.797 | 0.846 |
| All | All | 0.742 | 0.799 | 0.833 | 0.768 | 0.833 | 0.749 | 0.721 | 0.792 | 0.784 |

Table 2.9: Inputs Efficiency (Counties' agricultural population share)

| Group | Ag. Population Share | Labor | No irrigated Land | Irrigated Land | Machinery | Fertilizers | Electricity | PK | Traditional | Modern |
|---|---|---|---|---|---|---|---|---|---|---|
| B1 | <50% | 0.900 | 0.891 | 0.902 | 0.850 | 0.958 | 0.854 | 0.847 | 0.898 | 0.887 |
| B2 | 50%-75% | 0.757 | 0.809 | 0.811 | 0.712 | 0.838 | 0.707 | 0.706 | 0.792 | 0.752 |
| B3 | >75% | 0.722 | 0.787 | 0.834 | 0.779 | 0.820 | 0.754 | 0.714 | 0.781 | 0.784 |
| All | All | 0.742 | 0.799 | 0.833 | 0.768 | 0.833 | 0.749 | 0.721 | 0.792 | 0.784 |

Table 2.10: Aggregated Efficiencies Over Time

| Year | Output Efficiency | Input Efficiency | Traditional | Modern | PK |
|---|---|---|---|---|---|
| 1983 | 0.8280 | 0.7504 | 0.7570 | 0.7437 | 0.6229 |
| 1984 | 0.9028 | 0.6550 | 0.6666 | 0.6434 | 0.5906 |
| 1985 | 0.9142 | 0.7255 | 0.7619 | 0.6890 | 0.6621 |
| 1986 | 0.9052 | 0.7411 | 0.7641 | 0.7180 | 0.6670 |
| 1987 | 0.8210 | 0.7446 | 0.7683 | 0.7208 | 0.6122 |
| 1988 | 0.8841 | 0.8174 | 0.8310 | 0.8037 | 0.7324 |
| 1989 | 0.9001 | 0.7550 | 0.7660 | 0.7441 | 0.6810 |
| 1990 | 0.9642 | 0.8201 | 0.8247 | 0.8155 | 0.7934 |
| 1991 | 0.9456 | 0.8201 | 0.8060 | 0.8343 | 0.7771 |
| 1992 | 0.8916 | 0.8170 | 0.8114 | 0.8226 | 0.7303 |
| 1993 | 0.9787 | 0.7969 | 0.8133 | 0.7806 | 0.7813 |
| 1994 | 0.9057 | 0.8522 | 0.8828 | 0.8215 | 0.7561 |
| 1995 | 0.9286 | 0.8058 | 0.7942 | 0.8175 | 0.7419 |
| 1996 | 0.9506 | 0.8388 | 0.8180 | 0.8597 | 0.7948 |
| 1997 | 0.9244 | 0.7954 | 0.7958 | 0.7950 | 0.7370 |
| 1998 | 0.9190 | 0.8110 | 0.8032 | 0.8187 | 0.7427 |
| 1999 | 0.8954 | 0.7776 | 0.7686 | 0.7865 | 0.6993 |
| 2000 | 0.9362 | 0.7942 | 0.7950 | 0.7934 | 0.7463 |
| 2001 | 0.9027 | 0.7335 | 0.7372 | 0.7298 | 0.6679 |
| 2002 | 0.9407 | 0.7714 | 0.7804 | 0.7625 | 0.7271 |
| 2003 | 0.8890 | 0.7807 | 0.7780 | 0.7833 | 0.7037 |
| 2004 | 0.9108 | 0.8360 | 0.8224 | 0.8497 | 0.7715 |
| 2005 | 0.9087 | 0.7796 | 0.7786 | 0.7807 | 0.7178 |
| 2006 | 0.9702 | 0.9321 | 0.9464 | 0.9179 | 0.9007 |
| 2007 | 0.9799 | 0.8884 | 0.8766 | 0.9001 | 0.8701 |
| 2008 | 0.9980 | 0.8771 | 0.8786 | 0.8756 | 0.8758 |
| 2009 | 0.8768 | 0.7218 | 0.7168 | 0.7268 | 0.6323 |
| 2010 | 0.9453 | 0.8509 | 0.8332 | 0.8686 | 0.8083 |

Table 2.11: Changes in Efficiencies Over Time (Range adjusted)

| Year | Crops | Livestock | Labor | No irrigated Land | Irrigated Land | Machinery | Fertilizers | Electricity | PK |
|---|---|---|---|---|---|---|---|---|---|
| 1983 | 0.8892 | 0.7668 | 0.6402 | 0.8515 | 0.7794 | 0.7267 | 0.8237 | 0.6809 | 0.6229 |
| 1984 | 0.9044 | 0.9012 | 0.5664 | 0.7595 | 0.6741 | 0.6302 | 0.7828 | 0.5174 | 0.5906 |
| 1985 | 0.9302 | 0.8981 | 0.6922 | 0.8572 | 0.7362 | 0.6417 | 0.8102 | 0.6152 | 0.6621 |
| 1986 | 0.9483 | 0.8621 | 0.7040 | 0.8466 | 0.7417 | 0.7071 | 0.8221 | 0.6247 | 0.6670 |
| 1987 | 0.8643 | 0.7777 | 0.6760 | 0.8801 | 0.7489 | 0.7573 | 0.7864 | 0.6186 | 0.6122 |
| 1988 | 0.9128 | 0.8553 | 0.7599 | 0.9153 | 0.8180 | 0.8293 | 0.8715 | 0.7105 | 0.7324 |
| 1989 | 0.9159 | 0.8842 | 0.6846 | 0.8349 | 0.7786 | 0.7625 | 0.8087 | 0.6610 | 0.6810 |
| 1990 | 0.9488 | 0.9796 | 0.7751 | 0.8777 | 0.8212 | 0.8038 | 0.9100 | 0.7328 | 0.7934 |
| 1991 | 0.9399 | 0.9514 | 0.7818 | 0.7890 | 0.8471 | 0.8432 | 0.8174 | 0.8423 | 0.7771 |
| 1992 | 0.8781 | 0.9050 | 0.7845 | 0.7637 | 0.8860 | 0.7011 | 0.8399 | 0.9269 | 0.7303 |
| 1993 | 0.9933 | 0.9642 | 0.7724 | 0.8721 | 0.7954 | 0.7265 | 0.8343 | 0.7809 | 0.7813 |
| 1994 | 0.9975 | 0.8139 | 0.8595 | 0.8452 | 0.9438 | 0.7587 | 0.9174 | 0.7884 | 0.7561 |
| 1995 | 0.9156 | 0.9416 | 0.7876 | 0.7910 | 0.8040 | 0.8276 | 0.8657 | 0.7592 | 0.7419 |
| 1996 | 0.9832 | 0.9180 | 0.7959 | 0.8224 | 0.8357 | 0.8431 | 0.8871 | 0.8488 | 0.7948 |
| 1997 | 0.9476 | 0.9012 | 0.7531 | 0.8074 | 0.8268 | 0.7778 | 0.8675 | 0.7397 | 0.7370 |
| 1998 | 0.9707 | 0.8672 | 0.7691 | 0.7712 | 0.8693 | 0.8202 | 0.8485 | 0.7875 | 0.7427 |
| 1999 | 0.8689 | 0.9219 | 0.7161 | 0.7165 | 0.8733 | 0.7724 | 0.8470 | 0.7399 | 0.6993 |
| 2000 | 0.9461 | 0.9263 | 0.7366 | 0.7648 | 0.8836 | 0.8210 | 0.8196 | 0.7397 | 0.7463 |
| 2001 | 0.8870 | 0.9184 | 0.7079 | 0.7044 | 0.7993 | 0.7241 | 0.8282 | 0.6370 | 0.6679 |
| 2002 | 0.9598 | 0.9217 | 0.7342 | 0.7710 | 0.8359 | 0.7386 | 0.8189 | 0.7299 | 0.7271 |
| 2003 | 0.8918 | 0.8861 | 0.7370 | 0.6880 | 0.9090 | 0.7873 | 0.8141 | 0.7485 | 0.7037 |
| 2004 | 0.9171 | 0.9046 | 0.7994 | 0.7319 | 0.9357 | 0.8288 | 0.8631 | 0.8573 | 0.7715 |
| 2005 | 0.8930 | 0.9243 | 0.7144 | 0.6895 | 0.9319 | 0.7709 | 0.8191 | 0.7520 | 0.7178 |
| 2006 | 1.0000 | 0.9404 | 0.8978 | 0.9573 | 0.9841 | 0.9424 | 0.8791 | 0.9321 | 0.9007 |
| 2007 | 0.9883 | 0.9714 | 0.8446 | 0.8764 | 0.9089 | 0.8650 | 0.9071 | 0.9284 | 0.8701 |
| 2008 | 0.9959 | 1.0000 | 0.8414 | 0.9103 | 0.8840 | 0.8339 | 0.8823 | 0.9107 | 0.8758 |
| 2009 | 0.8382 | 0.9154 | 0.6864 | 0.6241 | 0.8398 | 0.6791 | 0.6605 | 0.8409 | 0.6323 |
| 2010 | 0.9319 | 0.9587 | 0.8127 | 0.7857 | 0.9012 | 0.8762 | 0.7992 | 0.9303 | 0.8083 |

Table 2.12: PK Scores for Different Group from Year 1983 to 2010

| Year | Agricultural Share in GDP | | | Agricultural Population Share in Total Population | | |
|---|---|---|---|---|---|---|
| | A1 | A2 | A3 | B1 | B2 | B3 |
| | 《10% | 10% - 20% | 》=20% | <50% | 50%-75% | >=75% |
| 1983 | 0.612 | 0.656 | 0.612 | 0.691 | 0.665 | 0.606 |
| 1984 | 0.561 | 0.610 | 0.644 | 0.697 | 0.616 | 0.577 |
| 1985 | 0.681 | 0.635 | 0.644 | 0.778 | 0.649 | 0.658 |
| 1986 | 0.670 | 0.645 | 0.685 | 0.794 | 0.643 | 0.665 |
| 1987 | 0.631 | 0.607 | 0.570 | 0.771 | 0.587 | 0.609 |
| 1988 | 0.744 | 0.688 | 0.754 | 0.821 | 0.681 | 0.742 |
| 1989 | 0.702 | 0.645 | 0.668 | 0.795 | 0.601 | 0.698 |
| 1990 | 0.806 | 0.750 | 0.813 | 0.844 | 0.793 | 0.790 |
| 1991 | 0.779 | 0.777 | 0.771 | 0.802 | 0.753 | 0.783 |
| 1992 | 0.706 | 0.726 | 0.818 | 0.874 | 0.644 | 0.747 |
| 1993 | 0.766 | 0.741 | 0.884 | 0.876 | 0.755 | 0.782 |
| 1994 | 0.719 | 0.726 | 0.881 | 0.906 | 0.716 | 0.759 |
| 1995 | 0.739 | 0.744 | 0.749 | 0.800 | 0.745 | 0.736 |
| 1996 | 0.772 | 0.774 | 0.889 | 0.804 | 0.786 | 0.797 |
| 1997 | 0.698 | 0.767 | 0.827 | 0.856 | 0.695 | 0.741 |
| 1998 | 0.719 | 0.737 | 0.833 | 0.903 | 0.722 | 0.727 |
| 1999 | 0.686 | 0.718 | 0.723 | 0.851 | 0.700 | 0.677 |
| 2000 | 0.691 | 0.842 | 0.830 | 0.922 | 0.712 | 0.733 |
| 2001 | 0.665 | 0.719 | 0.623 | 0.893 | 0.669 | 0.636 |
| 2002 | 0.696 | 0.772 | 0.782 | 0.911 | 0.762 | 0.689 |
| 2003 | 0.673 | 0.773 | 0.733 | 0.893 | 0.735 | 0.665 |
| 2004 | 0.729 | 0.835 | 0.853 | 0.899 | 0.755 | 0.760 |
| 2005 | 0.652 | 0.838 | 0.804 | 0.851 | 0.733 | 0.692 |
| 2006 | 0.882 | 0.927 | 0.921 | 0.927 | 1.000 | 0.872 |
| 2007 | 0.828 | 0.892 | 0.963 | 0.738 | 0.866 | 0.882 |
| 2008 | 0.826 | 0.972 | 0.932 | 0.835 | 0.853 | 0.888 |
| 2009 | 0.555 | 0.632 | 0.821 | 0.719 | 0.612 | 0.632 |
| 2010 | 0.782 | 0.845 | 0.848 | 1.000 | 0.760 | 0.799 |

