PRODUCTIVITY GROWTH, CONVERGENCE, AND DISTRIBUTION DYNAMICS IN THE KANSAS FARM SECTOR

by

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BS., Egerton University, Njoro-Kenya, 1998
MS., Michigan State University, MI, 2004

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2009

Abstract

This study applies recent advances in nonparametric techniques to investigate growth in labor productivity and convergence in the Kansas farm sector for a panel of 564 farms for the period 1993-2007. The study seeks to answer two questions: *First*, what are the sources of labor productivity growth in the farm sector and *second*, is there evidence of convergence or divergence in the growth rate of labor productivity across farms?

Following Kumar and Russell (2002), the nonparametric production frontier approach is used to decompose the growth in output per worker into three components: efficiency change, technical change, and capital deepening. Kernel density estimation methods are used to investigate the evolution of the entire distribution of labor productivity and the effects of each of those three growth components on the evolution of the distributions over the sample periods, 1993-07, 1993-02, and 1996-05. Cross-sectional regression methods (ordinary least square, partial linear model, and smooth coefficient model) are later employed to test for convergence in labor productivity growth and the contribution of each of the components to the convergence process.

The study yields the following results. *First*, capital deepening and technical change are the main sources of labor productivity growth. Efficiency change is a source of regress in productivity growth. *Second*, technical change is not neutral. *Third*, the distribution of labor productivity in the farm sector has remained unimodal. Capital deepening and technical change are the main factors contributing to labor productivity distributions. *Fourth*, despite no evidence of technological catching-up, efficiency change and capital deepening contributed to

convergence in the growth rate of labor productivity during the entire sample period. Technical change contributes to productivity disparity in the 1993-07 period. The contribution of technical change in the 1993-02 and 1996-05 periods are mixed with evidence of both convergence and disparity. *Finally*, the results for the 1993-07 period support the existence of a positive relationship between the annual growth in technical change and initial level of capital-labor ratio, suggesting that technology is embodied in capital accumulation.

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Acknowledgements

"*For waging war you need guidance, and for victory many advisers*"
Proverbs 24:6

I would like to express my sincere gratitude to some of the individuals who guided and helped me during my doctoral study. First, my doctoral work would not have been possible without the graduate assistantship from the Department of Agricultural Economics. I am deeply indebted to the individuals who admitted me into the doctoral program and made my funding possible.

I am much more indebted to my major Professor, Michael Langemeier, for initiating me in the "world" of productivity and efficiency analysis, and patiently guiding me through my dissertation. I cannot forget the many times we had lively discussions on productivity analysis and the critical inputs and extremely useful suggestions I received from him. I also benefitted immensely from Professor Allen Featherstone for his critical thinking and remarkable knowledge on my research topic. Dr. Featherstone worked very closely with me throughout my doctoral tenure enabling me to get two publications prior to my graduation. The patience, kindness and friendship I received from those two mentors made my PhD experience an enjoyable one. I deeply appreciate your keen interest in my studies, research endeavors, and personal well-being.

I also want to express my sincere gratitude to Professor John Crespi and my colleagues in the Research Methodology Class: Andrew Ojede, Kara Ross, and Lija Mo. Professor Crespi provided very useful suggestions during the proposal stage of my dissertation and my colleagues provided the necessary critique to polish my work.

I am thankful to Drs. Kevin Dhuyvetter and Dong Li for serving on my committee and providing valuable feedback on my dissertation. I would like to express my appreciation to professors in both the Departments of Agricultural Economics and Economics from whom I have learned a lot about applied economics and econometrics. I also want to acknowledge the friendship and moral support I received from the following individuals:

To David Nduiki: thank you for believing in my dream when there was little to believe in and inspiring me to soldier on.

To Dr. Gerald Nyambane: thank you for encouraging me to stand against odds even when the stakes were so high.

To Dr. Othelia Pryor: your resilience, determination, and friendship inspire me. Thank you for always showing me that godliness with contentment is great gain.

To Dr. George Opit: I am deeply grateful for your wisdom and counsel. I will forever cherish the friendship that you and Lucy accorded my family.

To Drs. Juvenal Higiro and Ebenezer Ogunyinka: thank you for standing with me in some of the critical moments in my life. I will forever value your friendship.

To Andrew Ojede and Yacob Zereyesus: your friendship and companionship made this journey enjoyable. I have great faith that we can accomplish a lot together yet.

To Drs. Lanier Nalley and John Michael Riley: I will always cherish your kindness and friendship.

To Raymond and Catherine Mutava: you are more than friends, you are allies in this walk of life.

To Wilbert Kigen: you are a rare friend and a gentleman. Thank you for welcoming me in Manhattan, Kansas.

To Asumini Anita: thanks for always reminding me where we have come from and where we should be going.

To all the dear friends who have been praying for me: climbing this "academic mountain" would not have been possible without your support.

Finally, I want to express my sincerest gratitude to my wife, Lucy Muracia, for her unwavering support during the writing of this dissertation. Our daughter, Joan Furaha, has been my greatest source of inspiration for finishing this dissertation.

To all, this is "*Ebenezer- Thus far the LORD has helped us*" I Samuel 7:12

Dedication

This dissertation is dedicated to my parents, William & Nyamiza Mugera, and to the memory of my brother Ali Elegwa.

CHAPTER 1 - INTRODUCTION

1.1. Problem Statement

This dissertation seeks to answer two key questions pertaining to the Kansas farm sector: *First*, what are the sources of labor productivity growth and *second*, is there evidence of productivity convergence/divergence across farms and time as postulated by neoclassical growth theory? To provide answers for those questions, the main focus of this study is the computation of labor productivity growth and its decomposition into components attributed to efficiency change, technical change, and capital accumulation, hereafter referred to as the tripartite decomposition. The study also investigates issues of labor productivity convergence/divergence across farms, distinguishing the contribution of the different tripartite components by means of a frontier approach. Unlike previous studies in productivity growth in general, and agricultural productivity growth in particular, this study will use nonparametric econometrics (i.e., bootstrap data envelopment analysis (DEA) and kernel estimation methods) to estimate the bias-corrected technical efficiency scores and to analyze the evolution of the cross-farm distribution of labor productivity in terms of the tripartite components. This study is related to a growing literature which develops a link between economic growth, the nonparametric production frontier, and convergence.

Labor productivity, or output per unit of labor, is a widely used indicator of efficiency in the general economy. It is a general consensus in economics that productivity growth is a major source of economic growth and welfare improvement. For instance, empirical evidence indicates that labor productivity accounted for roughly half of the growth in per capita gross domestic product (GDP) in the OECD[1] countries over the last two decades, with the other half primarily accounted for by increases in labor utilization, i.e., changes in demographics, unemployment and labor force participation rates (Margaritis et al., 2005).

Over the past two decades, GDP per capita has grown faster in the United States than almost every other advanced industrialized country. This strong per capita growth is attributed largely to strong labor productivity growth. The major factors driving this strong labor productivity growth are capital deepening and efficiency gains. Skill improvement (i.e., additional education, training, and on-the-job experience) is ruled out as a factor in explaining the accelerated productivity growth (Council of Economic Advisers, 2007). Capital deepening occurs when businesses invest in more or better machinery, equipment, and structures that make it possible for their employees to produce more output. Efficiency gains, or technical change, are achieved when businesses are able to produce more output with the same amount of inputs (Council of Economic Advisers, 2007).

United States agricultural productivity growth compares favorably to agricultural productivity growth in other industrialized countries and to productivity growth in the overall U.S. economy. Empirical evidence attributes the high growth rate in agricultural productivity to the growth of labor productivity (Fuglie et al., 2007; Mundlak, 2005). Fuglie et al. (2007) decomposed the source of labor productivity growth for the time period 1981-2004 into three components: total factor productivity (TFP), increase in inputs per worker, and improvement in quality of labor due to better education and more experience. Labor productivity grew at a rate

[1] The Organization for Economic Cooperation and Development (OECD) is an international organization of thirty countries that accept the principles of representative democracy and a free market economy. It provides a setting where governments can compare policy experiences, seek answers to common problems, identify good practice and coordinate domestic and international policies

of 3.7 percent during this period compared to output that grew at a rate of 1.6 percent. The growth rate in labor hours worked declined by 2.1 percent. The main sources of labor productivity growth were TFP (2.4%), increase in inputs per worker (1.2%), and improvements in quality of labor (0.1%).

Empirical studies examining economic growth often deal with the decomposition of output growth to factor accumulation and technical change using the production function approach. For the case of U.S. agriculture, underlying this exercise rests the broader and more fundamental question of what has been the driving force behind the high growth rate in labor productivity, relative to other inputs, in the farm sector. Family farms have been found to be both scale and technically inefficient and greater technical efficiency is found to be a driving trend towards increased farm size and dwindling competitiveness of small family farms (Paul et al., 2004). This structural transformation raises serious concerns about the future of family farms.

The specification and estimation of production frontiers and the measurement of the productivity and efficiency associated with production units has received substantial research attention in recent years, both at a micro and macro level. At a macro level, economic growth research has been dominated by three major strands. One strand has focused on the tendency for productivity growth rates to converge or diverge across regions over times (Barro and Salai-i-Martin, 1991; 1992). The other strand, going back to Solow (1956; 1957), has focused on decomposing growth into components attributed to capital deepening and technological progress. A third strand of research is relatively new; this method is based on the Malmquist productivity indices that decompose economic growth into components attributed to efficiency change, technological progress, and capital deepening (Kumar and Russell, 2002; Henderson and Zelenyuk, 2007).

The last 15 to 20 years have witnessed a striking resurgence of interest in empirical analysis of economic growth using both the endogenous growth and the exogenous growth theories. The endogenous growth theories, attributed to Romer (1986) and Lucas (1988), emphasize physical and human capital as the principle engines of growth and difference in technology across countries and over time as the source of convergence or divergence. The exogenous growth theory, attributed to Solow (1956; 1957), points to technological progress as the source of persistent growth and capital accumulation as the source of convergence or divergence.

Following Solow (1957), a large body of empirical research attributes TFP growth as the source of economic growth in the long run. However, underlying this analysis is the assumption that all units of production are efficient and, therefore, TFP growth is attributed to technological progress. However, as pointed out by Färe et al. (1994), inefficiency in production exists when production takes place inside the technological frontier because output can be increased given the same technology and input levels. The farther one is below the frontier, the larger is the inefficiency and so measuring inefficiency is equivalent to measuring the distance from the production frontier. Efficiency gains occur as this distance decreases. Technological progress occurs when the frontier shifts. Distinction between the two is important because once the frontier is reached, efficiency gains cannot occur without technological progress (Sharma et al., 2007; Maudos et al., 2000). Therefore, the possibility that part of TFP growth may have its origin in efficiency gains was neglected, thus leading to biased estimates of technological progress in the presence of inefficiencies (Salinas-Jime´nez, 2003). To avoid this bias, it becomes necessary to estimate sources of productivity change by decomposing TFP growth into two components, efficiency change and technical progress (Rae, et al., 2006; Salinas-Jime´nez, 2003; Färe et al., 1994).

The economic growth literature provides divergent views as to what are the sources of labor productivity growth. Solow (1957) held the view that labor productivity was primarily driven by TFP and capital accumulation. Mankiw et al. (1992) and Young (1995) held the view that factor accumulation is the crucial determinant of labor productivity growth. This view was questioned by Klenow and Rodrigues-Care (1997) and Hall and Jones (1999) who suggested that TFP growth is the main source of labor productivity growth. Färe et al. (1994) were the first authors to decompose TFP growth into two components, namely, technical change and efficiency change, and found that efficiency affects the growth of labor productivity. Various empirical studies on economic growth have also focused on convergence/divergence using standard regression analysis. Quah (1997) has argued that analyses based on standard regression methods focusing on the first moments of the distribution cannot adequately address the convergence issue. Quah (1997, p.29) advocated for the examination of the dynamics of the entire cross-section distribution.

A turning point in the analysis of labor productivity growth is the novel work of Kumar and Russell (2002), hereafter KR, which unified the above ideas. Following Färe et al. (1994), they decomposed labor-productivity growth into three components: (1) technical change (shifts in the world production frontier), (2) efficiency change (movements toward or away from the frontier), and (3) capital accumulation (movement along the frontier). In the spirit of Quah (1997), they analyzed the evolution of the distribution of labor productivity in terms of the tripartite decomposition. There is a growing literature building on the work of Kumar and

Russell (2002) in analyzing labor productivity growth and convergence across nations, regions, and states. Salinas-Jime´nez (2003) studied labor productivity growth and convergence processes in Spain. Henderson and Russell (2005) extend the KR approach by decomposing capital into physical capital and human capital. Enflo and Hjertsrand (2006) employed the tripartite decomposition of labor productivity to address the issues of regional productivity growth and convergence in Europe. Henderson and Zelenyuk (2007) extended the KR study by decomposing the sample into two groups (developed and developing countries) and analyzing catch-up effects for the whole sample, and between and within those two groups. Henderson and Zelenyuk (2007) applied recent bootstrapping techniques to the data envelopment analysis (DEA) framework to overcome the common critique that the DEA approach assumes away any measurement errors. Delgado-Rodriguez and Álvarez-Ayuso (2008) employ the tripartite decomposition approach to analyze the process of productivity growth and convergence in the European Union.