Figure 2.1: Output and Input Efficiency from year 1983 to 2010

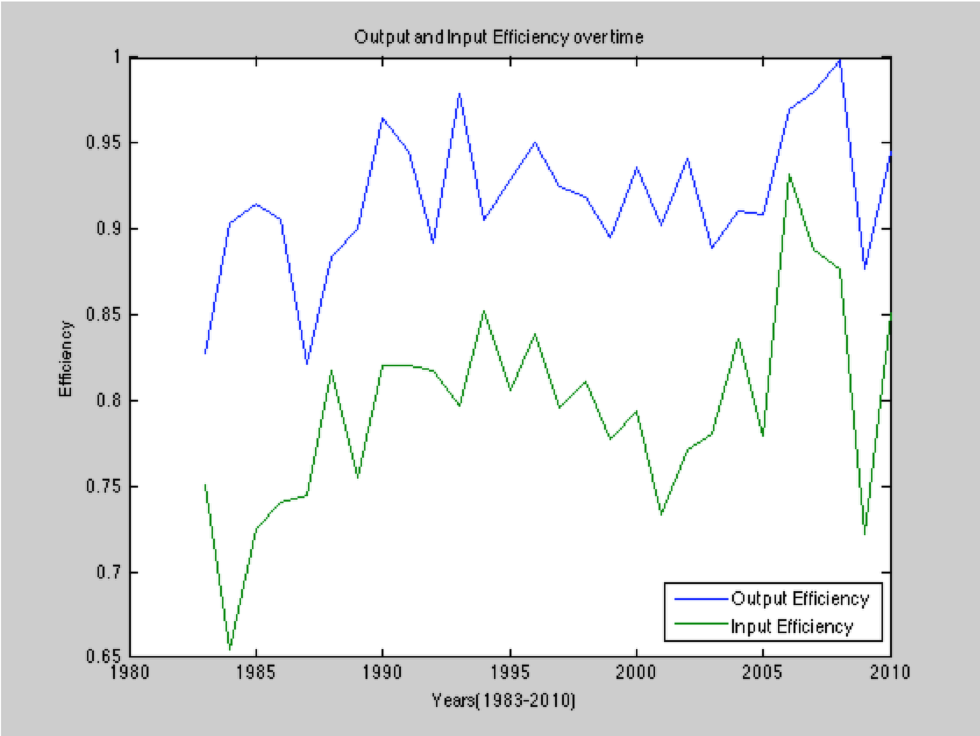



Figure 2.2: Traditional and Modern Input Efficiency from Year 1983 to 2010

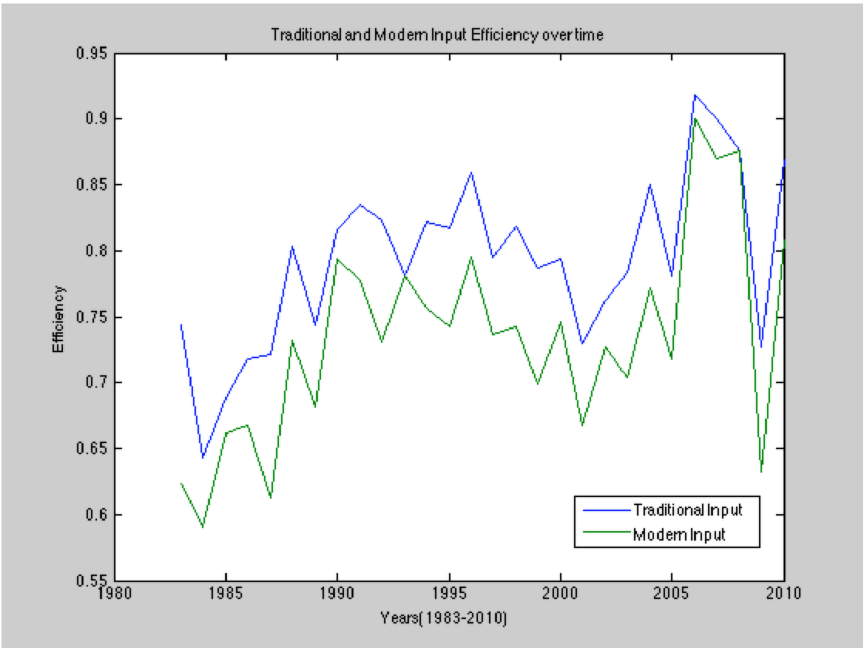


Figure 2.3: Output Efficiencies Over Time

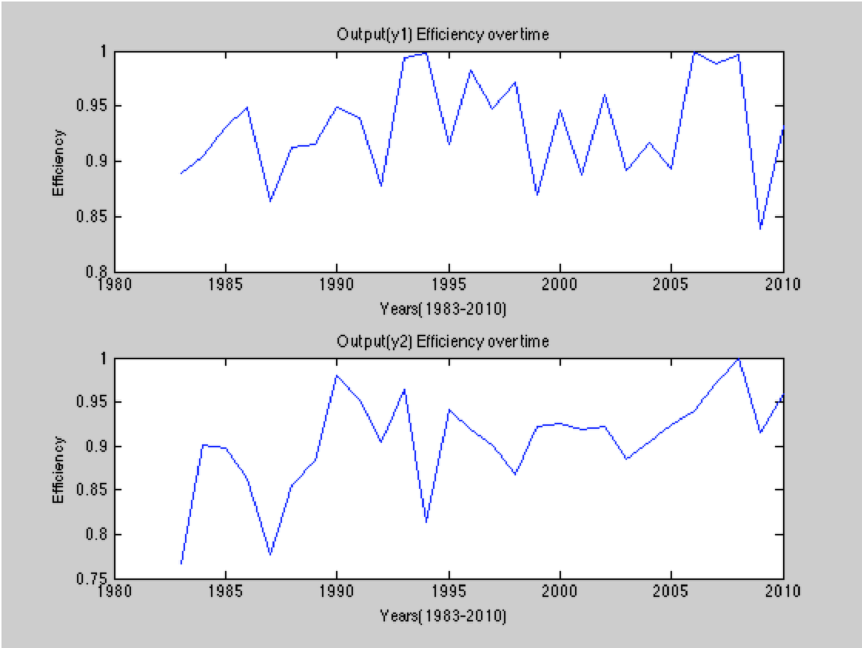



Figure 2.4: Input Efficiencies Over Time

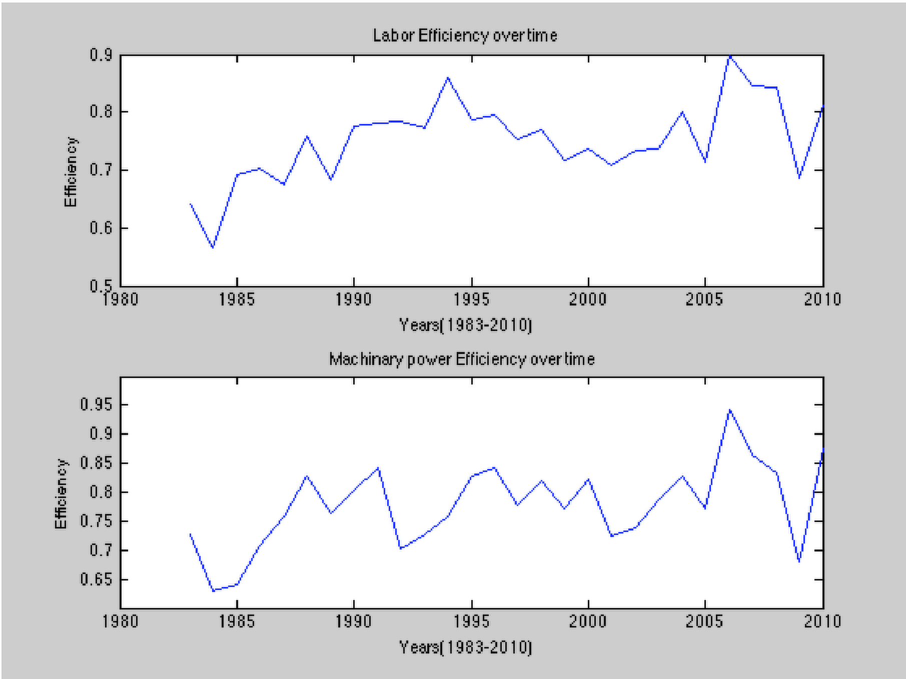


Figure 2.5: PK Efficiencies Scores Over Time

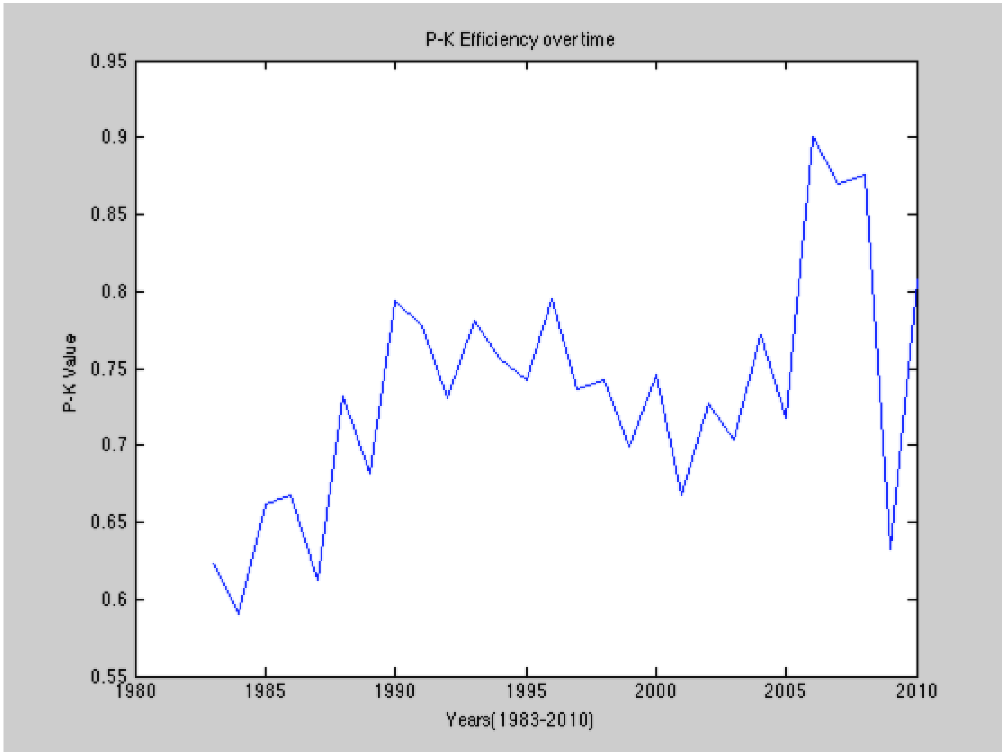



Figure 2.6: Regional P-K Efficiencies Scores Over Time (Income level)

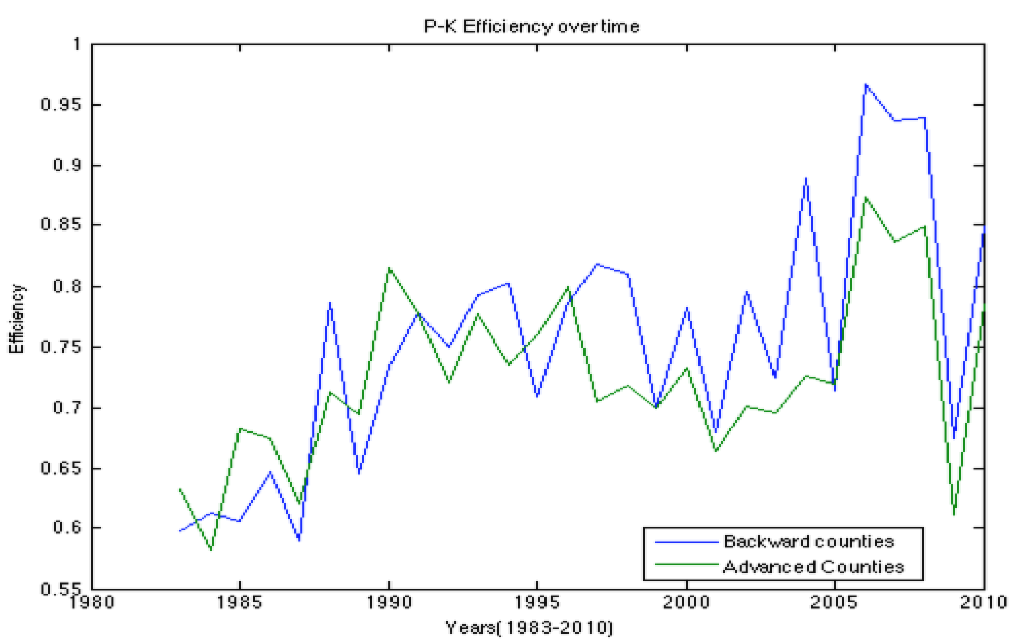


Figure 2.7: Regional PK Efficiencies Scores Over Time (Population share)

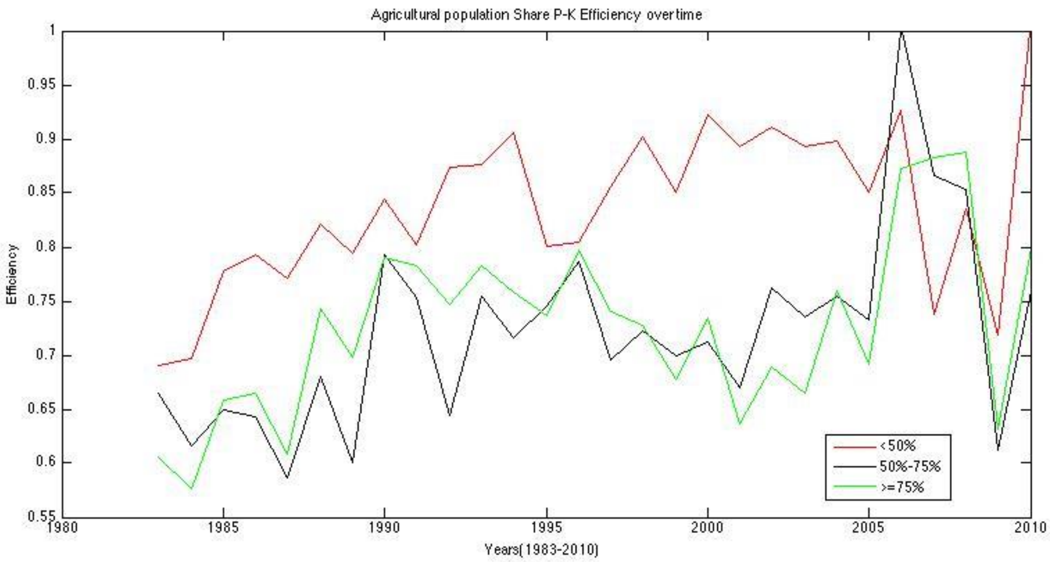
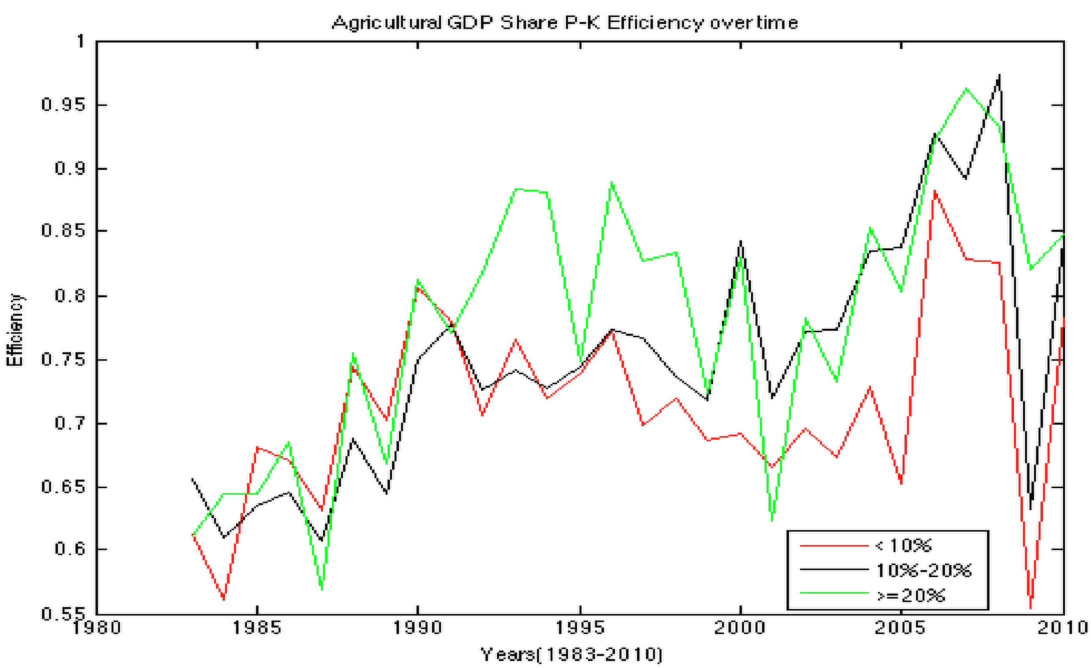



Figure 2.8: Regional P-K Efficiencies Score Over Time (GDP share)



# Chapter 3: Productivity Growth and Its Components in Chinese Agriculture

## 3.1 Introduction

Market-oriented reforms have brought unprecedented growth to the Chinese economy. China's agricultural growth has been accompanied by far-reaching changes in the structure of both output and input. Beginning in the late 1970s, Chinese economic reforms accompanying the household responsibility system (HRS) moved rural China away from collective agriculture. Villages divided up collectively owned land and leased it to individual households. Farmers could produce any crops for free markets. In 1990s, the abolition of state control of grain prices increased producer’s enthusiasm for grain crops, particularly for farmers near urban areas or other lucrative markets. These reforms resulted in remarkable progress in the Chinese agricultural sector. The output of grains increased from 305 megatons[19] in 1978 to 501 megatons in 2007, an increase by 64%. After two decades of progress, China has developed the capability to provide the basic food needs for 22% of the world’s population with only 7% of the world’s arable land (Gale, 2013). Today, China is the world’s largest agricultural economy, and it ranks as the largest global producer of pork, wheat, rice, tea, cotton, and fish. Understanding the sources of China's growth is important not the least because China's experience could shed light on the growth potential of other developing countries.

In this chapter we aim to investigate the temporal and spatial pattern of total factor productivity (TFP) growth and its components of agriculture in Shansi province after the

[19] 1 megaton equals to a million tons. 1 ton equals to 2240lb.

economic reforms.  We examine the agricultural sector of a single province, Shanxi, rather than the whole nation in order to ensure the geographical homogeneity. Shanxi province is ranked at the middle of the entire county in term of population density, agricultural development and household income level. It is a good case study to find the average agricultural performance of the whole nation.

We compute a nonparametric Malmquist index to measure the productivity change from one year to the next using the geometric mean of two Malmquist productivity indexes constructed using distance functions. Linear programming techniques are used to derive the values of distance functions. The TFP index measures an economy's long-term productivity change or technological dynamism. Many scholars have attributed this high growth in agricultural productivity to institutional reforms, technological innovation, research investment, education improvement, and industrial growth (Fan, 1991; Lin, 1992; Koo and Duncan, 1997; Fan and Zhang, 2002)[20]. In this chapter, using the Malmquist productivity index developed by Caves, Christensen, and Diewert (1982) and operationalized by Färe et al. (1992), we decompose the TFP into technical change and efficiency change. This technique allows us to identify contributions of improved technical efficiency and technological progress to Chinese agricultural productivity growth. The results of this study indicate that the Malmquist productivity index for Shanxi province increased by 1.2% per year over the 1983–2010 periods. Decomposition of the Malmquist productivity index shows that technical change contributed to the growth in productivity by 0.8% per year, while efficiency change increased productivity by 0.4% per year.

[20] There is a considerable volume of microeconomic literatures on Chinese agricultural productivity. For example, Jin et al. (2002) found that productivity of wheat increased by more than 20% between 1990 and 1995. Jin et al. (2002) emphasized the importance of investment in agricultural R&D for TFP growth.

Our analysis differs from the previous studies on Chinese agricultural productivity growth with the following features. First, most of the previous studies focused on TFP growth from the institutional reforms employing a specific functional form, usually the Cobb–Douglas production function. The nonparametric Malmquist index approach, by contract, does not require a specific functional form. The Malmquist index approach estimates production efficiency based on the observed data, and unlike the growth accounting approach, dose not rely on the maintained hypothesis of technical and allocative efficiency. In addition, the approach requires neither data on prices nor cost to aggregate inputs and outputs for measuring TFP growth. Secondly, unlike most of the studies, we use county-level data in Shanxi province. Finally, most of the previous studies covered only a short time period. Our study employs input and output data from all counties in Shanxi province covering a longer post-reform era (1983–2010), which helps shed light on the disparity in productivity growth over time.

The rest of this chapter is organized as follow. In section 2 of this chapter, we briefly review the current literature. Section 3 provides an overview of the nonparametric methodology. Section 4 reports the empirical finding and Difference in the rate of productivity change across different group of counties. The main conclusions and policy implications are summarized in Section 5.

## 3.2 Literature Review

There are many studies on Chinese agricultural and the literature has documented large positive growth rates in agricultural TFP. For example, Fan and Pardey (1997) showed that agricultural productivity increased 3.9% per year between 1985 and 1995. Wu et al. (2001) found an increase of 3.6% between 1990 and 1995. Jin et al. (2002) found that the productivity in wheat production increased by 3 to 4 percent annually between 1990 and 1995. Nin-Pratt et al. (2010) showed that agricultural TFP growth in 1990s was about 4.4% annually. Lin (1992) and Huang and Rozelle (1996) emphasized institutional reforms as the main source of agricultural growth during the early 1980s.

Three important points should be noted about the existing studies in Chinese agriculture productivity. First, most of these studies are based on province level data drawn from the nation. Second, none of these studies individually can be regarded as a long-term analysis of productivity in agriculture at the more aggregate level. Third, most of the studies use explicit parametric specification of the production function as the analytical format.

Some studies that used traditional parametric approaches to calculate total factor productivity in agriculture by estimating an aggregate production function (Mcmalin et.al., 1989; Jin, 2002; Restuccia, Yang and Zhu, 2008).Yu, Liao and Shen (2014) presented the production technology and components of Malmquist index by parametric decomposition. Using province level data, they also showed that the average productivity grew at 2 percent per year during 1978-2010. The level of technical efficiency averaged at 0.884, with low efficiency score in the North.

Some studies used non-parametric Malmquist productivity index to investigate the

TFP change in Chinese agricultural (Mao et.al 1997; Chen, 2003)[21]. Lambert and Parker (1998) studied the multifactor productivity indices for 1979-1995 period. They found a significant variation in productivity change from year to year and province to province. Wu et al. (2001) showed that total factor productivity grew at 2.4% annually with technical change contributing to productivity growth by 3.8% while efficiency change reduced productivity growth by 1.3%.

Using province level data, Fan (1991) found that total factor productivity (TFP) in agriculture grew at an average rate of 2.1% per year during 1965–86; 62% of this growth was attributed to efficiency improvement from institutional change, while the remaining 38% was imputed to technical progress. Lin (1992) found that all reform measures combined accounted for 42% of the growth in agricultural output during the time period of 1978–84. Huang, Hu and Rozelle (2002) noted that technical change was one of the most important factors contributing to agricultural growth during the entire reform period, particularly after 1984. By employing a varying coefficient model, Kalirajan et al. (1996) found that during the pre-reform period (1970–78) 20 out of 28 provinces had a negative TFP growth in agriculture. However, during the reform period (1978–84) almost all provinces had a positive TFP growth with efficiency change as the most dominant component, while 16 provinces had a negative TFP growth over the period 1984–1987. Xu and Jeffrey (1998) noted the regional difference in the effects of technical progress on rice.

There are a few studies that use county or farm level data to study productivity in Chinese agriculture sector. Wang et al. (1996) examined household-level production

[21] Chen (2003) used non-radial Malmquist productivity index to study Chinese major industries including agriculture.

efficiency by using farm survey data of 1990. Brummer, Glauben and Lu (2006) used farm-level data in Zhejiang province from 1986 to 2000 and showed that most of the rapid change in productivity growth was realized in China's second reform period (1985–1989). Using disaggregated county-level production data and the estimated weather index, Zhang and Carter (1997) found that weather was a critical factor in Chinese agricultural productivity growth in the early 1980s.

This study contributes to the existing literature in several ways. We investigate the TFP of Chinese agriculture at the county-level. We use Malmquist productivity to estimate the productivity score in agriculture sector from year 1983 to 2010. We also compare the agricultural productivity change of sub-regions as well as the differences in the productivity over time.

## 3.3 Methodology

### 3.3.1 Measure and Decomposition of Multi-factor Productivity Growth

Productivity is a measure of the ability to produce a good or service. It can be expressed as the ratio of output to inputs used in the production process. Productivity index shows how productivity of a firm or a county has changed from the base period. The rate of productivity growth is the difference in the growth rate of the output and input quantities respectively (Ray, 2002). For empirical estimation and decomposition of change in productivity, we may follow either a parametric or a non-parametric approach. The parametric approach involves an explicit estimated production function to measure and decompose the productivity growth. By contrast, a non-parametric approach does not specify any explicit production function and uses mathematical programming methods to estimate production function. A non-parametric method that has become popular over the past decades is the Data Envelopment Analysis (DEA). Subject to availability of suitable panel data, one can use this frontier estimation method to estimate firm level TFP growth without requiring any price information. Further, it does not require the assumption that all firms are fully efficient, cost minimizers and revenue maximizers. This is of importance when we are to analyze non-market sectors or non-profit institutions performances.

Malmquist TFP index measures the TFP change between two data points (e.g those of a firm in two adjacent time periods) by calculating the ratio of the distances of each data point relative to a common technology frontier. Malmquist productivity index was introduced by Caves, Christensen, and Diewert (1982) (CCD82) and was empirically applied by Fare,

Grosskopf, Lindgren, and Roos (1992)(FGLR92)[22]. They identified the two components of productivity change: technical change and technical efficiency change. CCD82 and FGLR92 both assumed constant returns to scales in their model. In this study, we use FGLR92's decomposition of Malmquist productivity index and assume constant returns to scales.

The Malmquist productivity index is defined using distance functions, which describes a multi-input, multi-output production technology. The input distance function characterizes the production technology by looking at a minimal contraction of the input variables, given the output vector. The output distance function characterizes the production technology by looking at a maximal expansion of the output variables, given the input vector. In this chapter, only an output distance function is considered in detail. The Malmquist productivity index must use the constant returns to scale (CRS) distance function even if CRS did not hold globally (Ray and Desli, 1997; Ray, 2004).

Consider the single input, single output case. If in period 0 a firm produces output $y_0$ from input $x_0$, its productivity is

$$AP_0 = \frac{y_0}{x_0} \ .$$

**Equation 19**

If in period 1 the same firm produces output $y_1$ from input $x_1$, its productivity is

$$AP_1 = \frac{y_1}{x_1} \ .$$

**Equation 20**

Then, the productivity index in period 1, with period 0 as the base, is

[22] In a subsequent paper Färe, Grosskopf, Norris, and Zhang (1994) (FGNZ94) allowed variable return to scale. However, Ray and Desli (RD) (1997) pointed out that FGNZ94's measure of technical change assumes constant returns to scales, which is inconsistent with any change in scale efficiency.

$$\Pi = \frac{AP_1}{AP_0} = \frac{y_1/x_1}{y_0/x_0} \,.$$

**Equation 21**

Now suppose that the production function is $y = f(x)$ and the same function is applicable in both time periods. Then

$$\Pi = \frac{AP_1}{AP_0} = \frac{\frac{y_1}{f(x_1)} . \frac{f(x_1)}{x_1}}{\frac{y_0}{f(x_0)} . \frac{f(x_0)}{x_0}} \,,$$

**Equation 22**

but $y_1/f(x_1) = TE^1(x_1, y_1)$ ,

and $y_0/f(x_0) = TE^0(x_0, y_0)$ .

Further, if the technology exhibits CRS, $\frac{f(x_1)}{x_1} = \frac{f(x_0)}{x_0}$ .

Hence, $\Pi = \frac{TE^1(x_1,y_1)}{TE^0(x_0,y_0)}$ .

That is, productivity change can be measure by the change in the technical efficiency relative to a benchmark technology exhibiting CRS.

Now, suppose that due to technical change, the production function changes from

$y = f^0(x)$ in period 0,

to $y = f^1(x)$ in period 1.

We assume CRS in both time periods. Now, as defined above,

$$\Pi = \frac{y_1/x_1}{y_0/x_0} = \frac{\frac{y_1}{f^1(x_1)} . \frac{f^1(x_1)}{x_1}}{\frac{y_0}{f^0(x_0)} . \frac{f^0(x_0)}{x_0}} \,.$$

**Equation 23**

However, even though CRS holds in both time periods, $\frac{f^1(x_1)}{x_1} \neq \frac{f^0(x_0)}{x_0}$. But, we can rewrite

$$\Pi = \frac{y_1/x_1}{y_0/x_0} = \frac{\frac{y_1}{f^1(x_1)} \cdot \frac{f^1(x_1)}{x_1}}{\frac{y_0}{f^0(x_0)} \cdot \frac{f^0(x_0)}{f^1(x_0)} \cdot \frac{f^1(x_0)}{x_0}} \ .$$

**Equation 24**

This time, $\frac{f^1(x_1)}{x_1} = \frac{f^1(x_0)}{x_0}$ due to CRS, and

$$\Pi = \frac{\frac{y_1}{f^1(x_1)}}{\frac{y_0}{f^0(x_0)}} \cdot \frac{f^1(x_0)}{f^0(x_0)} = \frac{TE^1(x_1, y_1)}{TE^0(x_0, y_0)} \cdot \frac{f^1(x_0)}{f^0(x_0)} \ .$$

**Equation 25**

Now, $\frac{f^1(x_0)}{f^0(x_0)}$ measures the shift in the production function between the two periods at the same input level $x_0$. An alternative decomposition of the productivity index is:

$$\Pi = \frac{\frac{y_1}{f^1(x_1)}}{\frac{y_0}{f^0(x_0)}} \cdot \frac{f^1(x_1)}{f^0(x_1)} = \frac{TE^1(x_1, y_1)}{TE^0(x_0, y_0)} \cdot \frac{f^1(x_1)}{f^0(x_1)} \ .$$

**Equation 26**

where the shift in the production function is measured at input level $x_1$. Following FGLR92, the productivity index is measured as :

$$\Pi = \frac{TE^1(x_1, y_1)}{TE^0(x_0, y_0)} \sqrt{\frac{f^1(x_0)}{f^0(x_0)} \cdot \frac{f^1(x_1)}{f^0(x_1)}} \ .$$

**Equation 27**

Here, $\frac{TE^1(x_1,y_1)}{TE^0(x_0,y_0)}$ is the technical efficiency change (TEC), and $\sqrt{\frac{f^1(x_0)}{f^0(x_0)} \cdot \frac{f^1(x_1)}{f^0(x_1)}}$ is technical change (TC). When the technical does not exhibit CRS, the decomposition will includes

another factor capturing the effect of the change in scale[23]. In the present dissertation, we use aggregated data for each county and assume CRS.

We can also evaluate the various distance functions by using DEA to measure and decompose the Malmquist productivity index non-parametrically.

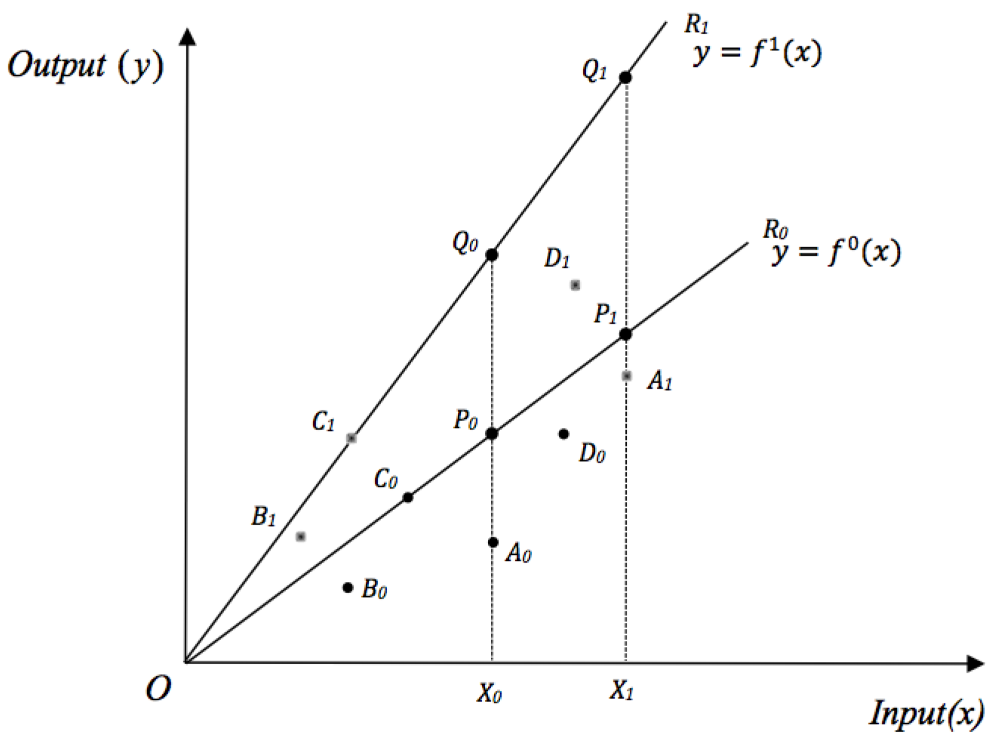



Figure 3.1 Geometry of the Malmquist productivity index and its decomposition

In Figure 3.1, suppose that the points $A_0$, $B_0$, $C_0$, and $D_0$ show the input–output combinations of four counties in period 0. Similarly, input–output combinations of these four counties in period 1 are shown by the points $A_1$, $B_1$, $C_1$, and $D_1$. The ray $OR_0$ passing through the point $C_0$ is the *CRS* production frontier in period 0. Similarly, ray $OR_1$ through

[23] See Färe, Grosskopf, Norris, & Zhang (1994) and Ray and Desli (1997).

$C_1$ is the production function in period 1. Consider the points $A_0$ and $A_1$ showing the input–output quantities of firm *A* in the two time periods. The firm produces output ${y^0}_A$ from input $x_0$ in period 0 and output ${y^1}_A$ from input $x_1$ in period 1.

The point $P_0$ is the output-oriented projection of the point $A_0$ onto the (CRS) frontier in period 0. Thus,

$$D_C^0(x_0, y_A^0) = \frac{A_0x_0}{P_0x_0}$$

**Equation 28**

Similarly, in period 1,

$$D_C^0(x_1, y_A^1) = \frac{A_1x_1}{P_1x_1}$$

**Equation 29**

The average productivity levels of county *A* are

$AP_A^0 = \frac{A_0x_0}{Ox_0}$ in period 0 and

$AP_A^1 = \frac{A_1x_1}{Ox_1}$ in period 1.

Thus, the productivity index of county *A* is

$$\pi_A = \frac{AP_A^1}{AP_A^0} = \frac{\frac{A_1x_1}{Ox_1}}{\frac{A_0x_0}{Ox_0}} = \frac{\frac{A_1x_1}{P_1x_1}\frac{P_1x_1}{Ox_1}}{\frac{A_0x_0}{P_0x_0}\frac{P_0x_0}{Ox_0}} = \frac{\frac{A_1x_1}{P_1x_1}}{\frac{A_0x_0}{P_0x_0}} = \frac{D_C^0(x_1, y_A^1)}{D_C^0(x_0, y_A^0)}$$

**Equation 30**

One alternative way to factorize this productivity index are

$$\pi_A = \frac{\frac{A_1x_1}{Ox_1}}{\frac{A_0x_0}{Ox_0}} = \frac{\frac{A_1x_1}{Q_1x_1}\frac{Q_1x_1}{Ox_1}}{\frac{A_0x_0}{Q_0x_0}\frac{Q_0x_0}{Ox_0}} = \frac{\frac{A_1x_1}{Q_1x_1}}{\frac{A_0x_0}{Q_0x_0}} = \frac{D_C^1(x_1, y_A^1)}{D_C^1(x_0, y_A^0)}$$

**Equation 31**

When we take the geometric mean of the two productivity equations, we get

$$\pi_A = \left[\frac{\frac{A_1x_1}{Q_1x_1}}{\frac{A_0x_0}{Q_0x_0}} \frac{\frac{A_1x_1}{P_1x_1}}{\frac{A_0x_0}{P_0x_0}}\right]^{1/2}$$

**Equation 32**

which leads to

$$\pi_A = \left[\frac{\frac{A_1x_1}{Q_1x_1}}{\frac{A_0x_0}{P_0x_0}}\right] \cdot \left[\frac{Q_1x_1}{P_1x_1} \cdot \frac{Q_0x_0}{P_0x_0}\right]^{\frac{1}{2}}.$$

**Equation 33**

The first term in the right-hand side

$$\frac{\frac{A_1x_1}{Q_1x_1}}{\frac{A_0x_0}{P_0x_0}} = \frac{D^1\,(x_1, y_A^1)}{D^0\,(x_0, y_A^0)}$$

**Equation 34**

measures the ratio of technical efficiencies of the county in two periods. We call it the Technical Efficiency Change (TEC) factor.