Turning to U.S. agriculture, many reasons have been proposed to explain agricultural productivity growth. Those include agricultural research and development (Huffman and Evenson, 1992; McCunn and Huffman, 2000), human capital (Huffman and Evenson, 1992; McCunn and Huffman, 2000, Yee et al., 2002), and production contracts (Key and McBride, 2003). A stylized fact that has emerged from both theoretical and empirical work is that public agricultural research, public extension, and education have significant positive impacts on productivity growth. Some empirical studies have focused on the decomposition of total factor productivity into components attributed to technical change, technical and allocative efficiency, and scale efficiency while others have focused on convergence or divergence of TFP in agriculture (Managi and Karemera, 2004; Ball et al., 2004).

Despite the recent theoretical and empirical advances in labor productivity analysis, there is no empirical study that has analyzed the sources of labor productivity growth at the farm level using the tripartite decomposition approach. Neither has any study investigated issues of convergence/divergence of productivity growth at the farm level. The tripartite decomposition facilitates the interpretation of labor productivity developments and can provide a first indication of the driving factors behind labor productivity growth. An accurate measure of efficiency change, technical change, and capital accumulation improvement for the farm sector provides useful information to indicate how economic welfare is being advanced through labor productivity gains. The motivation for decomposing productivity growth into various subcomponents is deep-seated in economics and emanates from the revival of the economic profession's interest in the sources of economic growth (Grosskopf, 2003. p.464). Productivity growth has been a more important source of economic growth in the U.S. agriculture than it has been in the private nonfarm economy (Jorgenson and Gollop, 1992; Ball et al., 1999).

1.2. Objectives

The purpose of this study is to use production frontier methods to analyze the distribution of labor productivity at the farm level in Kansas. In the spirit of Kumar and Russell (2002), labor productivity growth is decomposed into three components attributed to (1) efficiency change, (2) technical change, and (3) capital deepening. The evolution of the cross-farm distribution of labor productivity growth is analyzed in terms of the tripartite decomposition and the relative contribution of each of those components to convergence. Specifically, following the hypothesis of catching-up in labor productivity growth, the study investigates whether there is convergence or divergence in the farm sector (i.e., whether small farms grow faster than larger farms through technological diffusion).

The specific objectives of this study are as follows:

1. To estimate the technical efficiency and scale efficiency indices of the Kansas farm sector for the period 1993-2007 using the nonparametric production function approach (i.e., data envelopment approach, DEA).
2. To decompose labor productivity into components attributed to efficiency change, technical change, and capital deepening.
3. To analyze the entire distribution of labor productivity growth and the effects of each of the three growth components on the evolution of the distribution over the sample period using kernel estimation methods.
4. To determine whether there has been a tendency for labor productivity to converge across Kansas farms and whether the convergence can be explained by the tripartite decomposition components using regression analysis.

1.3. Rationale and Methodological Approach

This study makes two main contributions to the productivity analysis literature in agriculture. *First*, to the best of our knowledge this study is the first study to use the tripartite decomposition approach to analyze labor productivity in U.S. agriculture. *Second*, we use the recent advances in data envelopment analysis to compute the cross-farm efficiency scores. Another distinct feature of this study is that it deals with farm-level data, not aggregate, state, or national data that may suffer from aggregation bias. Labor productivity growth analysis can provide a useful tool in helping design policies for improving the economic health of the farm sector. Efficiency change provides insight about the effectiveness with which the best available knowledge and technology are accessed and translated into productivity growth while technical change provides a measure of the level of innovativeness demonstrated in the farm sector. Capital deepening provides a measure of capital intensity in the farm sector.

The traditional DEA approach commonly used in productivity studies has been criticized on two fronts: *first*, it is not able to account for statistical noise and potentially suffers from outliers in the data (Murillo-Zamorano, 2004; Enflo and Hjertsrand, 2006; Henderson and Zelenyuk, 2007). *Second*, it assumes away any measurement errors by holding that there is no imprecision in the data (Liu, 2008; Wu et al., 2006). Nonetheless, a number of techniques to account for those limitations have been suggested in the efficiency literature, such as the techniques for detecting possible outliers (Cazals et al., 2002) and stochastic programming approaches (Cooper et al., 1998). Notably, Simar and Wilson (1998, 2000a; 2000b) and others have introduced bootstrapping into the DEA framework to allow for consistent estimation of the production frontier, corresponding efficiency scores, as well as standard errors and confidence intervals. Thus, to circumvent problems associated with the potential inability of DEA to account for statistical noise, this study computes the efficiency scores using the bootstrap DEA approach as suggested by Simar and Wilson (1998; 2000a; 2000b).

CHAPTER 2 - LITERATURE REVIEW

This chapter relates relative efficiency and labor productivity growth to other strands of research within the economics literature. The brief theoretical review touches upon strands of economic growth theories relevant to the issues discussed later and serves as a background for understanding and appreciating the literature on labor productivity decomposition and the issues of convergence and divergence. A selective review of empirical literature on efficiency and productivity in the U.S. agriculture is also presented. The goal of this section is to provide the economic theory underpinning productivity analysis and review recent relevant literature on the decomposition of labor productivity.

Productivity (total and labor) plays a prominent role in economic growth, business cycles, and labor demand. The scope of productivity discussion in the literature has been wide. On the one hand is the narrow perspective of the productivity of a single resource, such as capital, land, or labor or in the production of a particular commodity at a given point in time in a given state, region, or country (e.g., the productivity of research and development in agriculture across the U.S. states). On the other hand is the broad perspective of productivity of all resources (i.e., total factor productivity) in generating growth of aggregate output over a long period across a number of states, regions, or countries. The extensive empirical literature in this area has focused on two main issues: the convergence hypothesis (whether the poor economies are catching up with the rich) and the sources of economic growth and convergence or divergence.

Both positive and normative perspectives have been adopted in the analysis of productivity. The former perspective has focused on accounting for observed variations across commodities or locations at a point in time while the later has focused on policies designed to influence productivity and growth.

2.1. Theory of Economic Growth

The evolution of the literature on economic growth and productivity development has resulted in a broad consensus on the factors driving productivity growth across geographical regions and the patterns of convergence and divergence. There are two main theories that explain economic growth: (1) the exogenous growth theory associated with Solow (1956; 1957) and (2) the endogenous growth theory associated with Roomer (1986; 1989; 1990) and Lucas (1988). We begin with the standard neoclassical growth model where growth is exogenous followed by the endogenous growth models.

2.1.1. *Exogenous Growth Models*

The traditional neoclassical growth theory, which introduced the concept of productivity analysis and convergence, begins with the work of Solow (1956). The Solow model postulates convergence of per capita incomes, driven primarily by the assumption of diminishing returns to capital accumulation at the economy wide level. The Solow model allows for factor substitutability to achieve a stable equilibrium. This model is consistent with stylized facts related to economic growth such as the relative constancy of capital-output ratio over time and factor income shares. The model postulates that growth in per capita output will converge to zero in the steady state. The steady state growth, however, is dependent on exogenous technology, implying that government policies have no effect in the long run stability of the economy. Thus, the dynamics of the model imply that initial differences in per capita income and capital endowments across countries will vanish in the long run. In the steady state, diminishing returns are offset by technological progress, the principle source of long-run economic growth. One implication of the model is that countries with similar technologies and preferences will converge to the same steady state output level.

The computation of TFP based on economic theory was pioneered by Solow in his seminal paper, "Technical Change and the Aggregate Production Function" (Solow, 1957). In this paper, Solow devised a framework for distinguishing the contribution of labor, capital, and technical change to economic growth, thus forming the basis of the growth accounting exercise. The growth of labor productivity in the U.S. is decomposed into components attributable to increases in capital per worker and changes in TFP. Solow postulated a constant returns to scale aggregate production function with capital and labor as inputs and a Hicks neutral shift parameter, A_t, as follows:

(2.1) $$O_t = A_t F(K_t, L_t),$$

where O_t is aggregate real output, K_t is capital input and L_t is labor input. In the outlined model, Solow treated A_t as exogenous. Solow assumed that each input is paid its marginal product and differenced the above equation logarithmically to arrive at the following equation:

(2.2) $$R_t = g_t - s_{kt} g_{kt} - s_{lt} g_{lt}.$$

In the above equation, g_t denotes the growth rate of aggregate output, g_{kt} the growth rate of capital, g_{lt} the growth rate of labor and s_{kt} (s_{lt}) the share of capital (labor) in output. The term on the left had side, R_t, is the famous Solow residual, which is a measure of the rate of growth of technology, A_t. According to Solow, this rate of productivity growth is constant and exogenous. Solow's article has been the foundation of a vast literature on productivity and economic growth, including some of the articles later reviewed in this section.

The Solow growth model has faced several criticisms based on empirical observations: (1) the model predicts stable growth independent of policy decisions, (2) it predicts convergence of countries with technologies and preference to the same steady state output levels, and (3) predicts that returns to capital are higher in developing countries than in developed countries, thus implying that most new investment would occur in developing countries. Empirical evidence suggests a positive correlation between investment rates and growth and little evidence of convergence from a broad sample of countries (De Long, 1988; Romer, 1989).

2.1.2. *Endogenous Growth Models*

The endogenous growth models are an attempt to overcome some of the problems associated with the Solow model. The models take two main approaches: (1) remove the fixed factor constraint of the Solow model by allowing for constant returns to reproducible factors or (2) endogenize technological change by explicitly modeling the introduction of new technologies.

The seminal paper by Arrow (1962) was one of the first attempts to endogenize technical progress in the Solow model by incorporating the concept of learning-by-doing. In this framework, the level of knowledge is itself a productive factor which depends upon past levels of investment. Thus, each firm learns from the investment activity of other firms as well as from its own investment. The productivity of a firm is assumed to be an increasing function of cumulative aggregate investment for the industry and knowledge acquired by labor is a fraction of the total capital stock. Increasing the capital stock through investment by the firm raises the level of knowledge elsewhere, stemming from the notion that knowledge is a public good, and thus causing the economy as a whole to operate subject to increasing returns. The ultimate determinant of economic growth in this model is, however, non-amenable to policy action and endogenous technological change is reflected in level effects as opposed to growth effects.

The Romer (1986; 1989) models also adopt a learning-by-doing framework. The key innovation in these papers is that the very process of being engaged in a productive activity generates learning effects and allows those who are engaged in productive tasks to become more efficient at performing them. The models posit that knowledge generation may be positively related to the scale of economic activity, which is assumed to be proportional to capital accumulation and sustained growth is tied to constant returns to reproducible factors. Romer (1989) postulates that knowledge displays increasing marginal productivity but investment in research technology that is used to create new knowledge, the ultimate determinant of long-run growth produced by investment in research technology, exhibits diminishing returns. In other words, creation of new knowledge by one firm raises productivity possibilities for other firms and, therefore, increasing returns in goods production. Thus, the learning spillover effects ensure that the efficiency of the labor input at the social level will improve. The three important features of this model are that: (1) knowledge creates externalities, (2) output production exhibits increasing returns, and (3) there are decreasing returns in production of new knowledge. Thus, acquisition of knowledge by rational economic agents explains endogenous technical change. The striking implication of this model is that there is no longer convergence in income per capita across countries.

The Lucas (1988) model builds on the notion that capital should be considered as a broad concept that includes both human and intangible capital. In this model, economic growth is driven by accumulation of knowledge or human capital, which is a public good. The model posits that human capital accumulation by each worker plays a dual role. First, it raises the worker's productivity and second, it creates an additional external effect by raising the average level of human capital in the economy. Therefore, the model postulates that a worker with a given endowment of human capital is more productive in an economy in which the average level of human capital is higher. This implies that the social marginal product of human capital is higher than the private marginal product for each worker with human capital. Thus, there is need for public policy to internalize the externality otherwise workers would accumulate less human capital than would be socially optimal. One implication of this model is that cross country convergence depends on the extent of international knowledge spill-over that allow less productive economies to catch up with more advanced economies.

The Romer (1990) model treats knowledge as a private good, rather than a pure public good as in the Romer (1986) model, in order to overcome the limitations of the notion of a public good and allow for rational agents to undertake purposeful innovation of technology. Thus, the inventor is rewarded for what she does by being allowed to exclude other economic agents from employing her inventions or changing them. Adopting the assumption that knowledge is a mixed good, with both public and private characteristics, implies that economic agents consciously engage in technological change and innovation by responding to market incentives and are able to internalize the net marginal benefits from undertaking innovative activity.

Helpman (1990) models innovation as an activity which produces "blueprints" for the manufacture of a variety of final products. Thus, learning by doing takes place in the innovation industry so that the unit labor cost of producing a blueprint diminishes as the cumulative number of existing blueprints increases. Thus, a learning externality is created in the innovation industry in which there is competition and free entry. The final product is modeled as a monopolistically competitive one. The rate of growth of blueprints is the rate of innovation in the economy and its steady state value is endogenously determined.

Helpman and Rangel (1999) addressed the issue of how the economy reacts to the arrival of a new major technology by focusing on the interplay between technological change and two types of human capital- technology-specific experience and education. They show that technological change that requires more education and training produces an initial slowdown in productivity. On the other hand, technological change that lowers the training requirements can produce either a bust or a boom. Three key properties that determine those outcomes are: (1) the productivity of inexperienced workers, (2) the speed with which experience raises productivity, and (3) the level of general skills required to operate the new technology.