The ratio

$$\frac{Q_0x_0}{P_0x_0} = \frac{D^0\,(x_0, y_A^0)}{D^1\,(x_0, y_A^0)}$$

**Equation 35**

is the shift in the production function between two periods based on input level $x_0$.

Similarly,

$$\frac{Q_1 x_1}{P_1 x_1} = \frac{D^0\,(x_1, y_A^1)}{D^1\,(x_1, y_A^1)}$$

**Equation 36**

is the production function shift between two periods based on input level $x_1$. The geometric mean of the two equations is the second factor, which represents the technical change (TC). Therefore, assuming CRS through out, we get

$$\pi_A = TC * TEC$$

**Equation 37**

### 3.3.2 The Nonparametric Methodology

In order to operationalize the decomposition of Malmquist productivity index, we need to calculate the same period technical efficiency (TE) under CRS. Also, we need the cross period TE under CRS. The following are the DEA LP models that we need to solve first to measure Malmquist productivity index.

In the multiple-output multiple-input case, with the assumptions of convexity of the production possibility set and along with free disposability of both outputs and inputs, the production possibility set (CRS) can be constructed as the following (Ray, 2004):

$$T = \left\{(x, y):\ x \geq \sum_{j=1}^{N} \lambda_j\, x^j;\ y \leq \sum_{j=1}^{N} \lambda_j\, y^j;\ \lambda_\mathrm{j} \geq 0\ ; (\mathrm{j} = 1,2, \dots , \mathrm{N})\right\}$$

**Equation 38**

Where $(x^j, y^j)$ is the observed input and output bundle of an individual county *j* in a sample of *N* counties in the dataset. Under this production possibility set, for single input, single

output bundle, the output-oriented distance function under CRS can be obtains as:

$$D^t\ (x_t^k, y_t^k) = \frac{1}{\varphi_k^*}$$

$$\varphi_k^* = max\, \varphi_k\ ;$$

$$\max \varphi_k$$

$$\text{s.t.}\ \sum_1^N \lambda_j\, y_t^j \geq \varphi y_t^k\ ;$$

$$\sum_1^N \lambda_j\, x_t^j \leq x_t^k\ ;$$

$$\lambda_\text{j} \geq 0\ (\text{j} = 1,2, \dots, \text{N})\ .$$

**Equation 39**

The value of $D^t\ (x_t^k, y_t^k)$ can be derived from the solution of the linear programming problem that is specified in equation 39. We use this model to measure same period TE. The first constraint states that to produce the observed output in the $k^{\text{th}}$ county, the actual use of input *j* for county *k* should be greater than or equal to the theoretically efficient input usage that is a weighted sum of input *j* for all counties. The second equation requires that, given the actual amount of inputs used by the $k^{\text{th}}$ county, the maximum feasible output of county *k* should be less than or equal to the theoretically efficient output that is a weighted sum of all counties' outputs.

For the cross-period (CRS) distance function $\{D_C^s(x_t^k, y_t^k), s = 0,1; t = 0,1; t \neq s\}$, we need to solve the following optimization problem:

$$D_C^S(x_t^k, y_t^k) = \frac{1}{\varphi_k^*}$$

$$\varphi_k^* = \max \varphi_k$$

$$\text{s.t.} \ \sum_1^N \lambda_j \, y_t^j \geq \varphi y_{t+1}^k \, ;$$

$$\sum_1^N \lambda_j \, x_t^j \leq x_{t+1}^k \, ;$$

$$\lambda_\text{j} \geq 0 \ (\text{j} = 1,2, \dots, \text{N}) \, .$$

**Equation 40**

This model is to measure the cross-period output-oriented efficiency under CRS. The two-period distance function, $D_C^t(x_t^k, y_t^k)$, involves observations in time *t* + 1 with respect to technology at time *t* and represented by equation 40. The value of $D_C^t(x_t^k, y_t^k)$ for observed production in time *t* with respect to technology at time *t* + 1 was estimated using equation 40, which is the model with superscripts *t* and *t* + 1 interchanged. Thus, we can use the results of the above two DEA models to calculate each component of the Malmquist productivity index.

In the following section we investigate the aggregated county-level TFP growth and its composites using the Malmquist productivity index.

## 3.4 The Empirical Analysis and Results

In this section, we first present a summary description of average performance of productivity for Shanxi province. Then we examine the temporal and spatial patterns of changes in productivity and its components. Finally, we discuss the disaggregated results for each year and individual county in terms of growth and variations in productivity and its components.

The rate of agricultural TFP growth for Shanxi province increases moderately over time, as showed in the in Table 3.1. Average change in the Malmquist productivity index over the 1983–2010 periods is 1.2% annually for the entire province. This change in productivity is essentially due to an outward shift the frontier rather than moving closer to the frontier. On average, technical change contributes to the growth in productivity by 0.8% per year, while efficiency change increases productivity by 0.4% per year.

The Malmquist productivity index of all counties varies from a 50.2% increase in 2008/09[24] to a 15.3% decrease in 1994/95 (Table 3.5). The decomposition of productivity growth into technical change and technical efficiency change reveals the technological innovation and efficiency improvement over years. Variations in productivity growth due to technological innovation range from an increase of 49.7% in 2008/09 to a decrease of 21.7% in 1984/85, while variations in the efficiency improvement effect range from an increase of 19.8% in 2009/10 to a decrease of 11.9% in 1994/95. From 1983/84 to 1989/90, the average TFP growth is 0.1%. From 1990/91 to 1999/2000, there is a rapid technical progress but a decrease in technical efficiency. The overall TFP in 1990s grows at rate of 2.75%. From 2000/01 to 2009/10, both TC and TEC increase at 1.8% per year. The rate of increase in TFP in 2000s is 3.68% (Table 3.4). Some of the key factors behind technical progress as recognized by Stone (1993) include the development of chemical fertilizers use, water control technology, cultivation practices (greenhouses, plastic sheeting), and new crop varieties (hybrid, pest and disease resistant varieties in rice and wheat).

In the second half of 1980s, there is a decrease of productivity in agricultural sector.

[24] This unusually high increase in TFP in one year is in reality a result of a moderate growth in productivity that is magnified by 3 successive years of decline in the previous years.

This is in part because labor, particularly young and educated farmers, moved from the agricultural sector to the industrial sector. Also, there is a sharp price drop of agricultural inputs in 1985. This may have caused the over use of inputs. These factors led to the productivity decline in late 1980s (Lin, 1992; Kalirajan et al., 1996). Most rapid increase of productivity index is during the last two years of 2000s (Table 3.6). This can be caused by two reasons. First, the agricultural machinery subsidy policy was introduced in year 2007. This may have affected the machinery inputs and increase the overall productivity. Second, in 2009, there was a 19.3% output increase due to a bump harvest, but input increased only by 7% (Table 3.8). The unexpected outputs increase and regular inputs increase can cause the big jump in total factor productivity. This may be explained by the increase of rainfall. The total rainfall in 2009 is 2% higher than 30-year average, and 10% higher than year 2008. Figure 3.1 shows the Malmquist productivity and its components change over time.

The disparity in productivity growth among counties in Shanxi province persisted over the entire study period. Differences in the growth in TFP and its components are related to local conditions such as infrastructures and labor quality. We group counties according to income per capita, share of agricultural GDP and share of agricultural population. The results show that the Malmquist index of productivity change is fast-, moderate- and slow-growing in different groups (Table 3.2, 3.3, 3.4).

The fast productivity growth group by income level is advanced counties, which have higher score in both TC (1.2%) and TEC (0.2%) on average (Table 3.1). Counties in this group accounts for 83.5% of adjusted gross value of crops output, 78.9% of livestock production, 76.8% of agricultural labor, 64.7% of non-irrigated land and 85.7% of the irrigated land in the province. In the group of advanced counties, productivity growth rate

averaged at 1.4% per year, which is higher than the entire province average.  Backward counties have negative average TC, but overall productivity increase rate is 0.7% per year. Table 3.6 shows that the largest growth of productivity for both groups happened in year 2008-2009. Figure 3.6 shows how the Malmquist productivity index changes over time for two groups.

In the group classified by agricultural GDP share, the highest productivity growth is groupA3 (Table 3.2).  Both TC (2.3%) and TEC (0.4%) are higher than other two groups. In this group, technical change contributes to most part of the productivity growth. The slowest productivity growth is for groupA1. This group has only 0.2% growth rate in TC and 0.1% growth rate in TEC on average. The overall productivity growth rate is 0.3% over the study periods. Figure 3.2, figure 3.3, and figure 3.4 show the Malmquist productivity index change for each group over time.

In the group classified by agricultural population share, the fast productivity growth is groupB3 (Table 3.3).  Both TC (1.0%) and TEC (0.7%) are higher than other two groups. In this group, the contributions of technical change and efficiency change to productivity are similar. The slow productivity growth is groupB2. This groupB2 has negative growth rate in both TC and TEC on average. Its overall productivity index is 0.3% over the study periods. Table 3.8 shows that all groups have more than 10% decrease in TFP at 1994-1995. In addition, there is a 20% decrease in agricultural outputs and 9.8% decrease in inputs from 1994 to 1995 (Table 3.9).

Overall, the TC growth rate is bigger than TEC's. Therefore, In addition to promoting technical change, efficiency improvement should be a major focus for policymakers,

particularly for those counties in slow TFP growing groups. The increase of investment in agricultural research and technological development in agriculture should be able to improve TC. To improve the efficiency performance, future reforms should encourage production specialization on the basis of regional comparative advantage and reduce government intervention in agriculture.

## 3.5 Conclusion

This chapter provides a county level analysis of total factor productivity growth of a regional agricultural sector in China. For all counties over the 1983–2010 period, we find the Malmquist productivity increased at 1.2% per year on average.  The productivity grows in 13 years out of a total of 27 years, varies from a 50.2% increase in 2008/09 to a 15.3% decrease in 1994/95.  Decomposition of growth reveals that technical change increased productivity in 15 years. Technical efficiency performance shows increases in 13 years. Technical change contributes to growth by 0.8%, while the technical efficiency performance contributes productivity growth by 0.4%.

This study also provides valuable insights into the spatial and temporal nature of TFP growth in the average performance of Chinese agriculture. Productivity growth in the fast - and slow-growing groups shows, respectively, an increase of 3.2% and a decrease of 0.4%. Possible reasons for the disparity in productivity growth include differences in the level of local infrastructure, agricultural investments, and labor qualities. A W-shaped productivity growth rate plot is found in this post-reform period: decrease from 1985/86 to 1989/90, near stagnation from 1990/91 to 1998/99, and rapid growth from 2005/06 to 2009/10.

The spatial and temporal disparity in productivity growth reveals the need for different

policy measures to be undertaken in various groups of counties. Some group's low TEC scores caught the attention of policymakers to concern with the better utilization of agricultural resources, which led to the introduction of further agricultural reforms. Also, reasons of large productivity change in particular years need to be investigated.

With the growth of population and industrializing, China is placing further demands on agricultural outputs with limited potential of traditional inputs increase such as agricultural lands and labor. Therefore, most of the incremental agricultural production to meet growing demand in China must come from higher yields through technological innovation and more efficient use of the limited agricultural resources. Accordingly, competitive pressure and capital investment should be emphasized to enhance productivity growth in Chinese agriculture for the future.

## Tables and Figures

Table 3.1:Malmquist Index with Price adjusted (by Income/capita)

| Group | Name | TC | TEC | Malmquist Index |
|---|---|---|---|---|
| C1 | Backward | 0.999 | 1.008 | 1.007 |
| C2 | Advanced | 1.012 | 1.002 | 1.014 |
| All | All | 1.008 | 1.004 | 1.012 |

Table 3.2: Malmquist Index with Price adjusted (by Ag. GDP share)

| Group | GDP share | TC | TEC | Malmquist Index |
|---|---|---|---|---|
| A1 | <10% | 1.002 | 1.001 | 1.003 |
| A2 | 10%-20% | 1.013 | 1.005 | 1.019 |
| A3 | >20% | 1.023 | 1.009 | 1.032 |
| All | All | 1.008 | 1.004 | 1.012 |

Table 3.3: Malmquist Index with Price adjusted (by Ag. Population share)

| Group | Population share | TC | TEC | Malmquist Index |
|---|---|---|---|---|
| B1 | <50% | 1.002 | 1.001 | 1.003 |
| B2 | 50%-75% | 0.999 | 0.996 | 0.996 |
| B3 | >75% | 1.010 | 1.007 | 1.016 |
| All | All | 1.008 | 1.004 | 1.012 |

Table 3.4: Malmquist Index and Its Components

| Geometric mean | TC | TEC | Malmquist |
|---|---|---|---|
| 1983-1989 | 0.9828 | 1.0194 | 1.0019 |
| 1990-1999 | 1.0417 | 0.9863 | 1.0275 |
| 2000-2010 | 1.0187 | 1.0178 | 1.0368 |
| Simple mean | TC | TEC | Malmquist |
| 1983-1989 | 0.9921 | 1.0238 | 1.0081 |
| 1990-1999 | 1.0444 | 0.9887 | 1.0336 |
| 2000-2010 | 1.0306 | 1.0123 | 1.0419 |

Table 3.5: Malmquist Index and Its Components by Year

| Start Year | End Year | TC | TEC | Malmquist Index |
|---|---|---|---|---|
| 1983 | 1984 | 1.291 | 0.916 | 1.183 |
| 1984 | 1985 | 0.783 | 1.111 | 0.871 |
| 1985 | 1986 | 1.008 | 0.980 | 0.988 |
| 1986 | 1987 | 0.965 | 0.938 | 0.905 |
| 1987 | 1988 | 0.962 | 1.163 | 1.119 |
| 1988 | 1989 | 0.963 | 0.940 | 0.906 |
| 1989 | 1990 | 0.972 | 1.118 | 1.087 |
| 1990 | 1991 | 0.995 | 0.971 | 0.967 |
| 1991 | 1992 | 1.098 | 0.984 | 1.080 |
| 1992 | 1993 | 1.124 | 1.018 | 1.145 |
| 1993 | 1994 | 0.937 | 1.053 | 0.987 |
| 1994 | 1995 | 0.926 | 0.914 | 0.847 |
| 1995 | 1996 | 1.039 | 1.080 | 1.122 |
| 1996 | 1997 | 1.128 | 0.895 | 1.010 |
| 1997 | 1998 | 1.066 | 1.013 | 1.080 |
| 1998 | 1999 | 0.999 | 0.883 | 0.882 |
| 1999 | 2000 | 1.132 | 1.075 | 1.216 |
| 2000 | 2001 | 1.018 | 0.928 | 0.944 |
| 2001 | 2002 | 1.032 | 1.081 | 1.115 |
| 2002 | 2003 | 1.003 | 0.981 | 0.984 |
| 2003 | 2004 | 0.953 | 1.060 | 1.010 |
| 2004 | 2005 | 0.953 | 0.955 | 0.910 |
| 2005 | 2006 | 0.793 | 1.082 | 0.859 |
| 2006 | 2007 | 1.018 | 0.881 | 0.896 |
| 2007 | 2008 | 1.033 | 0.939 | 0.970 |
| 2008 | 2009 | 1.497 | 1.019 | 1.525 |
| 2009 | 2010 | 1.007 | 1.198 | 1.206 |

Note: we use geometric mean to aggregate the yearly average values.

Table 3.6: Malmquist Productivity Index by Regions and Year (1)

| Start Year | End Year | Backward | | | Advanced | | |
|---|---|---|---|---|---|---|---|
| | | TC | TEC | Malquist | TC | TEC | Malquist |
| 1983 | 1984 | 1.233 | 0.988 | 1.219 | 1.313 | 0.891 | 1.170 |
| 1984 | 1985 | 0.869 | 0.957 | 0.832 | 0.753 | 1.175 | 0.886 |
| 1985 | 1986 | 0.908 | 1.017 | 0.924 | 1.047 | 0.967 | 1.012 |
| 1986 | 1987 | 0.938 | 0.971 | 0.911 | 0.975 | 0.926 | 0.903 |
| 1987 | 1988 | 1.059 | 1.243 | 1.316 | 0.929 | 1.135 | 1.054 |
| 1988 | 1989 | 0.880 | 0.929 | 0.817 | 0.996 | 0.944 | 0.940 |
| 1989 | 1990 | 1.039 | 1.071 | 1.113 | 0.948 | 1.136 | 1.077 |
| 1990 | 1991 | 0.947 | 1.000 | 0.947 | 1.014 | 0.961 | 0.974 |
| 1991 | 1992 | 1.118 | 0.984 | 1.099 | 1.089 | 0.984 | 1.072 |
| 1992 | 1993 | 1.117 | 1.048 | 1.172 | 1.127 | 1.005 | 1.133 |
| 1993 | 1994 | 0.957 | 1.051 | 1.006 | 0.927 | 1.054 | 0.977 |
| 1994 | 1995 | 0.951 | 0.844 | 0.802 | 0.913 | 0.956 | 0.872 |
| 1995 | 1996 | 1.029 | 1.126 | 1.159 | 1.044 | 1.056 | 1.103 |
| 1996 | 1997 | 1.124 | 0.908 | 1.020 | 1.130 | 0.891 | 1.006 |
| 1997 | 1998 | 1.029 | 1.018 | 1.048 | 1.082 | 1.011 | 1.094 |
| 1998 | 1999 | 0.946 | 0.887 | 0.839 | 1.019 | 0.882 | 0.899 |
| 1999 | 2000 | 1.115 | 1.080 | 1.204 | 1.138 | 1.073 | 1.221 |
| 2000 | 2001 | 0.977 | 0.904 | 0.883 | 1.034 | 0.937 | 0.969 |
| 2001 | 2002 | 1.027 | 1.158 | 1.189 | 1.035 | 1.052 | 1.088 |
| 2002 | 2003 | 0.995 | 0.975 | 0.970 | 1.006 | 0.984 | 0.990 |
| 2003 | 2004 | 0.972 | 1.034 | 1.005 | 0.946 | 1.070 | 1.012 |
| 2004 | 2005 | 0.968 | 0.942 | 0.912 | 0.947 | 0.960 | 0.909 |
| 2005 | 2006 | 0.702 | 1.381 | 0.970 | 0.832 | 0.985 | 0.819 |
| 2006 | 2007 | 0.983 | 0.837 | 0.823 | 1.110 | 1.000 | 1.110 |
| 2007 | 2008 | 1.003 | 0.935 | 0.938 | 1.045 | 0.941 | 0.983 |
| 2008 | 2009 | 2.256 | 0.725 | 1.635 | 1.219 | 1.208 | 1.473 |
| 2009 | 2010 | 0.889 | 1.244 | 1.106 | 1.057 | 1.180 | 1.248 |

Table 3.7: Malmquist Productivity Index by Regions and Year (2)

| Start Year | End Year | End Year | | | Population Share | | |
|---|---|---|---|---|---|---|---|
| | | A1 | A2 | A3 | B1 | B2 | B3 |
| | | <10% | 10%-20% | >20% | <50% | 50%-75% | >75% |
| 1983 | 1984 | 1.171 | 1.161 | 1.243 | 1.505 | 1.161 | 1.243 |
| 1984 | 1985 | 0.910 | 0.835 | 0.818 | 0.678 | 0.835 | 0.818 |
| 1985 | 1986 | 0.980 | 0.982 | 1.015 | 1.063 | 0.982 | 1.015 |
| 1986 | 1987 | 0.919 | 0.921 | 0.849 | 1.018 | 0.921 | 0.849 |
| 1987 | 1988 | 1.124 | 1.106 | 1.120 | 0.988 | 1.106 | 1.120 |
| 1988 | 1989 | 0.891 | 0.882 | 0.976 | 0.954 | 0.882 | 0.976 |
| 1989 | 1990 | 1.086 | 1.116 | 1.055 | 0.969 | 1.116 | 1.055 |
| 1990 | 1991 | 0.938 | 0.975 | 1.040 | 0.975 | 0.975 | 1.040 |
| 1991 | 1992 | 1.014 | 1.130 | 1.275 | 1.108 | 1.130 | 1.275 |
| 1992 | 1993 | 1.117 | 1.117 | 1.291 | 1.112 | 1.117 | 1.291 |
| 1993 | 1994 | 0.968 | 0.994 | 1.036 | 0.861 | 0.994 | 1.036 |
| 1994 | 1995 | 0.857 | 0.842 | 0.823 | 0.901 | 0.842 | 0.823 |
| 1995 | 1996 | 1.083 | 1.092 | 1.288 | 1.213 | 1.092 | 1.288 |
| 1996 | 1997 | 0.948 | 1.040 | 1.202 | 0.906 | 1.040 | 1.202 |
| 1997 | 1998 | 1.085 | 1.075 | 1.070 | 1.057 | 1.075 | 1.070 |
| 1998 | 1999 | 0.923 | 0.858 | 0.779 | 1.004 | 0.858 | 0.779 |
| 1999 | 2000 | 1.164 | 1.451 | 1.158 | 1.348 | 1.451 | 1.158 |
| 2000 | 2001 | 1.032 | 0.905 | 0.734 | 1.224 | 0.905 | 0.734 |
| 2001 | 2002 | 1.031 | 1.228 | 1.304 | 0.908 | 1.228 | 1.304 |
| 2002 | 2003 | 0.949 | 1.016 | 1.075 | 1.080 | 1.016 | 1.075 |
| 2003 | 2004 | 0.978 | 1.033 | 1.100 | 0.912 | 1.033 | 1.100 |
| 2004 | 2005 | 0.879 | 0.868 | 1.048 | 0.882 | 0.868 | 1.048 |
| 2005 | 2006 | 0.847 | 0.725 | 1.059 | 0.834 | 0.725 | 1.059 |
| 2006 | 2007 | 1.389 | 0.652 | 0.942 | NaN | 0.652 | 0.942 |
| 2007 | 2008 | 0.946 | 1.576 | 0.749 | 0.697 | 1.576 | 0.749 |
| 2008 | 2009 | 1.525 | NaN | NaN | NaN | NaN | NaN |
| 2009 | 2010 | 1.252 | 1.289 | 0.938 | 1.649 | 1.289 | 0.938 |

Table 3.8: Yearly Changes of Inputs, Outputs and MOP

| Start Year | End Year | Change of Y | Change of X | MOP |
|---|---|---|---|---|
| 1983 | 1984 | 0.240 | 0.036 | 0.204 |
| 1984 | 1985 | -0.168 | -0.060 | -0.108 |
| 1985 | 1986 | -0.066 | 0.032 | -0.097 |
| 1986 | 1987 | -0.008 | 0.007 | -0.016 |
| 1987 | 1988 | 0.126 | 0.039 | 0.087 |
| 1988 | 1989 | -0.044 | 0.046 | -0.090 |
| 1989 | 1990 | 0.184 | 0.046 | 0.138 |
| 1990 | 1991 | -0.066 | 0.030 | -0.096 |
| 1991 | 1992 | -0.058 | -0.115 | 0.057 |
| 1992 | 1993 | 0.198 | 0.062 | 0.136 |
| 1993 | 1994 | 0.063 | 0.126 | -0.063 |
| 1994 | 1995 | -0.200 | -0.098 | -0.102 |
| 1995 | 1996 | 0.143 | 0.020 | 0.123 |
| 1996 | 1997 | -0.033 | 0.051 | -0.084 |
| 1997 | 1998 | 0.126 | 0.006 | 0.120 |
| 1998 | 1999 | -0.128 | 0.033 | -0.160 |
| 1999 | 2000 | 0.240 | 0.004 | 0.237 |
| 2000 | 2001 | -0.111 | 0.012 | -0.123 |
| 2001 | 2002 | 0.246 | 0.025 | 0.221 |
| 2002 | 2003 | 0.011 | -0.013 | 0.024 |
| 2003 | 2004 | -0.053 | 0.018 | -0.071 |
| 2004 | 2005 | 0.041 | -0.004 | 0.044 |
| 2005 | 2006 | -0.008 | 0.054 | -0.062 |
| 2006 | 2007 | 0.084 | 0.058 | 0.026 |
| 2007 | 2008 | 0.083 | 0.022 | 0.061 |
| 2008 | 2009 | 0.193 | 0.074 | 0.118 |
| 2009 | 2010 | -0.130 | -0.158 | 0.028 |

Figure 3.1: Malmquist Productivity and Its Components Over Time

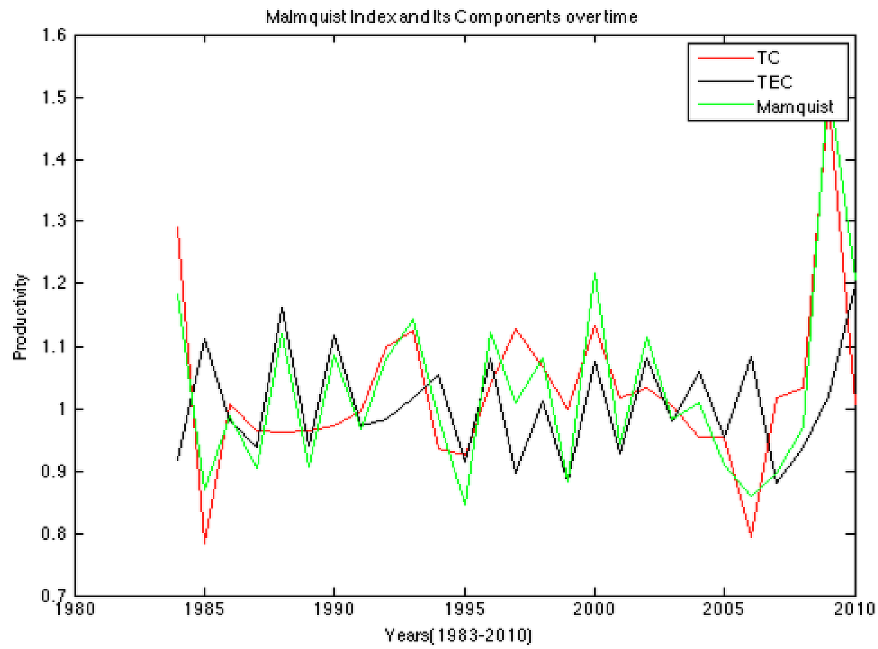



Figure 3.2: Malmquist Productivity Index by Region (Income/capita)

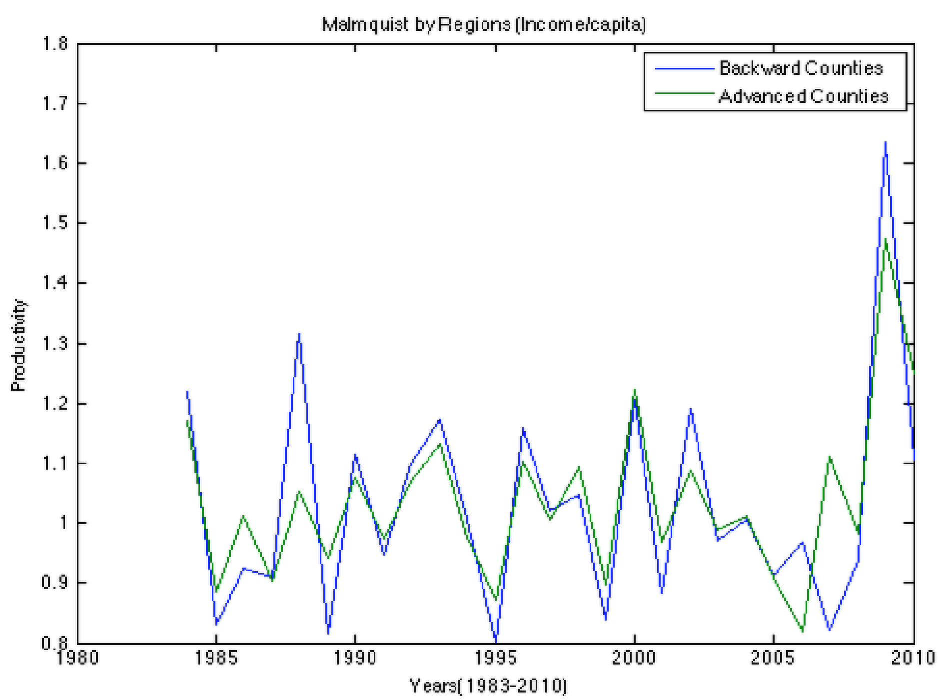


Figure 3.3: Malmquist Productivity Index by Region (Agricultural GDP Share)

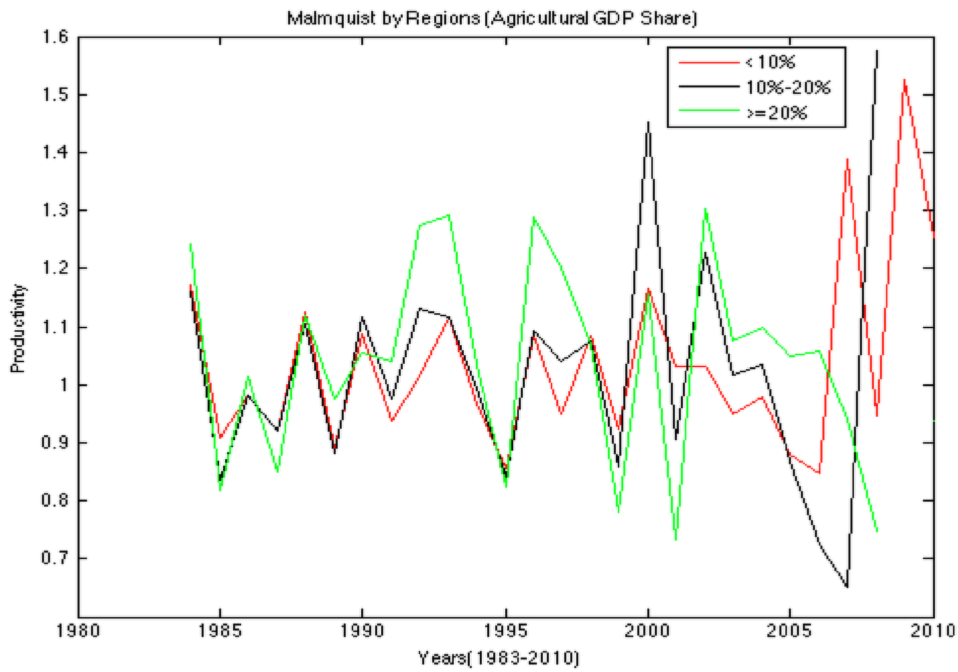



Figure 3.4: Malmquist Productivity Index by Region (Agricultural Population Share)

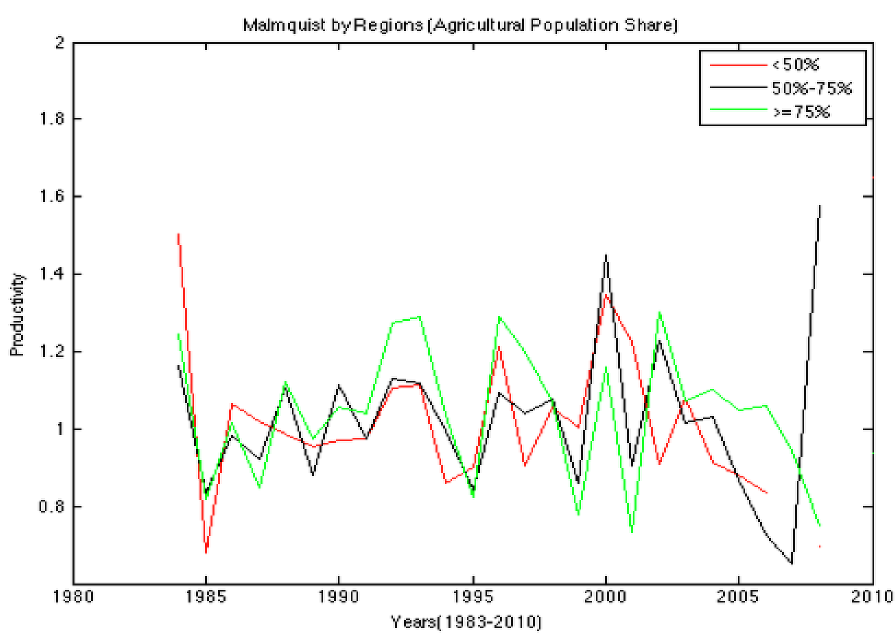


Figure 3.5: Decomposition of Malmquist Productivity Index by Region (Income)