2.1.3. *Convergence Analysis*

The classical literature provides two main concepts of convergence: beta-convergence and sigma-convergence. Absolute beta-convergence is a said to occur if poor economies tend to grow faster than rich economies. This concept is often estimated using the following regression:

(2.3) $$\gamma_{i,t,t+T} = \alpha + \beta \log(y_{i,t}) + \varepsilon_{i,t}.$$

In the above equation, $\gamma_{i,t,t+T}$ is economy *i*'s annualized growth rate of GDP between time *t* and *t* + T, $\log(y_{i,t})$ is the logarithm of economy *i*'s GDP per capita at time *t*, and $\varepsilon_{i,t}$ is the error. The data are said to exhibit absolute beta-convergence if $\beta < 0$ (Salai-i-Martin, 1996, p.1020). This follows from the assumption of diminishing returns, which imply higher marginal productivity of capital in a capital-poor country.

Sigma-convergence is said to occur if the dispersion of a group of economies real per capital GDP levels tend to decrease over time. If we have the following relationship:

(2.4) $$\sigma_{t+T} < \sigma_t,$$

where σ_t is the time t standard deviation of $\log(y_{i,t})$ across i. A necessary condition for sigma-convergence is the existence of beta-convergence, although beta-convergence itself does not guarantee a reduction in the distribution dispersion. Thus, beta-convergence is a necessary but not sufficient condition for sigma-convergence (Salai-i-Martin, 1996).

An alternative approach for testing convergence was proposed by Bernard and Durlauf (1996) and Bernard and Jones (1996c). This approach is based on the time series properties of the productivity growth series and the issue of convergence is examined by testing whether long-run forecasts of productivity differences tend to zero as the forecasting horizons tends to infinity. Convergence is tested using the augmented Dickey-Fuller (ADF) and cointergration tests.

Islam (2003) provides a comprehensive review of the convergence literature. The author points out that the convergence research has helped both the exogenous and endogenous growth theories to adapt and evolve. The research has brought to the forefront the existence of large technological and institutional differences across countries and given rise to new methodologies for quantifying and analyzing these differences. Absence of absolute convergence in large samples of countries has forced the exogenous growth theorists to recognize the differences in steady state income levels across countries. Empirical findings of conditional convergence have led to the emergence of endogenous growth models that have convergence implications.

2.1.4. *Summary*

The neoclassical growth theory (Solow, 1956; 1957) postulates convergence of per capita incomes that are driven by the assumption of diminishing returns to capital accumulation at the economy wide level. Thus, in the long run, initial differences in per capita income and capital endowments vanish as technological progress offsets diminishing returns (Mulder and De Groot, 2007). The new or endogenous growth theory yields a more diverse picture concerning patterns of convergence (Lucas, 1988; Romer 1986, 1990). The theory builds on the notion that capital should be considered as a broad concept that includes human and intangible capital. Economic growth is driven by accumulation of human capital, which is a public good. Therefore, convergence across nations depends on the extent of knowledge spillover that allows less productive economies to catch up with more advanced economies. The theory also suggests that growth differentials may persist or even increase due to learning effects, externalities, and market imperfections that allow for economy-wide increasing returns to capital accumulation and the existence of multiple steady states. Technological diffusion and knowledge spillover are also local rather than global, which raises the possibility that convergence patterns depend on the spatial dimension of technological progression (Mulder and De Groot, 2007).

2.2. Empirical Studies on Labor Productivity Decomposition

The articles reviewed in this section are inspired by two major turning points in the empirical analysis of economic growth and convergence. First, Bernard and Jones (1996a) observed that the empirical convergence literature, prior to 1996, envisaged a world in which convergence, or the lack of it, is a function of capital accumulation. This focus, the authors argue, ignores a long tradition among historians and growth theorists that emphasizes technological progress as a driving force behind economic growth. Therefore, Bernard and Jones (1996a, p.1043) called for both theoretical and empirical research on economic growth and convergence to focus more carefully on technology. Specifically, the call was to unravel why different countries have different levels of technology, how technology changes over time, and how to measure technology and the contribution of technology to convergence versus contribution of capital-labor ratio.

Second, a vast majority of earlier empirical studies on economic growth and convergence evolved from standard cross-country regression analysis that take a negative correlation between initial productivity and average annual growth in subsequent periods as evidence of the unconditional convergence hypothesis. Quah (1996a) has argued compellingly that analyses based on standard regression methods focusing on the first moments of the distribution cannot adequately address the convergence issue.

There are two distinct definitions of convergence in empirical work based on whether the analysis is cross-sectional or time-series. Cross-sectional analyses focus on the tendency of countries with relatively high initial levels of output per worker to grow slowly (beta convergence) or the reduction in cross-sectional variance of output per worker (sigma convergence) (Barro and Salai-i-Martin, 1991, 1992). Absolute or beta convergence is said to occur if poor economies tend to grow faster than rich ones while sigma convergence is said to occur if the dispersion of real per capita GDP levels for a group of economies tends to decrease over time (Salai-i-Martin, 1996). Time-series studies test for convergence using the framework of cointergration under the assumption that initial conditions do not matter within samples (Bernard and Jones, 1996b).

Quah (1993, 1996a, 1996b, 1997) has criticized the appropriateness of the cross-sectional methodology. The traditional regression analysis approach reveals information on whether a single economy is tending towards its own steady state. Quah (1996b) suggested that the issues of convergence should be related to the evolution of the whole income distribution, i.e., one wants to know what is happening to the entire cross-sectional distribution of economies. Quah (1996b) employed distributional dynamics and described the evolution of cross-country per capita income distribution between 1960 and 1988 as increasingly polarized into "twin peaks" or "convergence clubs" of rich and poor countries. Quah (1997) suggests that this bimodal income distribution is attributed to the pattern of technological diffusion. The approach by Quah (1996b) turns out to be more informative than regression analysis which gives no insight on whether poor countries are catching up with rich ones.

2.2.1. *Kumar and Russell (2002)*

Kumar and Russell (2002) addressed the concerns of Bernard and Jones (1996a) by decomposing labor productivity growth into components attributed to efficiency change, technical change, and capital accumulation. This was achieved by the construction of a world production frontier using deterministic methods requiring no specification of the functional form for the technology or any assumptions about market structure or the absence of market imperfections. Each of those three components of labor productivity growth is calculated for 57 countries (industrial, newly industrialized, and developing countries) over the 1965-1990 period.

One output and two inputs are used in the analysis. The measure of aggregate output is real GDP and the measures of inputs are capital stock per worker (capital) and real GDP per worker (employment) measured in 1985 international prices. Following the argument of Quah (1993, 1996a and 1997) that analyses based on standard regression methods focusing on first moments of the distribution cannot adequately address the convergence issue, Kumar and Russell (2002) examined the evolution of the entire distribution of the three growth factors using kernel based methods.

Although the Kumar and Russell (2002) analysis is quite simple, it yielded some striking results. *First*, there is substantial evidence of technological catch-up with the degree of catch-up directly related to initial distance from the frontier. However, technological catch-up has not contributed to convergence because the degree of catch-up is not related to initial productivity. *Second*, technical change is decidedly nonneutral with no improvement at very low capital/labor ratios, modest expansion at relatively low capital/labor ratios, and rapid expansion at high capital/labor ratios. *Third*, both growth and bimodal polarization are driven primarily by capital deepening.

This study does not purport to provide fundamental reasons for the phenomena that are being measured but it is rather a growth-accounting exercise with a new twist. The findings from this study are consistent with different models of economic growth and different fundamental causes of the growth process. The study develops a link between economic growth and convergence literature and the deterministic frontier production function literature.

2.2.2. *Salinas-Jime´nez (2003)*

Salinas-Jime´nez (2003) studied labor productivity growth and the convergence process undergone by Spain between 1965 and 1995. Total factor productivity (TFP) gains were decomposed into technological progress and efficiency change by means of Malmquist productivity indices. Labor productivity growth was decomposed into components attributed to technical change, efficiency gains, and capital accumulation. The analysis was carried out at the aggregate level and for the main sectors of private activity using one output (gross value added at factor cost) and two inputs (private capital and labor). Separate production frontiers were estimated for the economy as a whole and for the agriculture (excluding energy), construction, and private service sectors. Furthermore, the dynamics of the overall distribution of labor productivity and the relative contribution of each of its components to convergence were analyzed.

Three main conclusions were drawn from the analysis. *First*, Spain operated on an average efficiency level of around 80 percent between 1965 and 1990 with efficiency change accounting for approximately 15 percent of labor productivity growth. Thus, capital accumulation and technological progress were the main driving forces behind labor productivity growth. *Second*, Spain experienced some level of technological catch up and convergence in efficiency levels whereby the less efficient regions in 1965 underwent greater efficiency gains than the more efficient ones. *Finally*, analysis of the overall evolution of labor productivity distribution and the relative contribution of each of its components indicated that none of those components alone were able to explain the evolution of the distribution. However, changes in efficiency were found to be the main driving force explaining the changes in the distribution of output per worker.

2.2.3. *Henderson and Russell (2005)*

Henderson and Russell (2005) extended the KR analysis by decomposing capital into physical and human capital. Using nonparametric production-frontier methods, labor productivity growth was decomposed into four components: technical change, efficiency change, and physical and human capital accumulation. The study was inspired in part by early theoretical work on endogenous growth models pioneered by Lucas (1988) and Romer (1990). Empirical studies indicated that human capital accumulation accounts for a significant proportion of productivity growth or of cross-country differences in productivity levels. Thus, introduction of human capital into the KR framework results in a quadripartite decomposition of labor productivity. The study analyzed the contribution of these four components to the growth of productivity and the shift in the worldwide distribution of productivity using 52 countries (industrial, newly industrialized, and developing countries) over the 1965-1990 period. Human capital was measured based on the survey of wage equations evaluating the returns to education by Psacharopoulos (1994).

The study generated several interesting results. *First*, about one-third of the increase in mean productivity attributed by KR to the accumulation of physical capital was the result of the accumulation of human capital. *Second*, efficiency change, with some help from physical and/or human capital accumulation accounted for the qualitative shift from the unimodal to bimodal distribution. This is in contradiction to the KR conclusion that physical capital accumulation accounts for the shift in the distribution from a unimodal to a bimodal distribution. *Third*, the study confirmed the KR conclusion that technical change was decidedly nonneutral, with virtually all progress taking place in the highly capital-intensive region of input space. In principle, the study lends support to both theoretical and empirical research, as well as simple intuition, suggesting that human capital is an element of the growth process that is too important to ignore.

2.2.4. *Nissan and Niroomand (2006)*

Nissan and Niroomand (2006**)** look deeper into the results provided by Kumar and Russell (2002) by disaggregating their data for 57 countries into four segments. Each of those segments is concerned with a particular set of countries categorized as low income, low-middle income, high-middle income, and high income. The motivation for segmentation by income levels is due to the unequal spatial distribution of income, technology, economic growth, and economic opportunities across income groups. Countries with similar income tend to converge together resulting in multiple steady states in output per worker. The purpose of the study was to test for the equality of means using analysis of variance and to propose a measure of convergence for the four groups of countries as well as all the countries using regression methodology.

The paper concluded that inter-country dispersion among the four income groups was wider in 1990 as compared to 1965 for both the efficiency index and output per worker. Also, with the exception of efficiency, the contribution to growth of output for technology and capital accumulation differed among the groups. Convergence was found to prevail for the efficiency index for each of the groups as well as for all the countries in contrast to output per worker where divergence prevailed, especially when the countries were grouped into one set.

2.2.5. *Enflo and Hjertstrand (2006)*

Enflo and Hjertstrand (2006) addressed the issue of regional productivity growth and convergence for 69 Western European regions from France, Germany, Italy, Spain, and Ireland between 1980 and 2002. Labor productivity was decomposed into efficiency change, technical change, and capital accumulation using DEA. Unlike previous studies on productivity, this study follows Simar and Wilson's (1998, 2000a) approach in using bootstrapping methods to incorporate stochastic elements into the DEA models. The bootstrap method allows the authors to gauge the relative sensitivity of the estimated efficiency scores to the inherent bias of DEA. The authors specifically analyzed whether regions' relative efficiency levels change after the bias-correction and whether DEA distinguishes regions on the production frontier as significantly more efficient than other regions in the sample. The study also investigated the driving forces behind regional labor productivity growth using the tripartite decomposition components.

Major findings from this study were that relative efficiency rankings of the regions remain stable after the bias correction and that DEA successfully identified regions on the production frontier as significantly more efficient than most other regions in the sample. The decomposition showed that most regions have fallen behind the production frontier in efficiency and that capital accumulation has had a divergent effect on the labor productivity distribution. Only eight of the sixty nine regions improved their relative efficiency and caught-up with the technological leaders. The observed increase in labor productivity was explained by capital accumulation and expanded technological opportunities. Capital accumulation also played the expected converging role in initially unproductive regions.