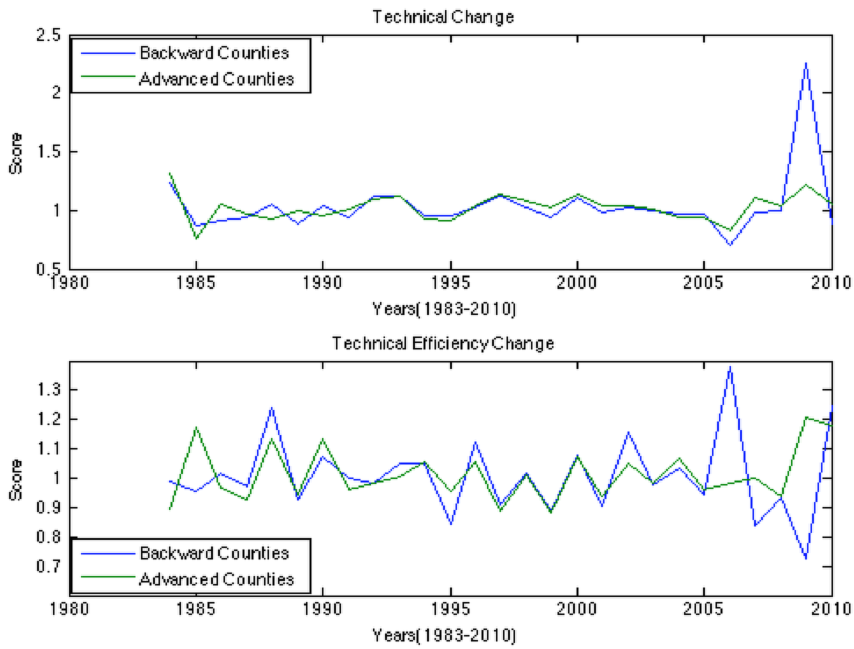



Figure 3.6: Decomposition of Malmquist Productivity Index by Region (Agricultural GDP Share)

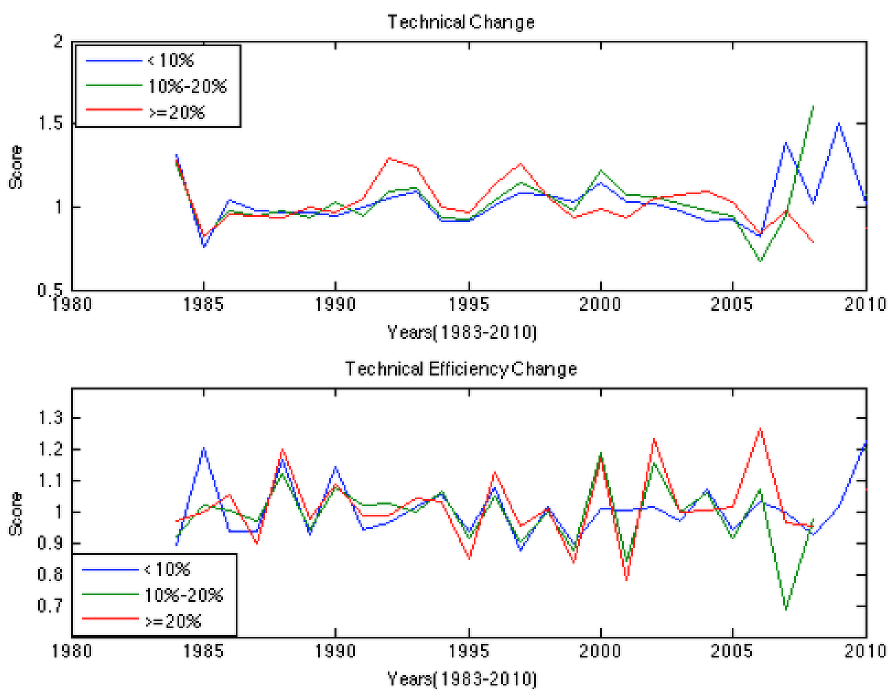
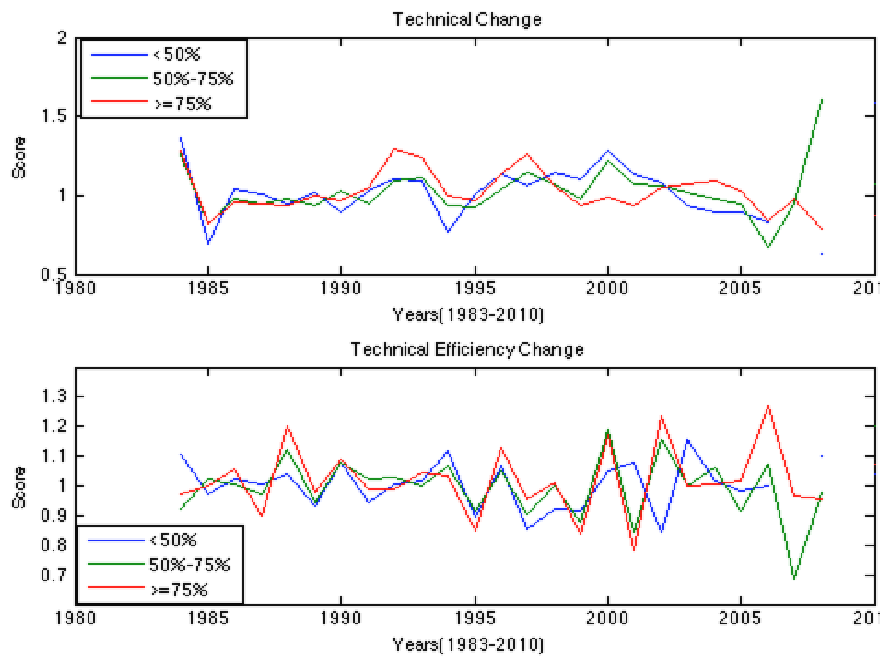


Figure 3.7: Decomposition of Malmquist Productivity Index by Region

(Agricultural Population Share)



# Chapter 4: Production Efficiency Variations in Chinese Agriculture: Policies Assessment of the Post-reform Period

## 4.1. Introduction

In the past decade, China has implemented a series of agricultural policy reforms to expand its agricultural sector and increase farmers' income. Most significant among them are entry into the World Trade Organization (WTO) in 2001, elimination of agricultural tax in 2006, and province-level agricultural machinery subsidy in 2007. Also, local governments engage in reallocation land of from the agricultural sector to industrial and commercial uses[25]. The mix of policies evolves as the Chinese agricultural sector becomes more commercialized and faces competitive pressures from imports. It is, therefore, of considerable interest to evaluate the impact of policies on agricultural production efficiency at both state and regional level.

In the year 2001, China's accession to WTO lowered barriers to agricultural imports, and its economic growth has generated new demands for agricultural commodities. China also liberalized trade policies to become more integrated with the world economy in order to complement domestic market reforms. Before 2001, agricultural trade was long dominated by state-owned trading enterprises, monopolies for strategic products that imported and exported at the behest of State planners (Martin, 2001). Trade policy reforms led directly to changes in policy instruments, such as tariffs, nontariff barriers, coverage of trade rules, and regional agricultural market (Ianchovichina and Martin, 2004). WTO accession gave China the

[25] See Ray (2014).

opportunity to press for reductions in these barriers to help create improved market access opportunities. In Shanxi province, the major crop was wheat before 2001. With the trade policy reform after accession to WTO and delimitation of local protection policy[26], wheat production was greatly affected. Farmers switched farmland use from wheat to other kinds of crops because planting wheat had no comparative advantage over nearby provinces after year 2001.

Between 2004 and 2011, China introduced a series of measures to increase farmers' income and enhance agricultural economic development. China is the most prominent example of a developing country that has shifted from taxing to subsidizing its agricultural sector. There has been increasing attention regarding China's shift from a taxer of agriculture to a subsidizer and the increasing allocation of resources to public spending (Gale et al., 2005, 2013)[27]. Because of the rapid growth of the industrial sector, the contribution of agricultural income tax to the government's fiscal revenue dropped from 40% in 1950 to 2.6% in 2002. Later, in 2006, the tax was eliminated nationwide. By Chinese official estimates, the value of agricultural tax reductions to farmers was at $21 billion yuan in year 2007.

The agricultural policies in China can be categorized into two historical stages. The first stage (1949-1997) subsidized consumers to support urban development, and was characterized by depressed food prices. The second stage (1998-current) implemented direct subsidies to farmers to enhance agricultural production and increase farmer's income. There are many kinds of output and input subsidy program such as grain, seeds, fertilizers, and machinery subsides at both national and provincial levels. In this chapter, we examine the

[26] Local protection policies include price control and trade barriers et. al.
[27] Gale et al. described China's agricultural policy changes up to 2013.

impact of agricultural machinery subsidy program starting from 2007 in Shanxi province. It is the most important subsidy program in Shanxi province and the amount of machinery subsidy has more than tripled in three years.

Inter-county variation in the DEA measure of efficiency and its components can be partially explained by differences in the physical, social, institutional environment and policy change. An analysis of the measured efficiency level can help to identify factors that enhance or hinder efficient resource utilization. This becomes helpful for public policy for improving efficiency and productivity. In this study we also identify a number of important factors and discuss their relevance as determinants of efficiency in agricultural production in Shanxi province in China. These factors are agricultural population share, agricultural GDP share[28], GDP per capita, and local infrastructure level (road density) of a county.

Even though a substantial amount of research has been done on agricultural performance and policy impact on Chinese agriculture, only a few studies have attempted to look into county-level data and explain the relationship of efficiency with explanatory factors. In addition, there is no systematic analysis in the existing literature on measuring the effect of machinery subsidy policy on agricultural production efficiency. Furthermore, most of the previous work focused on the national scale and used national level data. However, we use a newly constructed dataset at county level within a single province. This study fills the gap in studying the policy impact on efficiency and productivity in a regional scale.

In this chapter, using a panel data fixed effects regression in the second stage, we examine the inter-county variation in the DEA measure of efficiency and its components. We

[28] Contribution of agriculture and agriculture-related industries to gross domestic product (GDP) of the county.

also explain the observed variation in efficiency across different counties and over the years covered. The results of this study indicate that both WTO accession and elimination of agricultural income tax has positive impact on input efficiency. However, machinery subsidy has negative impact on Pareto-Koopmans efficiency. Local infrastructure level (road density) and GDP per capita have no significant effects on overall efficiency scores.

The rest of the chapter is organized as follows. In section 2, we briefly review the current literature. In section 3, we identify the scope of the three agricultural policies and how they are administered. In section 4, we provide an overview of the methodology. Section 5 describes the dataset, study region and reports the empirical findings. Variations in the efficiency scores across counties and years are explained in section 5. The final section concludes.

## 4.2. Literature Review

The agricultural sector remains one of the most important economic sectors in the national economy of China. The foundation for China’s current agricultural support program was started in year 2000, when rural poverty, underemployment, and high taxation of farmers were major concerns (Gale, 2013). Studies on China’s agricultural sector have generally focused on identifying the effects of agricultural policy (McMilan et.al, 1989; Fang and Beghin, 2000; Fu and Hou, 2008; Cater et.al, 2009; Wang, 2010; Zhang and Ye, 2005; Zheng et.al, 2013). China’s accession to WTO was reshaping the country’s policy landscape. Agricultural trade issues have been frequently studied after China’s accession to WTO. Chen (1999) concluded that trade reforms can increase efficiency of competitive sectors such as silk and vegetable products in China. Johnson (2000) emphasized high rates of productivity growth, especially for labor, will be important if China is to maintain its competitiveness in labor-intensive agricultural exports. Diao, Fan and Zhang (2003) analyzed the impact of China's WTO accession and concluded that rural income increased less than urban income.

There are quite a few studies on the impact of tax-for-fee reform (Kennedy, 2007; Ran & Qin, 2007; Wang and Shen, 2014). Gale et al. (2005) argued that China's agricultural tax abolition (and implementation of a direct grain subsidy) was symbolically important as a reversal of its historic taxation of farmers, but provided only a modest increase in rural incomes. Heerink et al. (2006)[29] found that agricultural tax abolition had a positive impact on agricultural production and income, with income effects ranging from 5 to 11%, and that it tended to reduce income inequality within villages. Zhou and Chen (2005) used the county-

[29] Heerink et al. (2006) used a general equilibrium model and simulation method with data from two villages in Jiangxi Province.

level data in seven provinces during 1999-2002, finding that the tax-for-fee reform contributed over 40% of farmers' net income increase during this period. Chen and Wang (2014) showed that the abolition of agricultural tax increased agricultural productivity and rural income. The existing literature on the impact of agricultural tax abolition on efficiency or productivity is thin, possibly due to lack of data.

There has been an increasing interest in China's agricultural subsidization and the rising level of investment in both direct farmer subsidies and other allocations of state funds to agriculture (Gale et al., 2005; Yu and Jensen, 2010; Huang et al., 2004, 2011)[30]. Based on a survey in Henan and Liaoning provinces, Xiao, et.al (2005) analyzed farmers' assessments and expectations regarding direct agricultural subsidies. They found that most farmers were satisfied with the program, but that some hoped for higher subsidy payments. Huang et al. (2013) used data from household-based surveys, focusing on China's grain, seeds, and machinery subsidy programs. Subsidies are mostly being given to the land contractor, not the tiller and machinery subsidy is based on farmers' actual purchase of machineries. Few of the papers are focus on the policy impact on agricultural production growth.

Several of the studies have sought to explain the observed variation in technical efficiency in terms of a number of farm characteristics such as the farmer's education and experience, contacts with agricultural extension stations, local policies, and farm size. In addition, under the household responsibility system, farm size remains small and fragmented in China, but no consensus exists on whether the small farm size and land fragmentation are a

[30] Yu and Jenson (2010) reviewed recent development of China's agricultural domestic support policy, especially the transition from taxing farmers and agriculture to providing direct subsidies to grain production and purchased inputs.

drag on productivity or efficiency (Wan and Cheng, 2001). The role of human capital has inspired many discussions. For agriculture sector, Huffman (1977), and for Chinese agriculture in particular, Fan (1991), Yang (1997), and Chen et.al (2009) have shown effects of farmers' schooling and labor migration on technical and allocative efficiency. However, none of these studies focus on a regional scale to ensure geographical homogeneity.

There has been only limited research studying the variation of production efficiency, especially in terms of policy impact. Factors such as infrastructure level and agricultural labor ratio have not been studied comprehensively. On the other hand, one of main barriers to understanding China’s agricultural subsidy policy is lack of access to data about the nature of subsidies at the farm or county level. To the best of our knowledge, there are no published analyses on the effects of agricultural machinery subsidy policy on agricultural production. We are particularly focusing on three important policies, which were implemented at both national and regional levels. They are WTO accession, elimination of agricultural tax, and subsidies on agriculture machinery.

## 4.3. Background of Agricultural Policies

### 4.3.1 WTO Accession

China's trade policies are moving from the national centrally planned regime to market-oriented regime considering global agricultural trade. Trade policy reforms flowing from China's accession to WTO led domestic producers to play an active role in developing its labor-intensive agricultural exports. In Shanxi province, in order to face the international competition, government announced new agricultural development strategy in 2003 and supported several products that have comparative advantage such as grain crops, grazing livestock, fresh fruit and vegetables.

A two-tier pricing system of paying a lower price for deliveries within the quota than those in excess of the delivery quota for each farm was long used to impose a substantial tax burden on China's farmers (Sicular, 1998). As Sicular observed, this made it possible to redistribute income from farmers to urban consumers in a more or less lump- sum fashion through sales of food to urban consumers at concessional, rationed prices. The existence of this system suggests that redistribution of incomes between the urban and the rural sector has been a key objective of rural policy in China (as in other countries). This policy has been used in reverse since 1996, with the procurement price set above market prices to create transfers to producers (Martin, 2001).

China's agricultural production and trade grew rapidly during 2002–2010, the period immediately after WTO accession. Agricultural GDP increased on average by 4.5 percent annually over this period. At the same time, agricultural exports increased by more than 15 percent annually, and total agricultural trade volume more than doubled from the level in

2002. In year 2014, China became the largest importer and fourth largest exporter of crop products in the world[31].

China's entry into the WTO has brought the country's farmers face-to-face with the world's most competitive producers, who are relatively large in production scale and abundant in agricultural infrastructure. Within China, concerns focus on the potentially negative effects of WTO accession on the profitability of land intensive products such as cotton and soybeans (Colby, Diao, and Tuan, 2001). With imports growing faster than exports during the post WTO accession years, China has reversed its long time status as a net agricultural exporting country to that of a net importing country since 2004. WTO entry also raises the pressure for farmland reform and agricultural labor migration. World competition intensified by WTO entry requires scale economies to reduce production costs, and many view China's present rural land system as a barrier to the transfer of land-use rights to increase the scale of production.

### 4.3.2 Elimination of the Agricultural Tax

Although the agricultural tax had played an important role in supporting industrialization and modernization, the central government planned to eliminate it for two main reasons. First, with the relative decrease in importance of the agricultural sector to in the total GDP, the agricultural tax no longer constituted an indispensable fiscal source. In 1950, the agricultural tax accounted for 40% of the nation's fiscal income. However, with the rapidly growing industry in the post-reform years, the contribution of agricultural tax to the

[31] From USDA database

government's fiscal revenue dropped to 2.6% in 2002[32]. Second, farmers, particularly for the low-income groups in rural area, seemingly could still regard the agricultural tax as a burden. Elimination of agricultural income tax can also give farmers incentive to stay working in the agricultural sector.

Historically, the "agricultural tax" was paid by delivering grain to authorities. By the 1990s, the tax was often paid in cash based on a farm household's capacity to produce grain (Mushtaq et.al, 2008). The tax rate was about 8% in the 1990s. In 2004, central government announced a national program to phase out the agricultural tax. The tax was eliminated nationwide in 2006. Chinese officials have estimated the value of agricultural tax reductions to farmers at $21 billion per year.

There are two stages of agricultural tax reform. The first stage is from 2000 to 2003, which is also called the tax-for-fee reform because its main content is to eliminate all the fees in rural China, leaving agricultural tax as the only burden on farmers. The second stage is from 2004 to 2005. Agricultural tax is gradually abolished at province level starting with Jiangxi province. In 2004, the government announced that the agricultural tax would be abolished within 5 years. In fact, it was abolished on January 1st, 2006. Since Shanxi province is not one of the pilot agricultural provinces, the agricultural income tax was abolished in year 2006.

[32] In 1950, agricultural tax revenue is about 40 percent of China's total tax revenue. This share shrank to 5.5 percent in 1979 and to less than 1 percent in 2004 (Department of Finance).

### 4.3.3 Agricultural Machinery Subsidy

In the past decade, there has been a sharp rise in the level of mechanization. Agricultural machinery subsidy program plays an important role in the modernization of Chinese agriculture. The goals of the subsidy program are to improve the agricultural production efficiency and to ensure the supply of major agricultural products.

The machinery subsidy program supports on average 7.3% of the total purchase price of the machinery for all provinces (Huang et.al, 2013). Because the machinery subsidy fund is from both central government and provincial government, each different province has its own subsidy budget. In Shanxi province, the machinery subsidy program, started in 2007, is based on farmers or agricultural cooperatives' actual purchase of machineries. The subsidized amount in 2007 was 95 million RMB[33]. In 2008, there were 1043 kinds of agricultural machine that could be subsidized and the total amount was 125 million RMB. The average subsidy expense was 20 million RMB at major agricultural counties, and 0.3 million at counties in mountain regions. The total amount of subsidies for machinery purchase increased to 580 million RMB in year 2010, six times the amount than in 2007.

There are 137 kinds of agricultural machinery products included in Shanxi province's subsidy program, such as land cultivating machinery, sowing machinery, fertilizing machinery, harvesting machinery, husbandry and aquaculture machinery, and agricultural products processing machinery. Each individual buyer can be subsidized for no more than one large machine (80 horse power or larger) and three tractor implements. Each cooperative buyer can be subsidized for no more than three large machines and 15 tractor implements. The number of machine and equipment that got subsidized was 117,000 units in year 2010.

[33] 1 USD = 6.5 RMB on Apr.1st, 2016

Because the average farm size is small (only 0.6 hectares per farm—versus more than 500 hectares per farm in the US), there is no way that a household can afford the machinery necessary to plow, plant and harvest. Therefore, there has been a rise in Specialized Custom Plowers[34], Planters and Harvesters (SCPPH) teams (Zhang and Yang, 2012). Most typically, SCPPH teams are made up of two to three family members. These teams act as private agents and purchase the machines for agricultural needs. People in the SCPPH team do not even have their own contract land or have rented out their own contract land.

## 4.4. The Methodology

### 4.4.1 The Econometric Model

The efficiency and productivity scores reported in Chapter 2 and Chapter 3 provide a productive performance audit for the individual county after the economic reforms. We disaggregate the overall efficiency into two components representing output and input efficiencies. The decomposition permits us to focus separately on the inputs like labor and agricultural machinery. To examine the policy impacts, we include policy dummy variables in the regression for each policy change.

We analyze up the DEA scores obtained in Chapter 2 with a fixed effects panel data regression in the second stage trying to explain the observed variation in efficiency across different states and over the years covered. We estimate five separate regressions with input efficiency, output efficiency, Pareto-Koopmans efficiency and specific input/output

[34] Privately operated firms that provide agricultural machinery services.

efficiency, as the dependent variables.

In this study, the explanatory variables included are share of the rural population, road density, income level, share of agriculture in the GDP, machinery subsidy, and policy dummies.

Consider the linear unobserved effects model for *n* observations and *t* time periods:

$$y_{it} = X_{it}'\beta + \alpha_i + u_{it} \quad (t = 1, \dots 10; i = 1, \dots 119),$$

**Equation 41**

where $y_{it}$ is the dependent variable observed for individual $i$ at time $t$ ; $X_{it}$ is the vector of regressors varying across individuals and time; $\alpha_i$ is the unobserved time-invariant individual effect and $u_{it}$ is the error term. Following the standard assumptions of a fixed effect model, $E(u_{it}) = 0$, $E(u_{it}^2) = \sigma_u$ , and $E(u_{it}\, u_{js}) = 0 \; for \; i \neq j \; and \; t \neq s.$

### 4.4.2 Explanatory Variables

The objective of this study is to investigate which factors can impact regional agricultural efficiency. We estimate separate regressions with input efficiency (IN), output efficiency (OUT), and Pareto-Koopmans efficiency (PK), and each components of the overall efficiency. The explanatory variables are road density, share of agriculture in the GDP, share of the agricultural population, GDP per capita, machinery subsidy, and policy dummies for WTO accession and abolition of agriculture tax.

Road density is the ratio of the length of the county's total road network to the county's total land area. It reflects the development of a region’s infrastructure level. Road density is also important for agricultural production because inputs and outputs need to be transported in and out at affordable cost. Further, in order to enhance the use of agricultural machinery, road is also the most important infrastructure. The road network includes all roads in the county: motorways, highways, state or national roads, secondary or regional roads, and other urban and rural roads. In this study, we only take the paved roads into account.

Agricultural GDP share can reflect how a county’s economy is constructed. In Shanxi province, counties with low share of agricultural GDP are counties close to big cities and consumer markets. By contrast, counties with high share of agricultural GDP are usually far from markets and have poor infrastructures.

The per capita GDP is especially useful when comparing one county to another because it shows the relative overall performance of the county’s economy. A higher per capita GDP tends to imply a more developed regional economy. In Shanxi province, counties with high GDP per capita are those counties with heavy industry like coal mining and steel producing industry.

Machinery subsidy is an independent variable that reflects the government’s support on new machinery purchases for different counties over years. We collect data on the amount of subsidy for each county from 2007 to 2010 in order to analyze its impact on agricultural efficiency. The value of machinery subsidy variable, for each county, is calculated using total subsidy amount divided by the machinery power used.

We have two dummy variables reflecting two policy changes, one associated with China's entry to WTO and the other with the agricultural tax elimination.

## 4.5. The Empirical Analysis

### 4.5.1 Data Description

A panel dataset of 119 counties in Shanxi Province is used to analyze the efficiency and productivity growth in China's agricultural sector over the period 1981-2010. This data set contains dependent variables and explanatory variables. The dependent variables are: (1) Overall efficiency; (2) Input efficiency; (3) Output efficiency; (4) Traditional input efficiency; (5) Modern input efficiency; (6) Machinery input efficiency; (7) Labor input efficiency. The independent variables are: (1) Road density; (2) Share of agriculture in the GDP; (3) Share of the rural population; (4) GDP per capita; (5) Machinery subsidy; (6) Accession to WTO dummy; (7) Elimination of agricultural income tax dummy. The road network data are from Shanxi Transportation Department 2014. Population data are from *Shanxi Agricultural Statistical Yearbook 1981-2010.* Machinery subsidy data are from *Department of Finance*. Efficiency score we used in this study are from previous two chapters. We collect the GDP data of each county and each year from *Department of Statistics of Shanxi Province*.

We show the detailed information about the dataset in Table 4.2. Summary statistics for the scores of overall efficiency and its components are reported. Summery statistics of explanatory variables are also reported.

### 4.5.2 Results

We estimate five separate regressions with input efficiency (IN), output efficiency (OUT), Pareto-Koopmans efficiency (PK), labor efficiency (LIE) and agricultural machinery efficiency (AME), as the dependent variables. Explanatory variables included are (1) road density (RD), (2) share of agriculture in the GDP, (3) share of the rural population, (4) GDP per capita, (5) subsidy per machine, (6) two policy dummies.

In the regression for Pareto Koopmans efficiency (PK), three variables, share of agriculture in the GDP, dummy variable for tax abolition and machinery subsidy variable are significant (Table 4.3). The estimate coefficient implies that every 1% increase of share of agriculture in GDP could increase of PK efficiency by 0.593%. Other two variables, road density and GDP/capita are not significant. The dummy variable for accession into WTO is not found significant.  Abolition of agricultural tax has a highly significant positive coefficient (0.172) with a ‘t’ ratio to 7.34 in the regression. This shows that the elimination of agricultural income tax since 2006 has enhanced PK efficiency score by 17.2%. An interesting point in Table 4.3 is that the coefficient of machinery subsidy is significantly negative (-0.0077). This means an increase of 10 thousand CNY in the subsidy could decrease the PK efficiency score by 0.7%. The negative sign and also the statistical significance of the coefficient reveal the subsidy policy reduce the agricultural performance in Shanxi province after 2007. The reason can be that farmers buy more machine and equipment to at reduced price due to the subsidy policy. However, the increased machinery power have not been used nor used properly into agricultural production. For example, the number of agricultural three-wheel transporter has increased a lot, but farmers in fact used the transporter for non-agricultural purpose.

In the regression for output efficiency (OUT) shown in Table 4.4, variables, agriculture population share (0.003), and road density (-2.56E-05) have no significant effect. GDP/capita (7.23E-07) also has small effect but the coefficient is not significant. Three variables, share of agriculture in the GDP, dummy variable for tax abolition and machinery subsidy variable are significant. A 1% increase of share of agriculture in GDP increase could cause the output efficiency increased by 0.171%. Counties with higher share agriculture in the GDP could mean a comparative advantage in farming and a higher allocative efficiency in the choice of crops resulting in higher output efficiency. This maybe an explanation for the positive effect of an increase in share of agriculture GDP. WTO accession (-0.025) with p-value is 0.106, and machinery subsidy (-0.0046) has negative effect on output efficiency. As pointed out above, WTO accession effected the planting of crops in Shanxi province. It is possible that the newly planted crops may have lower value than the previews crops (but higher net return), which can reduce the agricultural output value. The negative coefficient of subsidy in this regression implies a detrimental impact of the policy on output efficiency. There is no obvious explanation of this negative effect and remain to be explained future. No surprisingly, the tax policy (0.073) has positive effect on output efficiency. The coefficient of tax policy is also statistical significant. The end of agriculture income tax provides farmers more incentive to produce more outputs with greater flexibility.

In the regression for input efficiency (INP) shown in Table 4.5, share of agriculture in the GDP, dummy variable for tax abolition and machinery subsidy variable are significant. Share of agriculture in the GDP (0.5699) has a strong impact in the regression, which implies a 10% increase of GDP share could cause the input efficiency increase by 5.7%. Apparently counties with agriculture as the major economic activity can utilize the input use more

efficient. Comparing with the impact on output efficiency (Table 4.4), we find that agricultural GDP share has greater impact on input efficiency other than output efficiency. Agricultural population share (0.174) also has positive impact on input efficiency but the level is small. The two dummy variables, WTO accession (0.031) and tax reform (0.138) have positive impact on input efficiency. Although with P-value of 0.149, WTO is not quite significant. On the other hand, while subsidy has negative impact on input efficiency, the effect is significant. Farmers buy more machine and equipment than needed due to the subsidy policy. However, the increased machinery power have not been used nor used properly into agricultural production.

When we look at the regression for PK, IN and OUT as the whole picture, we find that WTO accession has positive impact on input efficiency but negative impact on output efficiency with the similar absolute values and moderately significant. This variable enhanced input efficiency but lowered output efficiency. In the regression for Pareto Koopmans efficiency, these opposing effects worked against each other. As a result, overall PK coefficient of WTO accession is not found significant. Road density and GDP per capita have no significant effects on all three efficiencies. On the other hand, machinery subsidy policy has negative coefficients in both input and output regressions. The impact on PK efficiency is most pronounced.

The dependent variable input efficiency is a summery measure of utilization of all inputs. One may wonder whether a negative or positive impact of any explanatory variable on overall input efficiency is holding a positive impact on some inputs, which might have been more than canceled by a negative impact on some other input. For a disaggregate analysis, we separate the input into two broad categories- traditionally input (labor and land) and modern

input (machinery, fertilizers and electricity) to better understand how the variables are affecting input efficiency.

In the regression for both traditional input efficiency (Table 4.6) and modern input efficiency (Table 4.7), the same three variables- agricultural GDP share, tax abolition and machinery subsidy are significant. Among them, agricultural GDP share has slightly higher impact on modern input (0.534) than traditional input (0.529). Similarly, the tax abolition dummy also has a stronger marginal effect for modern input (0.1504) compare to traditional input (0.1382). For the subsidy variable, the efficiencies are negative and almost the same in size for both modern input (-0.00523) and traditional input ((-0.00518). In the next stage, for a further disaggregate analysis, we run two aggressions. One is machinery (the modern input) and the other is labor (the traditional input).

In the regression for agricultural machinery efficiency (AME) shown in Table 4.8, share of agriculture in GDP (0.522) has a strong impact in the regression, which implies counties with agriculture as the major economic activity can utilize machinery use more efficiently. A 10 percent increase of agricultural GDP share can increase machinery usage efficiency by 5.2%. Tax reform (0.89) has a positive impact on machinery input efficiency. There is a negative impact of WTO accession (-0.026) on machinery but the coefficient is not significant. However, because we only have one year data before 2001, the impact of WTO accession still needs discussion and future study. It is no surprise that the subsidy (-0.0053) has negative effect on machinery efficiency. We explained the possible reasons above.

In the regressions for labor input efficiency (LIE) shown in Table 4.9 and machinery efficiency in Table 4.10, the same three variables, agricultural GDP share, tax abolition and

machinery subsidy are significant with same sigh. However, there are noticeable differences in magnitude of some of the coefficient between labor efficiency and machinery efficiency. The coefficient of the agricultural GDP share is smaller within (0.5228) for machinery compare to labor efficiency (0.6037). Similarly, the agricultural tax dummy has a smaller coefficient with (0.0890) for machinery than labor efficiency (0.1547). The subsidy variable has nearly an equal and negative impact in both regressions (about -0.0053).

As we have already noticed, subsidized access to machinery may have induced farmers to buy more machines than needed for productive use. This maybe an explanation of the negative impact of subsidy on machine use efficiency. However, the explanation of the negative impact on labor efficiency is not obvious. It is possible that widespread use of machinery diverted labor from directly productive activity to operation and maintenance of machinery. This reallocation of labor can reduce the labor efficiency.

## 4.6. Conclusions

In this chapter, we examine the inter-county variation in the DEA measure of efficiency and its components, and evaluate the impact of three important policies on agricultural efficiency at both national and county level. Our findings are in the following:

- WTO accession has positive impact on input efficiency but negative impact on output efficiency (although not strictly significant). In the regression for Pareto Koopmans efficiency, these opposing effects worked against each other.
- Elimination of agricultural income tax since 2006 have a strong positive impact on PK efficiency score
- Subsidy on machinery has negative impact on Pareto-Koopmans, output and input efficiency.
- Road density and GDP per capita have not significant effects on all efficiency scores.
- The agricultural GDP share variable has strong impact on all efficiency scores.

We end this chapter with a general observation about the trend in Chinese agriculture. With out migration of labor from agriculture to industry and, at the same time, diversion of land from farming to industrial use, availability of traditional inputs is declining over time. Improvement in input efficiency in respect of modern inputs becomes more critical for agricultural growth in China. Future policies directed towards that goal would be desired.