2.2.6. *Weber and Domazlicky (2006)*

Following Barro and Salai-i-Martin's (1995) argument that regions within a nation should exhibit a stronger tendency towards convergence as compared with nations, Weber and Domazlicky (2006) investigated the contribution of the manufacturing sector to regional economic convergence in the U.S. Regions within a nation are likely to share the forces that promote convergence such as technology, structural characteristics, institutions, and preferences. The study also investigated whether capital deepening was a driving force in labor productivity growth at the state level. Employing similar methods as Kumar and Russell (2002) and using data on the manufacturing sector for the 50 states from 1977 to 1996, labor productivity growth was decomposed into changes due to enhanced efficiency, capital accumulation, and technological progress. The study found that capital deepening and efficiency change have contributed to beta convergence in labor productivity, although the effects of efficiency change are small and potentially insignificant. No evidence of sigma convergence was found. Technical change was found to have caused divergence in labor productivity within U.S. regions.

2.2.7. *Grosskopf et al. (2007)*

Grosskopf et al. (2007) employed a panel of state level manufacturing data for the U.S. to estimate productivity growth and its sources in the period 1990-1999. Following Kumar and Russell (2002), they augmented the usual Malmquist decomposition of productivity growth with a capital component. They also investigated the impacts of innovation, diffusion, and capital deepening of several policy related instruments including labor quality, industrial mix (measured by the high tech manufacturing share to total manufacturing output)[2], public capital stock, and the size of state government. They found that capital deepening and technical change was the major sources of labor productivity growth. A growing technology sector was a strong contributor to labor productivity growth, while a growing public sector was largely a drag on growth. Growth in average educational attainment appears to have had little impact on the pace of technical change or the diffusion of technology. However, capital deepening was significantly greater in states with a more educated population.

2.2.8. *Henderson and Zelenyuk (2007)*

Henderson and Zelenyuk (2007) used advances in DEA techniques to examine efficiency scores and investigate the issues of convergence and divergence for 52 countries using the same data set as Henderson and Russell (2005). The approach used in this study was different from the previous studies in several ways. *First*, the study incorporated bootstrapping methods in the DEA framework introduced by Simar and Wilson (1998, 2000a). The bootstrap DEA is used to check for the robustness of efficiency estimates. *Second*, the study divided the sample into two groups, developed and developing countries, and considered three types of catching-up: within the entire sample, within distinct groups in the sample, and between groups. The aim was to see if the efficiency scores exhibit club convergence.[3]

The study found that although many of the results in Henderson and Russell (2005) are robust, the efficiency scores of particular countries are sometimes highly biased when employing

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[2] High tech is defined as sum of machinery, electronics, and instrument industries (SIC code 355, 336, 338)
[3] Club convergence is based on models that yield multiple equilibrium. A group of countries may approach a particular equilibrium if they share the initial location or attribute corresponding to that equilibrium.

standard DEA techniques. Significant differences were found in the two groups both at the beginning and end of the period. The test of equality for densities reveals that the distributions of efficiency within the groups have not changed significantly. Analysis of changes across time suggested some evidence of ‘efficiency lagging behind’ within the group of developed countries and slight ‘efficiency catching up’ between the groups as well as ‘efficiency convergence’ between the groups. There was also evidence of ‘efficiency convergence’ within each group.

2.2.9. *Margaritis et al. (2007)*

Margaritis et al. (2007) analyzed trends in labor productivity, labor productivity’s underling determinants, and convergence in a panel of OECD countries from 1979 to 2002. The study started with cross-sectional analysis of convergence and analyzes the evolution of the cross-country distribution of labor productivity over time following Kumar and Russell (2002) and Henderson and Russell (2005). Stochastic convergence was investigated using panel unit root methods. Labor productivity growth was decomposed in terms of biased input and net technical change, efficiency change, and capital accumulation. Data envelopment analysis was used to construct the best practice production frontier and Malmquist productivity indices and their components for each country. This information was used to assess the contribution of the various components to convergence in labor productivity.

The results indicated that, on average, gaps in productivity or income levels were narrowing although there was no evidence to suggest that the entire OECD comprised a single convergence ‘club.’ Using kernel estimation methods, the study found that labor productivity and per capita GDP were settling towards a bimodal distribution. The panel root tests over the period 1960 to 2001 provided general support for the convergence hypothesis. Analysis of the contribution of productivity growth within industries and sectoral composition changes showed that aggregate productivity change was predominantly driven by 'net' within sector effects with very little contribution merging from sectoral shifts. For most countries, labor productivity growth in the last two decades was predominantly driven by technical change and regression results indicate that technical change has been a source of divergence for both labor productivity and per capita GDP.

2.2.10. *Henderson et al. (2007)*

The objective of the Henderson et al. (2007) study was to determine the sources of growth at the provincial level in China and to examine their impact on regional inequality. The paper differed from previous work in that it examined inter-provincial convergence by analyzing the entire distribution of provincial output per worker and its dynamics over the sample period. Specifically, the study determined whether the rapid economic growth of China over the reform period was driven primarily by TFP growth or by factor accumulation. The study uses the nonparametric production technology frontier method given by Henderson and Russell (2005), who decomposed labor productivity into four components: technical change, efficiency change, and physical and human capital accumulation. The study estimated the contribution of growth of each of those four components for 28 Chinese provinces over the period 1978-2000. In addition, the sample was split into two sub-periods to find evidence for a turning point regarding the rise of regional inequality. This study examined the inter-provincial convergence by analyzing the entire distribution of provincial output per worker and its dynamics for the sample period. In addition, the study applied nonparametric kernel methods to test formally for statistical significance of the relative contribution of each of the four components to changes in the shape of the distribution. The dataset includes output, labor, and physical and human capital variables for the 28 Chinese provinces.

Several findings arise from this study. *First*, the distribution of output per worker across Chinese provinces was multimodal with relatively few provinces in the upper modes and a majority of the provinces in the larger 'poor' mode. However, over the sample period several poor provinces were able to catch-up and move into the 'rich' modes. *Second*, technical change was decidedly nonneutral, with little improvements at very low capital-to effective-labor-ratios[4] and rapid expansion at high capital-to-effective-labor-ratios. *Third*, physical capital accumulation was the major driving force behind the growth performance of Chinese provinces over the reform period. Capital accumulation helped drive convergence between provinces. *Finally*, the initial rich coastal provinces were able to grow faster because of above average rates of technological progress and human capital accumulation. Thus, the lack of technological progress and human capital accumulation were identified as key factors responsible for rising regional disparities in China. These hindered the growth of poor regions despite their increases in efficiency and capital accumulation.

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[4] Capital to effective labor ratio differs from capital to labor ratio. In the former, human capital enters the technology as a multiplicative augmentation of physical labor input. Thus, the amount of labor inputs is measured in efficiency units by multiplying physical labor by human capital. Human capital is measured by a human capital index following Bils and Klenow (2002).

2.2.11. *Delgado-Rodriguez and Álvarez-Ayuso (2008)*

Delgado-Rodriguez and Álvarez-Ayuso (2008) analyzed labor productivity growth and convergence in the 15 EU economies during the period 1980-2001 by employing the Kumar and Russell (2002) and the Henderson and Russell (2005) models. Nonparametric analysis was used to estimate a common European production frontier and TFP was broken down by means of Malmquist productivity indices. Once the components of labor productivity growth were analyzed, the focus was shifted to their relative contribution to convergence using the beta-convergence concept. The authors provided empirical evidence that contributed to the debate on the economic consequences of European integration and the capacity of European policy designers to strengthen infrastructure and human capital allocation in promoting EU growth and convergence.

Results from this study showed that productivity improvement in the EU was attributable to the intense rate of capital strengthening and that TFP had a negative contribution. Labor productivity was positive in cohesion EU countries (Portugal, Spain, Ireland, and Greece) due to the intense process of capital accumulation. Both physical and human capital accumulation were the main driving force behind the convergence process while technological progress tended to contribute to divergence. The authors concluded that public investment in both physical and human capital constitutes an appropriate instrument for development and cohesion policy in the EU.

2.3. Productivity in the U.S. Agriculture

The agricultural economics literature on productivity, in general, is extensive but few studies have examined sources of productivity growth. Some of the available literature has focused on the importance of investment in public and private research and development (R&D) and public extension, and on convergence of productivity across states. Other studies have focused on farm production efficiency using the nonparametric approach.

Huffman and Evenson (1993) used public and private research stock and agricultural extension stocks to explain TFP. The data set included 42 U.S. states for the period 1950-1982. The impact of public research on agricultural productivity was found to be positive but applied livestock research had a negative impact on livestock sector productivity. Ball et al. (2001) investigated the relative levels of farm sector productivity for the United States and nine European countries for the period 1973-1993. The study found convergence of TFP over the sample period and support for the existence of a positive relationship between capital accumulation and productivity growth.

McCunn and Huffman (2000) tested for both beta and sigma convergence in state agricultural TFP growth rates and examined the contributions of public and private R&D to convergence for the period 1950-82. Their results reject sigma convergence but do support beta convergence. The rate of beta convergence was found to be variable and depended on R&D state spillover, private R&D, and farmers' education. The spillover effects of public agricultural R&D were found to be more regional than national, implying that farmers in a state where public agricultural research was conducted can expect more benefits of the research than those in another state.

Ball et al. (2004) investigated whether there was a tendency for TFP levels in agriculture to converge across states and whether the convergence rate could be explained by differences in the rates of growth of factor intensities or by productivity catch up. Data were for the period 1960-1999. The results were consistent with technological catch-up, the range of TFP has narrowed over time and states with lower initial levels of productivity grew more rapidly than those with high initial levels of productivity. Thus, those states that were far behind the technology leaders gained the most through diffusion of technical information. A positive and statistically significant relation between productivity growth and growth of the capital-labor ratio was observed, implying embodiment of technology in capital.

On farm production efficiency, Byrnes et al. (1987) investigated the relative technical performance of Illinois grain farms and observed that the major source of inefficiency was scale inefficiency, particularly for the large farms in the sample. Weersink et al. (1990) examined the relationship between farm size and technical efficiency using data from Missouri grain farms. The authors found that farm efficiency was positively related to farm size. Kalaitzandonakes et al. (1992), using both the parametric and nonparametric methods, examined the relationship between farm size and technical efficiency using data from Missouri grain farms. The authors reported that farm efficiency was positively related to farm size irrespective of the estimation methods used.

Chavas and Aliber (1993) analyzed economic, scale, and scope efficiency of Wisconsin crop and livestock farmers. The authors found that scale and scope efficiency measures depend on the farm size and financial structure. Featherstone et al. (1997) investigated technical, allocative, and scale efficiency for a sample of Kansas beef-cow farms and found that profitability was positively correlated with overall technical efficiency and that inefficiency was positively related to herd size and degree of specialization.

Rowland et al. (1998) evaluated the economic competitiveness of a sample of Kansas farrow-to-finish operations by estimating relative efficiency using nonparametric procedures. Measures of technical, allocative, scale, economic, and overall efficiency were then related to farm characteristics to identify sources of efficiency. Results indicated that overall efficient farms produced more pork per litter, produced a portion of their own feed, generated a large portion of their income from swine and other livestock enterprises, and had lower debt-to-asset ratios.

Wu et al. (2003) computed technical efficiency indices for Idaho sugarbeet farms and decomposed these indices into pure technical efficiency, scale efficiency, and congestion efficiency using nonparametric procedures. Improper scale of operation and input over-utilization were found to be the major sources of inefficiency for 55 percent of the sampled farms, the remaining 45 percent exhibited full efficiency. Technical efficiency was independent of farm size. Serra et al. (2008) investigated the influence of the decoupling of government payments on production efficiencies of a sample of Kansas farmers using a stochastic frontier model. Results indicated that an increase in decoupling will likely decrease technical efficiencies.

2.4. Summary

Empirical studies on labor productivity decomposition have been reviewed in this chapter and a summary is provided in Table A1 of Appendix A. The studies mainly focused on cross-country analysis of labor productivity distribution, with a few studies focusing on the regional level (China and Western Europe) or the state level (U.S.). Except for one study that focused on agricultural labor productivity, all the other studies focused on labor productivity in the entire economy or regions. Data envelopment analysis was the common approach to construct the production frontier; only one study used the stochastic frontier approach. Some studies, based on exogenous growth theory, used the tripartite decomposition where labor is decomposed into components attributed to efficiency change, technical change, and capital accumulation. Others followed the endogenous growth theory but decomposed labor productivity into efficiency change, technical change, and physical and human capital accumulation. The results from these studies provide mixed conclusions about the factors that drive labor productivity growth. However, almost all the studies point to capital deepening as a main source driving productivity. The results also provide mixed results on convergence and divergence of productivity across countries, regions, and states. An important observation from the literature on U.S agricultural productivity is the recognition of the importance of public agricultural research and its spillover effects. However, as noted, empirical analyses that look into sources of productivity growth in agriculture are lacking.

The reviewed theory and empirical literature motivates the conceptual framework for this dissertation. Taking a departure from the reviewed studies, this study provides a micro framework for labor productivity decomposition and convergence by focusing the analysis on the Kansas farm sector. Specifically, the study investigates whether trends in aggregate labor productivity witnessed at the macro level are also reflected at the micro farm household level.

CHAPTER 3 - METHODOLOGY

This chapter describes in detail the theory and methods used to conduct the economic analysis in this study. The chapter begins by providing an overview of the economic theory of production whose cornerstone is the production function that defines the production technology. Distance functions are used to describe the production technology without the need to specify a behavioral objective function such as cost minimization or profit maximization. Distance functions provide the conceptual underpinning to describe the nonparametric production function on the Data Envelopment Analysis (DEA) model used to compute the various efficiency and productivity measures. The chapter provides a description of the linear programming approach used in DEA followed by the bootstrap DEA approach popularized by Simar and Wilson (2000a, 2000b). Following Kumar and Russell (2002), a description of the process that augments the usual Malmquist decomposition of productivity growth with a capital deepening component is described. This tripartite decomposition approach decomposes labor productivity growth into three components: efficiency change, technical change, and capital deepening. This is followed by a description of the nonparametric kernel density estimation methods used to analyze the evolution of the cross-farm labor productivity in terms of the tripartite decomposition. Two tests of multimodality in a distribution are also described; the Silverman test and the Dip test, followed by the two sample Kolmogorov-Smirnov (KS) test used to test the equality of two distributions. The chapter ends by a description of the parametric and semi-parametric regression analyses techniques used to test for convergence in labor productivity growth. Two semi-parametric models are considered, the partial linear model and the smooth coefficient model.

3.1. Production Theory

Following Färe and Primont (1995), let a vector of *N* inputs be denoted by $x = (x_1, ..., x_N)$ and the vector of *M* outputs by $y = (y_1, ..., y_M)$. The technology set used to produce *y* output given *x* inputs is defined as:

(3.1) $$T = \{(x, y) : x \in \Re_+^N, y \in \Re_+^M, x \text{ can produce } y\},$$

where $\Re_+^N$ and $\Re_+^M$ are sets of nonnegative real *n*-tuples. For a given technology *T* and under the assumption of a single output (M = 1), the production function $F : \Re_+^N \rightarrow \Re_+$ is defined by:

(3.2) $$F(x) = \max_y (y : (x, y) \in T).$$

Conversely, one can also start with the production function *F* and define the technology set as:

(3.3) $$\overset{*}{T} = \{(x, y) : F(x) \geq y, y \in \Re_+\}.$$

From the above equations, the output distance function for the single-output case is given by:

(3.4) $$D_0(x, y) = \min_\theta \ \{\theta : \ F(x) \geq y/\theta\}.$$

However, since D_0 can take a value of $+\infty$ for some output vectors, the output distance function can formally be defined by:

(3.5) $$D_0(x, y) = \inf_\theta \ \{\theta > 0 : (x, y/\theta) \in T\}.$$

The output distance function can also be defined in terms of the output correspondence. For each input vector, *x*, the set of feasible outputs (production possibility set) can formally be defined as:

(3.6) $$P(x) = (y : (x, y) \in T).$$

In this case $(x, y) \in \mathrm{T}$ if and only if $y \in P(x)$ and, therefore,

(3.7) $$T = \left((x, y) : y \in P(x), x \in \Re_{+}^{N}\right).$$

Thus, given the technology set T and the set of feasible outputs P, an alternative and equivalent definition of the output distance function is given by:

(3.8) $$D_{0}(x, y) = \inf_{\theta}\left\{\theta > 0 : (y/\theta) \in P(x)\right\} \forall x \in \Re_{+}^{N}.$$

The production possibility set is a set of outputs that can be produced from a given level of inputs. This set is represented by:

(3.9) $$P(x) = \left\{(y) : x \textit{ can produce } (y)\right\}.$$

In general, an output distance function considers a maximal proportional expansion of the output vector given an input vector. It is the factor by which the production of all output quantities could be increased while still remaining within the feasible production possibility set for the given input level.

The above production technology can also be defined in terms of the input distance function. Let the input sets be defined as:

(3.10) $$L(y) = \left\{x : (x, y) \in T\right\}.$$

In the above equation T is the set of all feasible input-output vectors and is defined as

(3.11) $$T = \left\{(x, y) : x \in L(y), y \in \Re_{+}^{M}\right\}.$$

Therefore, $y \in P(x)$ if and only if $x \in L(y)$. The direct input distance function can be defined in terms of the input sets as:

(3.12) $$D_{i}(x, y) = \sup_{\lambda}\left\{\lambda > 0 : (x/\lambda) \in L(y)\right\} \forall y \in \Re_{+}^{M}.$$

The input isoquant can be represented by $IsoqL(y)$, and $x \in IsoqL(y)$ if and only if $D_i(y,x)=1$. The input distance function characterizes the production technology by looking at a minimal proportional contraction of the input vector, given an output vector. Under constant returns to scale, the input distance function is the reciprocal of the output distance function for any (x,y).

3.2. Axioms of Production

Several properties underpin the economic analysis associated with the production function $F(x)$. Those properties are listed below (Färe and Primont, 1995):

P.1 **Inactivity -** $O_M \in P(x) \forall x$ in $\Re_+^M$. This axiom says that inactivity is possible. Given any input set it is always possible to produce nothing $(y = O_M)$.

P.2 **Weak disposability of outputs –** For all (x,y) in $\Re_+^{N+M}$, if $y \in P(x)$ and $0 < \theta \leq 1$, then $\theta y \in P(x)$. This axiom says that if x can produce y, then x can produce any proportional reduction of y.

P.2.S **Strong disposability of outputs** - If $y \in P(x)$ and $y' \leq y$ then $y' \in P(x)$. The interpretation of this axiom is that the extra amount of outputs can be disposed of or eliminated at no cost.

P.3 **Scarcity** - For all x in $\Re_+^N, P(x)$ is a bounded set. This axiom says that finite amount of inputs can only produce finite amounts of outputs. Inputs finiteness refers to the basic scarcity problem of economics, thus scarcity of inputs implies scarcity of outputs.

P.4 **Output closedness** - For all x in $\Re^{N}_{+}, P(x)$ is a closed set. A set is closed if it contains its boundary. The property of closedness is needed for technical reasons. If a set does not contain its boundaries, then it is not possible to find the optimal plan when you maximize a function (e.g., production) subject to the technology constraint.

P.5 **No free lunch** - $y \notin P(0_N)$ if $y \geq 0_M$ is a bounded set. The axiom says that output cannot be produced without inputs being used. In other words, it is not possible to produce something from nothing.

P.6 **Weak disposability of inputs** - if $y \in P(x)$ and $\lambda \geq 1$, then $y \in P(\lambda x)$. This axiom says that if inputs are proportionally increased, outputs do not decrease.

P.6.S **Strong disposability of inputs** - if $y \in P(x)$ and $x^{'} \geq x$, then $y \in P(x^{'})$. The interpretation of this axiom is that the extra amount of inputs can be disposed of or eliminated at no cost.

P.7 **Input closedness** - $\{x : y \in P(x)\}$ is closed for all $y \in \Re^{M}_{+}$. This property of closedness is needed for technical reasons. It ensures that a cost function can be derived from the production function and possesses all the properties usually associated with cost functions in the vector of input prices.

P.8 **Input convexity** - The output correspondence is quasi-concave only if $\Re^{N}_{+}$. It is common to assume input convexity and weak disposability of inputs because those axioms are necessary for obtaining solutions to revenue maximization and cost minimization problems.

P.9 **Output convexity** - $P(x)$ is convex for all x *in* $\Re_{+}^{N}$. This axiom means that if two combinations of output levels can be produced with a given input vector, then any weighted average of these outputs vectors can also be produced.

3.3. Efficiency Measurement

The output and input distance functions defined above are important in defining the output oriented and input oriented technical efficiency indices. A feasible production plan, (x, y), is input efficient if x belongs to the efficient subset of $L(y)$ which is defined by:

(3.13) $$Eff\ L(y) = \left\{ x : x \in L(y), x' \leq x \Rightarrow x' \notin L(y) \right\}, y \geq 0_M.$$

The above equation implies that if $x \in Eff\ L(y)$, then any reduction in one or more of the inputs will render y an infeasible output vector. Alternatively, the feasible production, (x, y), is output efficient if y belongs to:

(3.14) $$Eff\ P(x) = \left\{ y : y \in P(x), y' \leq y \Rightarrow y' \notin P(x) \right\}, x \geq 0_N.$$

The input and output oriented technical efficiency indices can be computed using both parametric (econometrics) and nonparametric (mathematical programming) approaches (Färe and Primont, 1995).

3.4. Approaches to Computing Technical Efficiency

The economic literature traditionally assumed that production units are equally efficient when analyzing productivity. However, this assumption has been relaxed to enable estimation of existing differences in efficiency across agents. Thus, an idealized production frontier (best-practice frontier) is estimated and the deviation of all other agents from this frontier is calculated. Two main approaches can be taken to identify inefficiency, the stochastic econometric approach (parametric) and the data envelopment analysis approach (non-parametric).

The stochastic econometric approach separates inefficiency from a random error term assuming that inefficiency follows an asymmetric distribution while random fluctuations follow a symmetric normal distribution. To obtain technical inefficiency econometrically, Aigner et al. (1997) and Meesusen and van den Broeck (1977) proposed a production frontier with a composite error:

(3.15) $$y_{it} = f\left(x_{it}, \beta\right) + \varepsilon_{it} = f\left(x_{it}, \beta\right) + v_{it} - u_{it},$$

where y_{it} is the output, x_{it} is the set of inputs, and the error term is made up of two independent components: v_{it} that measures the statistical error and u_{it} represents the agent's technical inefficiency. The random fluctuations, v_{it}, are assumed to be drawn from a symmetric distribution while the inefficiencies , u_{it}, are assumed to be drawn from an asymmetric distribution because they can only decrease the production below the frontier levels. The term u_{it} measures technical inefficiency in the sense that it measures the difference between the output, y_{it}, and its maximum possible value given by the stochastic frontier $f\left(x_{it}, \beta\right) + v_{it}$. The estimate of the error term is obtained from the estimated residuals of the regression:

$$\hat{\varepsilon}_{it} = y_{it} - f\left(x_{it}, \hat{\beta}\right). \quad (3.16)$$

The conditional distribution of u_{it} given ε_{it} is used to decompose the estimated disturbance term. This distribution contains all the information that ε_{it} yields about u_{it}. The most common distributions used for the inefficiency term are the half normal, truncated normal, and exponential distributions. The stochastic econometric model is estimated by maximum likelihood estimation. The most common production functions used are the Cobb-Douglas and the Translog functions (see Kumbhakar and Lovell (2000) for a complete discussion of the stochastic frontiers).

Literature pertaining to the nonparametric analysis of productivity and efficiency involves two distinct strands; one identifiable as the *Charnes-Cooper* school, and the other as the *Afriat* school. The former school builds on the DEA approach that primarily focuses on observed input and output quantity data. The latter school assumes optimizing behavior of producers and uses both quantity and price information where the underlying production technology can be derived from the cost function using the neoclassical theory of duality.

3.5. Data Envelopment Analysis (DEA)

The foundation of DEA is Farrell's 1957 paper which focused on providing an adequate determination of empirical efficiency rather than theoretical efficiency and makes the distinction between technical and allocative efficiency. Technical efficiency was defined as the ability to obtain outputs from inputs. Farrell (1957) considered a single input-output case. In 1978, Charnes et al. (1978) generalized Farrell's single input-output case to a method for evaluating the relative efficiency of decision making units (DMUs) which use multiple inputs to produce multiple outputs. Data envelopment analysis evaluates the relative efficiency of a set of homogeneous DMUs by using the ratio of the weighted sum of outputs to the weighted sum of inputs. Specifically, DEA determines a set of weights such that the efficiency of a target, DMU_0, relative to other DMUs is maximized.

There are two frequently used DEA models that seek to determine the DMUs that form the efficient frontier: the CCR model named after Charnes, Cooper, and Rhodes (Charnes et al., 1978) and the BCC model named after Banker, Charnes, and Cooper (Banker et al., 1984). Other well known models include the Additive model, the Free Disposal Hull (FDH) model, and the Slacks-Based Measure of efficiency (SBM) model. More details on these models and their applications can be found in Cooper et al. (2007, p.87-114.). The DMUs that are on the efficient frontier are said to be technically efficient and have an efficiency score of one. The remaining DMUs are measured relative to the efficient DMUs and are defined as being technically inefficient because the efficiency score is less than one.