# Tables

Table 4.1: Inventory of Dataset

| Variables | Size | Period |
|---|---|---|
| Output Efficiency | 119 counties | 2000-2010 |
| Input Productivity | 119 counties | 2000-2010 |
| Overall Efficiency | 119 counties | 2000-2010 |
| GDP per Capita | 119 counties | 2000-2010 |
| Agricultural GDP Share | 119 counties | 2000-2010 |
| Total Population | 119 counties | 2000-2010 |
| Rural Population | 119 counties | 2000-2010 |
| Paved Road Length | 116 counties | 2000-2010 |
| Machinery Subsidy | 119 counties | 2007-2010 |

Source: Department of Agriculture: *Shanxi Agricultural Statistical Yearbook 1981-2010*
Shanxi Transportation Department 2014
Department of Finance

Table 4.2: Summary Statistics: All Counties and All years[35]

| Variables | Mean | Stdev | Max | Min |
|---|---|---|---|---|
| Crop efficiency | 0.914 | 0.178 | 1.000 | 0.201 |
| Livestock efficiency | 0.923 | 0.159 | 1.000 | 0.183 |
| Labor efficiency | 0.738 | 0.280 | 1.000 | 0.115 |
| Mon Irrigated land efficiency | 0.732 | 0.323 | 1.000 | 0.008 |
| Irrigated land efficiency | 0.882 | 0.228 | 1.000 | 0.086 |
| Machinery efficiency | 0.778 | 0.279 | 1.000 | 0.087 |
| Fertilizer efficiency | 0.796 | 0.265 | 1.000 | 0.101 |
| Elec. efficiency | 0.788 | 0.307 | 1.000 | 0.031 |
| PK efficiency | 0.727 | 0.277 | 1.000 | 0.160 |
| Output efficiency | 0.916 | 0.144 | 1.000 | 0.317 |
| Input efficiency | 0.764 | 0.243 | 1.000 | 0.247 |
| Modern input efficiency | 0.784 | 0.231 | 1.000 | 0.222 |
| Traditional input efficiency | 0.788 | 0.231 | 1.000 | 0.246 |
| Ag. Population Share | 0.796 | 0.132 | 0.988 | 0.074 |
| Road density | 63.276 | 67.197 | 1488.19 | 17.087 |
| Ag. GDP share | 0.154 | 0.118 | 0.566 | 0.002 |
| GDP/Capita | 11201 | 11645 | 103592 | 442 |
| Subsidy per machine | 202.22 | 280.84 | 2165.37 | 5 |

[35] The unit of road density is km/hundred km$^2$. The unit of GDP/capita is Chinese Yuan (CNY). The unit of subsidy is ten thousand CNY.

Table 4.3: Regression of Overall PK Efficiency

| | | | | |
|---|---|---|---|---|
| Fixed-effects (within) regression | | Number of obs | = | **674** |
| Group variable: **code** | | Number of groups | = | **111** |
| R-sq: within | = **0.1353** | Obs per group: min | = | **1** |
| between | = **0.1308** | avg | = | **6.1** |
| overall | = **0.1123** | max | = | **11** |
| | | F(**7,556**) | = | **12.43** |
| corr(u_i, Xb) | = **0.0036** | Prob > F | = | **0.0000** |

| pk | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| AGlaborShare | **.1781182** | **.1928681** | **0.92** | **0.356** | **-.200721** | **.5569575** |
| RoadDensity | **.0000819** | **.000126** | **0.65** | **0.516** | **-.0001657** | **.0003295** |
| AgriculturalGDPshare | **.5939396** | **.1276498** | **4.65** | **0.000** | **.3432048** | **.8446743** |
| GDPCapita | **5.95e-07** | **1.32e-06** | **0.45** | **0.653** | **-2.00e-06** | **3.20e-06** |
| policyWTO | **.0073441** | **.0242513** | **0.30** | **0.762** | **-.0402912** | **.0549794** |
| policyAGTAX | **.1728537** | **.0235543** | **7.34** | **0.000** | **.1265874** | **.21912** |
| Subsidy | **-.0077439** | **.0012291** | **-6.30** | **0.000** | **-.0101582** | **-.0053297** |
| _cons | **.435844** | **.1635479** | **2.66** | **0.008** | **.1145966** | **.7570913** |
| sigma_u | **.22871797** | | | | | |
| sigma_e | **.17644713** | | | | | |
| rho | **.6268991** | (fraction of variance due to u_i) | | | | |

F test that all u_i=0: F(**110, 556**) = **7.84** Prob > F = **0.0000**

Table 4.4: Regression of Output Efficiency

| | | | |
|---|---|---|---|
| Fixed-effects (within) regression | | Number of obs | = 674 |
| Group variable: **code** | | Number of groups | = 111 |
| R-sq: within | = **0.0775** | Obs per group: min | = 1 |
| between | = **0.0864** | avg | = 6.1 |
| overall | = **0.0652** | max | = 11 |
| | | F(**7,556**) | = 6.67 |
| corr(u_i, Xb) | = **0.0041** | Prob > F | = 0.0000 |

| outputEff | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| AGlaborShare | .0034553 | .1245912 | 0.03 | 0.978 | -.2412718 | .2481824 |
| RoadDensity | -.0000256 | .0000814 | -0.31 | 0.753 | -.0001856 | .0001343 |
| AgriculturalGDPshare | .1716619 | .0824607 | 2.08 | 0.038 | .0096892 | .3336345 |
| GDPCapita | 7.23e-07 | 8.55e-07 | 0.85 | 0.398 | -9.57e-07 | 2.40e-06 |
| policyWTO | -.0253851 | .0156661 | -1.62 | 0.106 | -.0561571 | .0053869 |
| policyAGTAX | .0730709 | .0152159 | 4.80 | 0.000 | .0431833 | .1029586 |
| Subsidy | -.0046099 | .000794 | -5.81 | 0.000 | -.0061695 | -.0030503 |
| _cons | .8922638 | .1056506 | 8.45 | 0.000 | .6847406 | 1.099787 |
| sigma_u | .10248474 | | | | | |
| sigma_e | .11398342 | | | | | |
| rho | .44702995 | (fraction of variance due to u_i) | | | | |

F test that all u_i=0: F(**110, 556**) = **3.84** Prob > F = **0.0000**

Table 4.5: Regression of Input Efficiency

```
Fixed-effects (within) regression               Number of obs      =       674
Group variable: code                            Number of groups   =       111

R-sq:  within  = 0.1176                         Obs per group: min =         1
       between = 0.0794                                        avg =       6.1
       overall = 0.0789                                        max =        11

                                                F(7,556)           =     10.59
corr(u_i, Xb)  = -0.0801                        Prob > F           =    0.0000
```

| InputEff | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| AGlaborShare | .173954 | .1720815 | 1.01 | 0.313 | -.1640553 | .5119634 |
| RoadDensity | .0001016 | .0001125 | 0.90 | 0.367 | -.0001194 | .0003225 |
| AgriculturalGDPshare | .5699345 | .1138922 | 5.00 | 0.000 | .346223 | .793646 |
| GDPCapita | 1.76e-07 | 1.18e-06 | 0.15 | 0.881 | -2.14e-06 | 2.50e-06 |
| policyWTO | .0312636 | .0216376 | 1.44 | 0.149 | -.0112377 | .073765 |
| policyAGTAX | .1382726 | .0210157 | 6.58 | 0.000 | .0969927 | .1795525 |
| Subsidy | -.0053 | .0010967 | -4.83 | 0.000 | -.0074541 | -.0031459 |
| _cons | .4663158 | .1459213 | 3.20 | 0.001 | .1796912 | .7529403 |
| sigma_u | .19651414 | | | | | |
| sigma_e | .15743032 | | | | | |
| rho | .60909337 | (fraction of variance due to u_i) | | | | |

```
F test that all u_i=0:     F(110, 556) =     7.62            Prob > F = 0.0000
```

Table 4.6: Regression of Traditional Input Efficiency

| | | | |
|---|---|---|---|
| Fixed-effects (within) regression | | Number of obs | = 674 |
| Group variable: **code** | | Number of groups | = 111 |
| R-sq: within | = **0.1114** | Obs per group: min | = 1 |
| between | = **0.1829** | avg | = 6.1 |
| overall | = **0.1415** | max | = 11 |
| | | F(**7**,**556**) | = 9.96 |
| corr(u_i, Xb) | = **0.0931** | Prob > F | = 0.0000 |

| traditionalinput | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| AGlaborShare | .1058656 | .1624516 | 0.65 | 0.515 | -.2132282 | .4249594 |
| RoadDensity | .0000943 | .0001062 | 0.89 | 0.375 | -.0001142 | .0003029 |
| AgriculturalGDPshare | .5289463 | .1075186 | 4.92 | 0.000 | .317754 | .7401385 |
| GDPCapita | 1.14e-06 | 1.11e-06 | 1.02 | 0.308 | -1.05e-06 | 3.33e-06 |
| policyWTO | .0163056 | .0204267 | 0.80 | 0.425 | -.0238173 | .0564285 |
| policyAGTAX | .1206673 | .0198396 | 6.08 | 0.000 | .0816975 | .1596371 |
| Subsidy | -.0051889 | .0010353 | -5.01 | 0.000 | -.0072224 | -.0031553 |
| _cons | .5602765 | .1377554 | 4.07 | 0.000 | .2896919 | .830861 |
| sigma_u | .18024176 | | | | | |
| sigma_e | .14862028 | | | | | |
| rho | .59527338 | (fraction of variance due to u_i) | | | | |

F test that all u_i=0: F(**110**, **556**) = **7.14** Prob > F = **0.0000**

Table 4.7: Regression of Modern Input Efficiency

| | | | |
|---|---|---|---|
| Fixed-effects (within) regression | | Number of obs | = **674** |
| Group variable: **code** | | Number of groups | = **111** |
| R-sq: within | = **0.1359** | Obs per group: min | = **1** |
| between | = **0.0418** | avg | = **6.1** |
| overall | = **0.0489** | max | = **11** |
| | | F(**7,556**) | = **12.49** |
| corr(u_i, Xb) | = **-0.1804** | Prob > F | = **0.0000** |

| mordeninput | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| AGlaborShare | **.1809091** | **.1613207** | **1.12** | **0.263** | **-.1359635** | **.4977817** |
| RoadDensity | **.0000816** | **.0001054** | **0.77** | **0.440** | **-.0001255** | **.0002886** |
| AgriculturalGDPshare | **.5345912** | **.1067701** | **5.01** | **0.000** | **.324869** | **.7443133** |
| GDPCapita | **-5.12e-07** | **1.11e-06** | **-0.46** | **0.644** | **-2.69e-06** | **1.66e-06** |
| policyWTO | **.024123** | **.0202845** | **1.19** | **0.235** | **-.0157206** | **.0639666** |
| policyAGTAX | **.1504916** | **.0197015** | **7.64** | **0.000** | **.111793** | **.1891901** |
| Subsidy | **-.0052304** | **.0010281** | **-5.09** | **0.000** | **-.0072498** | **-.003211** |
| _cons | **.4963572** | **.1367964** | **3.63** | **0.000** | **.2276562** | **.7650582** |
| sigma_u | **.20334327** | | | | | |
| sigma_e | **.14758572** | | | | | |
| rho | **.65497332** | (fraction of variance due to u_i) | | | | |

F test that all u_i=0: F(**110, 556**) = **8.59** Prob > F = **0.0000**

Table 4.8: Regression of Machinery Efficiency

| | | | |
|---|---|---|---|
| Fixed-effects (within) regression | | Number of obs = | 674 |
| Group variable: code | | Number of groups = | 111 |
| R-sq: within = | 0.0779 | Obs per group: min = | 1 |
| between = | 0.1880 | avg = | 6.1 |
| overall = | 0.1544 | max = | 11 |
| | | F(7,556) = | 6.71 |
| corr(u_i, Xb) = | 0.2135 | Prob > F = | 0.0000 |

| machinery | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| AGlaborShare | -.1152755 | .1847162 | -0.62 | 0.533 | -.4781025 | .2475515 |
| RoadDensity | .0001238 | .0001207 | 1.03 | 0.305 | -.0001133 | .0003609 |
| AgriculturalGDPshare | .5228956 | .1222544 | 4.28 | 0.000 | .2827585 | .7630326 |
| GDPCapita | 9.91e-08 | 1.27e-06 | 0.08 | 0.938 | -2.39e-06 | 2.59e-06 |
| policyWTO | -.0262213 | .0232262 | -1.13 | 0.259 | -.0718432 | .0194007 |
| policyAGTAX | .0890708 | .0225587 | 3.95 | 0.000 | .04476 | .1333816 |
| Subsidy | -.0053273 | .0011772 | -4.53 | 0.000 | -.0076395 | -.003015 |
| _cons | .7891693 | .1566353 | 5.04 | 0.000 | .4814999 | 1.096839 |
| sigma_u | .21420399 | | | | | |
| sigma_e | .16898932 | | | | | |
| rho | .61637417 | (fraction of variance due to u_i) | | | | |

F test that all u_i=0: F(110, 556) = 8.38 Prob > F = 0.0000

Table 4.9: Regression of Labor Efficiency

```
Fixed-effects (within) regression               Number of obs      =       674
Group variable: code                            Number of groups   =       111

R-sq:  within  = 0.1038                         Obs per group: min =         1
       between = 0.0498                                        avg =       6.1
       overall = 0.0573                                        max =        11

                                                F(7,556)           =      9.20
corr(u_i, Xb)  = -0.1096                        Prob > F           =    0.0000
```

| labor | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| AGlaborShare | .189635 | .2027876 | 0.94 | 0.350 | -.2086884 | .5879585 |
| RoadDensity | .000118 | .0001325 | 0.89 | 0.373 | -.0001423 | .0003784 |
| AgriculturalGDPshare | .6037959 | .134215 | 4.50 | 0.000 | .3401655 | .8674263 |
| GDPCapita | -7.05e-08 | 1.39e-06 | -0.05 | 0.960 | -2.80e-06 | 2.66e-06 |
| policyWTO | .0392242 | .0254985 | 1.54 | 0.125 | -.0108611 | .0893094 |
| policyAGTAX | .1547602 | .0247657 | 6.25 | 0.000 | .1061144 | .2034061 |
| Subsidy | -.0054355 | .0012923 | -4.21 | 0.000 | -.007974 | -.0028971 |
| _cons | .4115568 | .1719594 | 2.39 | 0.017 | .0737873 | .7493264 |
| sigma_u | .21945802 | | | | | |
| sigma_e | .18552205 | | | | | |
| rho | .58321232 | (fraction of variance due to u_i) | | | | |

```
F test that all u_i=0:     F(110, 556) =     7.28            Prob > F = 0.0000
```

# Chapter 5: Conclusions

## 5.1 Summary and Conclusion

This dissertation studies the productivity and efficiency of Chinese agriculture in Shanxi province after the economic reforms. We apply a non-parametric DEA method to estimate the technical efficiency of 119 counties in the sample. We estimate the input efficiency, output efficiency, and Pareto-Koopmans efficiency. We also analyze total factor productivity growth from 1982-2010. Finally, we examine the inter-county variation in the DEA measure of efficiency and its components, and evaluate the impact of three important policies and explanatory variables on agricultural efficiency at county level.

We find that there is clear evidence of an overall increase in input efficiencies, output efficiencies and PK efficiency over time. The Malmquist productivity increased at 1.2% per year on average. Also, WTO accession has positive impact on input efficiency but negative impact on output efficiency. It enhanced input efficiency but lowered output efficiency. In the regression for overall efficiency, these opposing effects worked against each other. Subsidy on machinery has negative impact on Pareto-Koopmans, output and input efficiency. The agricultural GDP share variable has strong impact on all efficiency scores.

## 5.2 Limitations of This Study and Directions for Future Research

We need to note some limitations of the data used and to acknowledge that the results should be interpreted with some caution. In the first place, we are using county-level aggregated data. Not only are the input–output data aggregates over a county, they are also aggregated over crops and, hence, across different varieties of any crop (like traditional and high yielding varieties of rice or wheat). Similarly, inputs (like fertilizers) are also aggregated.

An effective way to reduce the limitation of the non-statistical nature of DEA is to generate a statistical distribution of the estimates through techniques like bootstrapping. With the help of bootstrapping, we can empirically construct the confidence interval for the estimates and provide statistical information such as standard error of the result.

As more data gathered from a wider survey area become available, the methodology proposed in this dissertation can be employed to draw more reliable conclusions. A promising line of future research relative to this dissertation would be a comprehensive farm market level study of the local agriculture.

One of the weakest points of the entire study is the lack of detailed information about the local economies and geographical characteristics of individual counties. This has severely restricted the explanatory power of the regressions reported in chapter 4. An important line of future research would be to identify and collect information on the factors what may adequately explain the observed variation in efficiencies and productivity growth across counties. That would greatly enhance the usefulness of this study for policy purposes.

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