The conventional DEA model, first proposed by Charnes et al. (1978) can be expressed as:

$$(3.17) \qquad E_r = \max\left\{ \sum_{k=1}^{t} u_k y_{rk} \Big/ \sum_{j=1}^{s} v_j x_{rj} \right\} \text{ subject to } \left\{ \begin{array}{l} \sum_{k=1}^{t} u_k y_{ik} \Big/ \sum_{j=1}^{s} v_k x_{ij} \le 1, i = 1..., n, \\ u_k, v_j \ge 0. \end{array} \right\}.$$

Here, x_{ij} is the amount of j^{th} input (j =1… s) of the i^{th} DMU, y_{ik} is the amount of the k^{th} output (k = 1… t) of the i^{th} DMU, v_j is the multiplier (weight) given to the j^{th} input, u_k is the multiplier (weight) given to the k^{th} output and there are n DMUs. Each DMU places different levels of importance (weights) on particular inputs and outputs. The solution to the above model, E_r, gives the efficiency of the unit being evaluated. If E_r =1, then this unit is efficient relative to the other units but if it is less than one then some other units are more efficient than this unit, which determined the most favorable set of weights. The above model has an infinite number of solutions and Charnes et al. (1978) has shown that the problem can be avoided by solving the following linear programming problem:

$$\underset{u,v}{\text{Maximize}} \ \sum_k u_k y_{k,jo}$$

(3.18)
$$\text{subject to} \begin{Bmatrix} \sum_i v_i x_{i,jo} = 1 \\ \sum_i u_k y_{k,j} \leq \sum_i v_i x_{i,j} \forall j, \ i = 1,...,n, \\ u_k, v_i \geq 0 \end{Bmatrix}.$$

The above model is often referred to as the input-oriented CCR (Charnes, Cooper and Rhodes) model. The dual specification of this model can be written as follows:

$$\underset{\lambda}{\text{Minimize}} \ \mathrm{z}_0 = \theta_{j0}$$

(3.19)
$$\text{subject to} \begin{Bmatrix} \sum_j \lambda_j y_{k,j} \geq y_{k,j0} \\ \theta_{j0} x_{i,j0} \geq \sum_i \lambda_j x_{i,j} \\ \lambda_i \geq 0 \end{Bmatrix}.$$

The dual problem has an optimal real variable θ, denoted by θ* that is $0 < \theta^* \leq 1$. The output oriented primal CCR model can be specified as:

$$\frac{1}{g_k} = \text{Minimize} \sum_{i=1}^{m} v_i x_{i,k}$$

(3.20)
$$\text{subject to} \begin{Bmatrix} \sum_i u_k y_{k,j} = 1 \\ \sum_i u_k y_{k,j} \leq \sum_i v_i x_{i,j} \forall j, \ i = 1,...,n, \\ u_k \geq 0, \\ v_i \geq 0 \end{Bmatrix}.$$

The dual program of the above model can be specified as follows:

$$\frac{1}{g_k} = \text{Maximize } \theta_k$$

(3.21)
$$\text{subject to } \left\{ \begin{array}{l} \sum_i \lambda_{kj} x_{ij} \leq x_{ik} \forall i,\ i = 1, \ldots, n, \\ \sum_i \lambda_{kj} y_{rj} \geq \theta_k y_{rk} \\ \lambda_{kj} \geq 0, \end{array} \right\}.$$

All the above CCR DEA models assume constant returns to scale.

The Banker, Charnes, and Cooper (BCC) model is similar to the above models except that it adds an additional constant variable, c_k, in order to permit variable return to scale. The primal and dual input oriented BCC models can be specified as follows:

$$\underset{u,v}{\text{Maximize}} \sum_k u_k y_{k,jo} + c_k$$

(3.22)
$$\text{subject to } \left\{ \begin{array}{l} \sum_i v_i x_{ij} = 1 \\ \sum_i u_k y_{kj} \leq \sum_i v_i x_{ij} - c_k \forall j,\ i = 1, \ldots, n, \\ u_k \geq 0, \\ v_i \geq 0 \end{array} \right\}, \text{and}$$

$$\text{Minimize } h_k = \theta_k$$

(3.23)
$$\text{subject to } \left\{ \begin{array}{l} \sum_j \lambda_{kj} y_{ij} y_{rk,} \\ \theta_k x_{ik} \sum_i \lambda_{kj} x_{ij} \\ \sum_{j=1}^{n} \lambda_{kj} = 1 \end{array} \right\}.$$

Conversely, the primal and dual output oriented BCC DEA models can be written as follows:

$$\frac{1}{g_k} = \text{Minimize } \sum_{i=1}^{m} v_i x_{ik} + c_k$$

(3.24)

$$\text{subject to } \left\{ \begin{array}{l} \sum_i u_k y_{kj} = 1 \\ \sum_i u_k y_{kj} - c_k \le \sum_i v_i x_{ij} \forall j,\ i = 1, \ldots, n, \\ u_k \ge 0, \\ v_i \ge 0 \end{array} \right\}$$

and

$$\frac{1}{g_k} = \text{Maximize } \theta_k$$

(3.25)

$$\text{subject to } \left\{ \begin{array}{l} \sum_i \lambda_{kj} x_{ij} \le x_{ik} \forall i,\ i = 1, \ldots, n, \\ \sum_{j=1}^{n} \lambda_{kj} y_{rj} \ge \theta_k y_{rk} \\ \sum_{j=1}^{n} \lambda_{kj} = 1 \end{array} \right\}.$$

3.5.1. *Strengths and Limitations of DEA Approach*

The DEA approach has been favored over the stochastic frontier approach for several reasons. *First*, it makes no assumption about the distribution of the underlying data and deviation from the estimated frontier is interpreted purely as inefficiency. *Second*, DEA does not require specification of a functional form for the frontier just as economic theory does not imply a particular functional form. *Third*, technology can be modeled without cost data and this is very important if price or cost data are unavailable. *Fourth*, multiple inputs and outputs can be considered simultaneously, and inputs and outputs can be quantified using different units of measurement. *Fifth*, there is no need to assume that technical change is neutral, or make assumptions about market structure or the absence of market imperfections (Henderson et al., 2007; Coelli et al., 2005).

Although DEA offers several advantages over the stochastic frontier approach it is also not without limitations. Principle among the limitations is the sensitivity of the DEA method to statistical noise in the data and measurement errors in variables (Kuosmanen et al., 2007). Small changes in data can change DEA scores significantly because DEA focuses on frontiers or boundaries. Thus, an implicit assumption of the DEA method is that data are measured accurately and do not incorporate any random noise or measurement errors. Therefore, the classical DEA model only gives point estimates of efficiency and productivity that do not offer any information about the uncertainty in the firm specific estimates (Löthgren and Tambour, 1999).

The assumption of accurate measurement of data may not be realistic in production agriculture where inputs and outputs of a DMU are ever changing because of the weather, seasons, operating state, and so on (Guo and Tanaka, 2001). Factors used in production agriculture, such as labor, are often difficult to measure in a precise manner. Input measures are also often based on accounting data, even though the definition of accounting costs differs from that of economic costs by excluding the opportunity cost (Kuosmanen et al., 2007). Producer data are also sometimes available only in ordinal form, e.g., “high yield”, “low yield”, “labor intensive” or “capital intensive.” Thus, the classical DEA approach, as often used in the agricultural economics literature, is very sensitive to data measurement and changes in data, including outliers and missing data. These phenomena can have a significant impact on the efficient frontier.[5]

Recently, a number of techniques to account for measurement errors and statistical noise have been suggested in the efficiency literature, such as the techniques for detecting possible outliers (Cazals et al., 2002), and the stochastic programming approach (Cooper et al., 1998). Notably, Simar and Wilson (1998; 2000a; 2000b) and others have introduced bootstrapping into the DEA framework that allows for consistent estimation of the production frontier, corresponding efficiency scores, as well as standard errors and confidence intervals. However, as recently observed by Kuosmanen et al. (2007), the statistical properties and hypothesis tests suggested by Simar and Wilson (2000a; 2000b) focus exclusively on the effect of the sampling of firms from the production possibilities set and does not allow for data measurement errors of any kind. This observation has also been echoed by Coelli et al. (2005). Another limitation of the classical DEA method is that it cannot be used to predict the technical efficiency of other DMUs. As a result, artificial neural networks (ANNs) have been introduced as an alternative to assist in predicting efficiency frontiers for decision makers (Wu et al., 2006). The problem of accounting for statistical noise in the DEA approach is overcome by using the bootstrapping DEA method.

[5] This refers to the Charnes, Cooper and Rhodes (CCR) model that assume constant returns to scale (Charnes et al., 1978). The concept presented can equally be extended to the Banker, Charnes, and Cooper (BCC) model that assumes variable returns to scale (Banker et al., 1984).

3.5.2. *Bootstrap Data Envelopment Analysis*

The DEA approaches described in the previous section are considered to be *deterministic,* suggesting that the models have no statistical underpinnings (Murillo-Zamorano, 2004)**.** The DEA models above present point estimates of inefficiency with no measure or discussion of uncertainty surrounding these estimates. Yet, DEA measures efficiency relative to an estimate of the frontier and, therefore, those measures are subject to uncertainty due to sampling variation (Simar and Wilson, 2000a). The bootstrap methodology can be used to investigate the sampling properties of DEA estimates. These methods analyze the sensitivity of the efficiency measures to sampling variation, provide confidence intervals, and correct for bias inherent in the procedure. In this study, the "smoothed bootstrap "approach of Simar and Wilson (1998) as summarized by Subhash (2004, p.319-325) will be used. The theoretical underpinnings of this method can be found in the extensive work by Simar and Wilson (1998, 1999, 2000a, 2000b).

The idea of bootstrap was first introduced by Efron (1979) who proposed the use of computer-based simulations to obtain the sampling properties of random variables. Bootstrapping is a method of testing the reliability of a data set by creating a pseudo-replicate dataset and assessing whether the distribution is influenced by stochastic effects. The distribution can be used to build confidence intervals for DEA point estimates which normally cannot be derived analytically.

The starting point of any bootstrap procedure is a sample of observed data $X = \{x_1, x_2, ..., x_n\}$ drawn randomly from some population with an unknown probability distribution *f*. The key assumption behind the bootstrap approach is that the known bootstrap distribution will mimic the original unknown distribution if the known data generation process

(DGP) is a consistent estimator of the unknown DGP. The sample statistic $\hat{\theta} = \theta(X)$ from these observed values is merely an estimate of the corresponding population parameter $\theta = \theta(f)$. When it is not possible to analytically derive the sampling distribution of that statistic, one examines its density function empirically. However, the researcher has access to only one sample rather than multiple samples drawn from the same population. Therefore, a random sample with replacement from the observed values in the original sample can be treated like a sample drawn from the underlying population itself. Repeated samples with replacement yield different values of the sample statistic under investigation and the associated empirical distribution over those samples can provide the sampling distribution of this statistic.

The bootstrap sample, $X^* = \{x_1^*, x_2^*, ..., x_n^*\}$, is an unordered collection of n items drawn randomly from the original sample X with replacement. Therefore, any $x_i^* (i = 1, 2, ..., n)$ has $1/n$ probability of being equal to any $x_j^* (j = 1, 2, ..., n)$. However, some observations from the original data X may not appear in the bootstrap sample while other observations may be drawn repeatedly.

Let $\hat{f}$ denote the empirical density function of the observed sample X from which X* was drawn. Then it can take the form:

(3.26) $$\hat{f}(t) = \begin{Bmatrix} 1/n \text{ if } t = x_i^*, i = 1, 2, ..., n \\ 0 \text{ otherwise} \end{Bmatrix}.$$

The bootstrap distribution will mimic the original unknown sampling distributions of the estimators that we are interested in only if $\hat{f}$ is a consistent estimator of f. If we let

$\hat{\theta}^* = \theta\left(X^*\right)$ be the estimated parameter from the bootstrap sample X^*, the distribution of $\hat{\theta}^*$ around $\hat{\theta}$ in $\hat{f}$ is the same as that of $\hat{\theta}$ around θ in f. That is,

(3.27) $$\left(\hat{\theta}^* - \hat{\theta}\right) | \hat{f} \sim \left(\hat{\theta} - \theta\right) | f.$$

Thus, every time that we replicate the bootstrap sample we get a different sample X^*, and hence a different estimate of $\hat{\theta}^* = \theta\left(X^*\right)$. This creates the need to select a large number of bootstrap samples, B, in order to extract as many combinations of $x_j (j = 1, 2, ..., n)$ as possible. This type of bootstrap is called the naive bootstrap and its algorithm has the following steps:

i) Compute the statistics $\hat{\theta} = \theta\left(X\right)$ from the observed sample X.

ii) Select b^{th} (b =1, 2,…, B) independent bootstrap sample X_b^*, which consists of n data values drawn with replacement from the observed X.

iii) Compute the statistic $\hat{\theta}^* = \theta\left(X_b^*\right)$ from the b^{th} bootstrap sample X_b^*.

iv) Repeat steps (ii) to (iii) a large number of times (e.g., B = 2000 times).

v) Calculate the average of the bootstrap estimates of θ as the arithmetic mean:

$$\hat{\theta}^*(.) = \frac{1}{B}\sum_{b=1}^{B}\theta_b^*.$$

The bias measure used to measure the accuracy of an estimator $\hat{\theta}$ of the parameter θ is computed as follows:

(3.28) $$bias_f = bias_f(\hat{\theta}, \theta) = E_f(\hat{\theta}) - \theta.$$

Using the above measure, the bias corrected estimator is computed as:

(3.29) $$\hat{\theta}_{bc} = \hat{\theta} - bias_f.$$

The bias of the bootstrap estimator θ_b^* (b =1, 2… B) as an estimator of $\hat{\theta}$ is computed as $bias_{\hat{f}} = E_{\hat{f}}(\hat{\theta}_b^*) - \hat{\theta}$, where we use the average of the bootstrap estimators $\hat{\theta}^*(.)$ for the expectation of each bootstrap estimator θ_b^*. The estimated bias of the bootstrap estimator based on B replications is $bias_B = \hat{\theta}^*(.) - \hat{\theta}$. Taking $bias_B$ as an estimator of the unknown $bias_f$, the bias corrected estimator of θ is:

(3.30) $$\hat{\theta}_{bc} = \hat{\theta} - bias_B = 2\hat{\theta} - \theta^*(.).$$

If $\hat{\theta}^*(.)$ overestimates (underestimates) the statistic $\hat{\theta}$ from the original sample, then $\hat{\theta}$ will also overestimate (underestimate) the true population parameter θ. This implies that $\hat{\theta}_{bc} < \hat{\theta}\ if\, \hat{\theta}^*(.) > \hat{\theta}$.

A major drawback of the naïve bootstrap approach is that it is possible that a bootstrap sample will not include observations from the parent population that are not drawn in the initial sample. The empirical distribution $\hat{f}$ is a histogram that looks like a collection of boxes of width h. The bootstrap samples are drawn from a discrete population that fails to reflect the fact that the underlying population density function f is continuous. Consequently, the empirical distribution from the bootstrap sample is an inconsistent estimator of the population density function (Subhash, 2004).

This problem is overcome by use of kernel estimators as weight functions. The empirical distribution takes the following form:

(3.31) $$\hat{f}(t) = \frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{t - x_i}{h}\right).$$

In the above equation, h is the window width and k (.) is the kernel function, a symmetric probability density function like the normal density function, which satisfies the following condition:

(3.32) $$\int_{-\infty}^{\infty} k(x)\, dx = 1.$$

Assuming that we use the standard normal density function, ϕ , as the kernel density function k, the empirical density function can be written as:

(3.33) $$\hat{f}\,(t) = \frac{1}{nh}\sum_{i=1}^{n}\phi\left(\frac{t-x_i}{h}\right).$$

The smoothed bootstrap sample $X^{**} = \left\{x_1^{**}, x_2^{**}, \ldots, x_n^{**}\right\}$ can be generated as:

(3.34) $$x_i^{**} = x_i^{*} + h\varepsilon_i \sim f;\ i = 1, 2, \ldots, n,$$

where ε_i is a random deviation from the standard normal. A problem with the outlined method is that the kernel estimate does not take into account the boundary conditions that $t < 1$, and thus can be shown to be biased and inconsistent since the support of f is bounded (Simar and Wilson, 1998). Silverman (1986) suggested the use of the negative reflection method to overcome this difficulty. Suppose we are interested in values of x such that $x \geq \alpha$. If the resulting value from the bootstrap is $x_i^{**} < \alpha$, then we will reflect the x_i^{**}, such that $2\alpha - x_i^{**} \geq \alpha$. The empirical density function will be:

(3.35) $$\hat{f}\,(t) = \frac{1}{nh}\sum_{i=1}^{n}\left[\phi\left(\frac{t-x_i}{h}\right) + \phi\left(\frac{t-2\alpha+x_i}{h}\right)\right].$$

By virtue of the convolution theorem (Efron and Tibshirani, 1993), the smooth bootstrap sample $X^{**} = \left\{x_1^{**}, x_2^{**}, \ldots, x_n^{**}\right\}$ can be generated as follows:

(3.36) $$x_i^{**} = \begin{Bmatrix} x_i^* + h\varepsilon_i \sim \dfrac{1}{nh}\sum_{i=1}^{n} \phi\left(\dfrac{t - x_i}{h}\right) & \text{if } x_i^* + h\varepsilon_i \geq \alpha \\ 2\alpha - (x_i^* + h\varepsilon_i) \sim \dfrac{1}{nh}\sum_{i=1}^{n} \phi\left(\dfrac{t - 2\alpha + x_i}{h}\right) & \text{otherwise} \end{Bmatrix}.$$

In the above equation x_i^* is from the naïve bootstrap sample discussed earlier. From the foregoing analysis, a choice of the smoothing parameter (h) is crucial to the estimation of the empirical density function. Silverman (1986) has shown that the optimal window width, h, that minimizes the approximate mean integrated square error (MISE) is:

(3.37) $$h = 0.9An^{-0.2},$$

where A = min (standard deviation, interquartile range/1.34).

From the foregoing, the bootstrap procedure for DEA can be summarized in the following steps (Gocht and Balcombe, 2006):

i) For each of the DMU, solve the DEA problem to obtain the efficiency score $\hat{\theta}_k$. The computed scores $\hat{\theta}_k$ are different estimators of the unknown θ_k.

ii) Generate the smooth bootstrap sample, $\left(\theta_1^*, \theta_2^*, ..., \theta_n^*\right)$, which consist of n data values drawn with replacement from the estimated values of $\hat{\theta}_k$. The smoothed bootstrap sample is bounded and will be computed according to:

(3.38) $$x_i^{**} = \begin{Bmatrix} x_i^* + h\varepsilon_i & \text{if } x_i^* + h\varepsilon_i \geq \alpha \\ 2\alpha - (x_i^* + h\varepsilon_i) & \text{otherwise} \end{Bmatrix}.$$

iii) Create the b^{th} pseudo data set as $X_b^* = \left\{\left(x_{ib}^*, y_i\right) | \, i = 1, ..., n\right\}$ where $x_{ib}^* = \left(\hat{\theta}_i / \theta_{ib}^*\right) x_i$ for $i = \{1, ..., n\}$.

iv) Compute the bootstrap efficiency estimates $\left\{\hat{\theta}_i^* \mid i=1,...,n\right\}$ by solving the DEA model for each DMU using the new data X_b^*.

v) Repeat steps (ii) - (iv) B times to provide $k=\{1,...,n\}$ set of estimates for each DMU. The bootstrap efficiency score $\hat{\theta}_k^*$ represents approximation to the $\hat{\theta}_k$, just as the DEA efficiency scores $\hat{\theta}_k$ represents approximation to θ_k.

vi) Calculate the average of the bootstrap estimates, the bias, and the confidence intervals as described in the previous section.

In summary, it is important to note that contrary to the earlier notion that the DEA approach is deterministic and hence non-statistical in nature, statistical inference based on nonparametric frontier approaches to the measurement of economic efficiency is available by using bootstrap. Simar and Wilson (1998) show how to define a reasonable data-generation process and propose a reasonable estimator of it. Simar and Wilson (2000a) establish the procedure for constructing confidence intervals that depend on using bootstrap estimates of bias to correct for the bias of the DEA estimators. Simar and Wilson (1999) show an improved procedure which corrects for bias without the explicit use of a noisy bias estimator, and Simar and Wilson (2000b) extend the Simar and Wilson (1998) framework by allowing heterogeneity in the structure of efficiency.

Finally, it is important to emphasize the observation made by Kuosmanen et al. (2007) and Coelli et al. (2005) that DEA bootstrapping methods are designed to only deal with *sampling variation*. They provide an indication of the degree to which the efficiency estimates are likely to vary when a different sample is randomly selected from the population. However, the bootstrapping method does not account for random noise such as that which may result from imprecision due to measurement or specification errors.

3.6. Empirical Technology Model

We follow the approach of Henderson and Zelenyuk (2007) to define the underling production technology. For each farm *i* (*i* = 1, 2… *n*), the period-*t* input vector is $x_i^t = \left(K_i^t, L_i^t\right)$ where K_i^t is physical capital, and L_i^t is labor. Let y_i^t be a single output for farm *i* in period *t*. The technology for converting inputs for each farm *i* in each time period *t* can be characterized by the technology set:

(3.39) $$T_i^t \equiv \left\{\left(x_i^t, y_i^t\right) | \text{ can produce } y_i^t\right\}.$$

The same technology can be characterized by the following output sets

(3.40) $$P_i^t\left(x_i^t\right) \equiv \left(y_i^t \mid x_i^t \text{ can produce } y_i^t\right), x_i^t \in \Re_+^2.$$

We assume that the technology follows standard regularity assumptions under which the Shephard (1970) output-oriented distance function can be represented as:

(3.41) $$D_i^t\left(x_i^t, y_i^t \mid P_i^t\left(x_i^t\right)\right) = \text{ infinum}\left\{\theta | \, y_i^t/\theta \in P_i^t\left(x_i^t\right)\right\}.$$

This gives the complete characterization of the technology for farm *i* in period *t* in the sense that we always have

(3.42) $$D_i^t\left(x_i^t, y_i^t \mid P_i^t\left(x_i^t\right)\right) \leq 1 \Leftrightarrow y_i^t \in P_i^t\left(x_i^t\right).$$

This function is simply the ratio of maximal (or potential) output to actual output that can be produced from the same amount of inputs. The Farrell output-oriented technical efficiency measure can thus be defined as:

$$(3.43) \qquad TE_i^t \equiv TE_i^t\left(x_i^t, y_i^t \mid P_i^t\left(x_i^t\right)\right) = \text{supremum}\left\{\theta \mid y_i^t/\theta \in P_i^t\left(x_i^t\right)\right\} = 1\Big/D_i^t\left(x_i^t, y_i^t \mid P_i^t\left(x_i^t\right)\right).$$

A farm is considered to be technically efficient when TE_i^t=1 and technically inefficient when 0 < TE_i^t < 1.

The true technology and output sets are unknown and thus, the individual value of technical efficiency must be estimated using either the nonparametric (data envelopment analysis) or parametric (stochastic frontier analysis) techniques. For this paper, we use the nonparametric technique.

3.7. Empirical DEA Model

Given the production technology in equation (3.39), we use linear programming to estimate the output distance function. The Farrell input-based efficiency index for farm *i* at time *t* is defined as:

$$(3.44) \qquad e\left(Y_i^t, K_i^t, L_i^t\right) = \min\left\{\lambda \mid \left\langle Y_i^t/\lambda, K_i^t, L_i^t\right\rangle \in T^t\right\}.$$

In the above equation *Y* is output, *K* is capital, and *L* is labor. The subscript *i* refer to an individual farm and the superscript *t* represent the individual time period. The efficiency index value for each farm is found using the following:

$$
\underset{\lambda, z^1, \ldots, z^j}{\text{Minimize}}\ \lambda_i
$$

(3.45)
$$
\text{subject to} \begin{Bmatrix} Y_i / \lambda_i \le \sum_k z_k Y_k^t \\ K_i \ge \sum_k z_k K_k^t \\ L_i \ge \sum_k z_k L_k^t \\ z_k \ge 0 \forall k. \end{Bmatrix},
$$

where λ_i is the efficiency measure to be calculated for each farm_i at time t, and z_k is the intensity variable for farm_i.

The above model assumes constant return to scale (CRTS). Constant returns to scale suggest that all firms operate at an optimal scale. However, imperfect competition and financial constraints may cause farms to operate below optimal scale (Coelli et al., 2005). Thus, adding equation (3.45a) to the constraints in the above model imposes variable returns to scale (VRTS) and equation (3.45b) imposes nonincreasing returns to scale (NIRTS).

(3.45a)
$$
\sum_{k=1}^{k} Z_k = 1
$$

(3.45b)
$$
\sum_{k=1}^{k} Z_k < 1
$$

From the above equations, scale efficiency can be computed. Scale efficiency is a ratio of a farm's technical efficiency under CRTS to its technical efficiency under VRTS:

(3.45c) $\quad SE = TE_{CRTS}/TE_{VRTS.}$

Scale efficiency shows the degree of inefficiency that a unit is facing due to its scale of operation. Figure 3-1 illustrates the TE and SE concepts for a single input-single output technology.

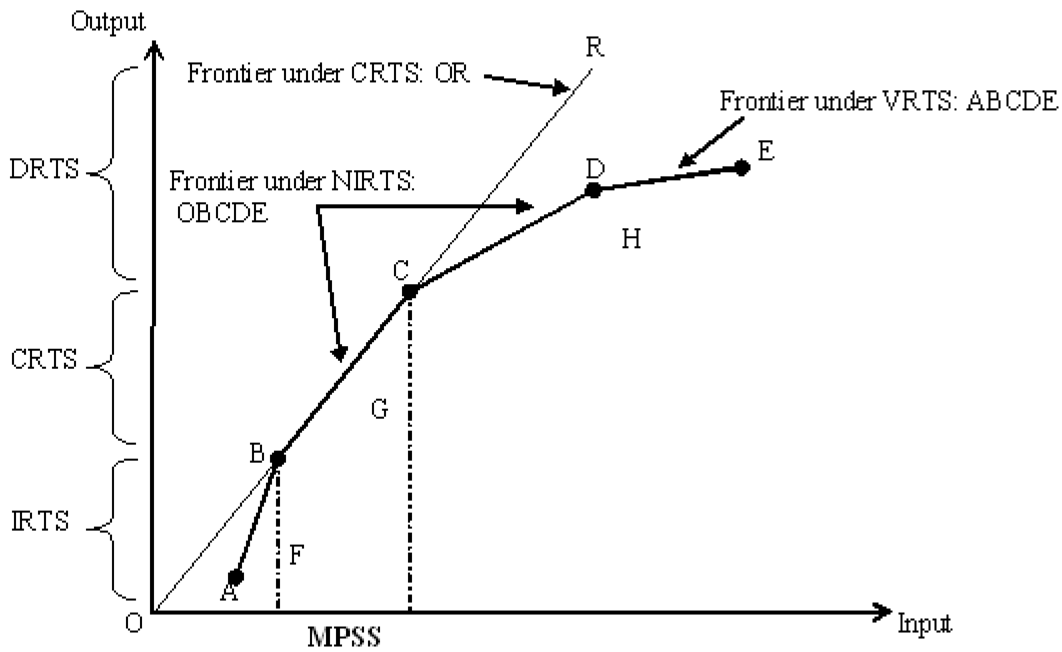

Figure 3-1 Efficiency Measures

The points A to H denote input-output observations for eight different farms. The frontier of the production possibility set under constant returns to scale (CRTS) is the ray OR passing through points B and C. The nonincreasing returns to scale (NIRTS) production possibility frontier is represented by the line OBCDE. The variable returns to scale frontier (VRTS) is the maintained assumption and is represented by the line ABCDE. The CRTS and NIRTS are mere artifacts that permit the examination of the different points on the VRTS frontier. The points A to E represents farms that are technically efficient under VRTS frontier. Farms D and E are technically efficient under VRTS and NIRTS while farms B and C lie in the region where CRTS, NIRTS, and VRTS coincide. Therefore, farms B and C are both technically and scale efficient and lie in the most productive scale size region (MPSS) where CRTS holds (i.e., no scale inefficiency). Farm G also lies in the MPSS region because it is scale efficient but technically inefficient. Farm A is technically efficient under VRTS frontier but inefficient under CRTS and NIRTS frontiers. Farm F is technically inefficient under all the three production possibility sets.

One can ascertain the returns to scale properties of a farm by comparing the technical efficiency levels with reference to VRTS, NIRTS, and CRTS frontiers. When the NIRTS and CRTS measures are equal but differ from the VRTS measure, increasing returns to scale (IRTS) holds (i.e., $TE^{NIRS}=TE^{CRTS}<TE^{VRTS}$). When VRTS and NIRTS measures are equal but differ from the CRTS measure, diminishing returns to scale (DRTS) holds (i.e., $TE^{VRTS} = TE^{NIRTS}<TE^{CRTS}$). The three measures are equal only at the most productive scale size (MPSS). The MPSS constitute two groups of farms, those that are both technically and scale efficient and those that are technically inefficient but scale efficient. For the purpose of this study, the former group is considered to be operation under CRTS (i.e., $TE^{NIRTS}=TE^{CRTS}=TE^{VRTS}=SE=1$) and the latter under MPSS (i.e., $TE^{NIRTS}=TE^{CRTS}=TE^{VRTS}<1$ and SE=1). Therefore, farms A and F are operating under IRTS, farms B and C under CRTS, farm G under MPSS, and farms D, E, and H under DRTS.

3.8. Tripartite Decomposition of Labor Productivity

After computing the technical efficiency scores, and following Kumar and Russell (2002), labor productivity growth is computed and decomposed into components attributed to changes in efficiency, technical change, and capital accumulation. Unlike Kumar and Russell (2002), the tripartite decomposition is computed under the assumption of variable returns to scale (VRTS) rather than constant returns to scale (CRTS) because not all farms are expected to operate at an optimal scale. To be consistent with the reviewed empirical literature, data on one output, gross farm income, and two inputs, capital and labor, are used to construct the production frontier using the technology defined by equations 3.44 and 3.45.

Assume the production function is represented by $Y = F(K, L)$, capital per worker by $k = K/L$, and output per worker by $y = Y/L$. Let subscripts *c* and *b* represent the current period and base periods, respectively, and e_c and e_b represent the current (c) and base (b) technical efficiency for farm *i*. The potential base year output per worker is:

(3.46) $$\bar{y}_b(k_b) = y_b / e_b,$$

and the potential current year output per worker is:

(3.47) $$\bar{y}_c(k_c) = y_c / e_c.$$

From the above equations, the labor productivity growth between the base and current year can be presented as:

(3.48) $$\frac{y_c}{y_b} = \frac{e_c \times \bar{y}_c(k_c)}{e_b \times \bar{y}_b(k_b)}.$$

If we multiply the numerator and the denominator of the above equation by the potential output per worker at current period capital intensity using the base period technology, $(\bar{y}_b(k_c))$, we obtain the following:

(3.49) $$\frac{y_c}{y_b} = \frac{e_c}{e_b} \times \frac{\bar{y}_c(k_c)}{\bar{y}_b(k_c)} \times \frac{\bar{y}_b(k_c)}{\bar{y}_b(k_b)}.$$

The above equation decomposes the relative change in output-labor ratio in the two periods into change in efficiency, $\left(\frac{e_c}{e_b}\right)$, technological change (i.e., shift of the frontier), $\left(\frac{\bar{y}_c(k_c)}{\bar{y}_b(k_c)}\right)$, and the effect of change in capital-labor ratio (i.e., movement along the frontier), $\left(\dfrac{\bar{y}_b(k_c)}{\bar{y}_b(k_b)}\right)$. In this case, technical change is measured at the current period capital-labor ratio.

Technical change can alternatively be measured in terms of the base period capital-labor ratio by multiplying the numerator and denominator of equation (3.48) by the potential output per worker during the current period at base period capital intensity using the current period technology, $(\bar{y}_c(k_b))$ to obtain:

(3.50) $$\frac{y_c}{y_b} = \frac{e_c}{e_b} \times \frac{\bar{y}_c(k_b)}{\bar{y}_b(k_b)} \times \frac{\bar{y}_c(k_c)}{\bar{y}_c(k_b)}.$$

The decomposition of productivity changes (i.e., technical change and capital deepening) is path dependent and the choice between equations (3.49) and (3.50) is arbitrary and would not yield the same results unless the technology is Hicks neutral. This ambiguity is resolved by following the approach of Caves et al. (1982) and Färe et al. (1994) by computing the geometric average of the two measures of the effects of technical change and capital deepening and multiplying the numerator and denominator of equation (3.48) by $(\bar{y}_b(k_c)\bar{y}_c(k_b))^{1/2}$ to obtain the measure of labor productivity change:

(3.51) $$\frac{y_c}{y_b} = \frac{e_c}{e_b} \times \left(\frac{\bar{y}_c(k_c)}{\bar{y}_b(k_c)} \times \frac{\bar{y}_c(k_b)}{\bar{y}_b(k_b)}\right)^{1/2} \times \left(\frac{\bar{y}_b(k_c)}{\bar{y}_b(k_b)} \times \frac{\bar{y}_c(k_c)}{\bar{y}_c(k_b)}\right)^{1/2}$$

$$= EFF \times TECH \times KACC \Rightarrow TFP \times KACC.$$

In the above equation, *EFF* is the measure of efficiency change, *TECH* is the measure of technical change, and *KACC* is the measure of capital accumulation between the base period *b* and current period *c*. The term *TFP* stands for total factor productivity.

The above piecewise linear technology and the decomposition of labor productivity change is illustrated in Figure 3-2. Labor productivity is measured on the vertical axis and capital-labor ratio is measured on the horizontal axis for the base period (b) and current period (c). The base and current capital-labor ratio are F^b and F^c, respectively. Technology in the current period is represented by $0T^c$ while the technology in the base period is represented by $0T^b$. Technical change measured by the shift in the frontier in the output direction at the current period capital-labor ratio is illustrated by the shift from point E^b to point D^c. In this case, the effect of capital deepening along the base-period technology is represented by the movement from point D^b to point E^b. Alternatively, technical change measured at the base period capital-labor ratio is from point D^b to point E^c.

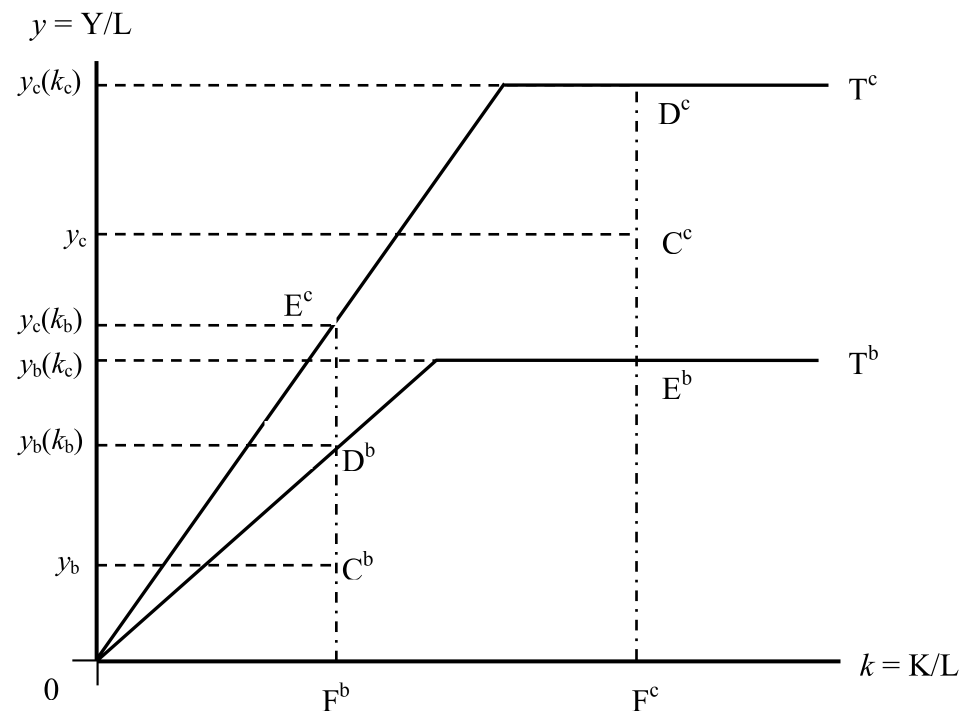

Figure 3-2 Labor Productivity Change

Capital deepening is measured by the movement along the current period frontier from point E^c to point D^c. Therefore, for the farm at C^c, its technical efficiency equals $e^c = F^cC^c / F^cD^c$. Labor productivity change can be represented as follows:

(3.52) $$y^c / y^b = \left(\frac{F^cC^c / F^cD^c}{F^bC^b / F^bD^b} \right) \times \left(\frac{F^cD^c}{F^cE^b} \times \frac{F^bE^c}{F^bD^b} \right)^{0.5} \times \left(\frac{F^cD^c}{F^bE^c} \times \frac{F^cE^b}{F^bD^b} \right)^{0.5}.$$

Using Färe et al. (1994) and Kumar and Russell (2002), we take the logarithms of both sides of equation (3.51) and divide by the number of years between the two periods to get:

(3.53) $$g_Y = g_{EFF} + g_{TECH} + g_{KACC},$$

where g_Y represents the average annual growth rate of output per worker, and g_{EFF}, g_{TECH}, and g_{KACC} are the average annual growth rate of the efficiency index, the average annual growth rate of technical progress, and the average annual growth rate of the potential outputs due to change in capital intensity, respectively. This approach is more appealing than just using equation (3.51) because we estimate the average annual growth rate of output per worker as the sum of the average annual growth rates of the efficiency index, technical progress, and the capital deepening between the two periods.

3.9. Analysis of the Distribution Dynamics of Labor Productivity

By using the tripartite decomposition of labor productivity growth (*EFF, TECH*, and *KACC*), we can explore the role of each of the three components in the transformation of the productivity distribution over the sample period. For this purpose, we adhere to the methodology of Kumar and Russell (2002) and rewrite equation (3.51) as follows:

(3.54) $$y^c = \left(EFF \times TECH \times KACC\right) \times y^b.$$

The above equation indicates that the labor productivity distribution in the current period can be constructed by multiplying the labor productivity in the base period by each of the three components. Therefore, we can also isolate the impact of each component by creating counterfactual distributions by introducing each of the components in sequence. For example, to assess the shift of the labor productivity distribution due solely to efficiency changes we examine the counterfactual distribution of the variable $y^c = \left(EFF\right) \times y^b$. The possible series of counterfactual distributions to be examined are presented below:

(3.55)

$$\begin{aligned}
y^{EFF} &= \left(EFF\right) \times y^b \\
y^{TECH} &= \left(TECH\right) \times y^b \\
y^{KACC} &= \left(KACC\right) \times y^b \\
y^{EFF \times TECH} &= \left(EFF \times TECH\right) \times y^b \\
y^{EFF \times KACC} &= \left(EFF \times KACC\right) \times y^b \\
y^{TECH \times KACC} &= \left(TECH \times KACC\right) \times y^b \\
y^c &= \left(EFF \times TECH \times KACC\right) \times y^b
\end{aligned}$$

The nonparametric kernel-based density estimation methods are employed to conduct the above analysis. The kernel density estimates in our case are simply “smoothed” histograms of labor productivity. The goal of density estimation is to approximate the probability density function *f*(.) of a random variable *X*. Assuming *n* independent univariate observations $x_1, x_2, \ldots, x_n,$ from the random variable *X*, the kernel density estimator of the density value *f*(*x*) at point *x* is defined as:

(3.56) $$\hat{f}(x) = \frac{1}{nh}\sum_{t=i}^{n} k\left(\frac{x_i - x}{h}\right),$$

where *k* (.) is a symmetric probability density satisfying the following conditions:

(3.57) $$\int_{-\infty}^{\infty} k\left[z\right]dz = 1; k \geq 0;\ k(x) = k(\text{-}x)\,.$$

x is the observations that the kernel is centered on, *n* is the number of observations, and *h* is the optimal bandwidth. The restriction on the kernel function *k* (.) is that it is nonnegative and integrated to 1 over its support (Pagan and Ullah, 1999, p.9-23).

There are many kernels that satisfy the above conditions, including the Gaussian, Epanechnikov, triangular, biweight, and rectangular (Silverman, 1986). For a large sample, any kernel function will be close to an optimal one and, therefore, the choice of kernel is a minor issue (Pittau and Zelli, 2004). Silverman (1986) evaluated the efficiency of many potential kernels in terms of mean integrated squared errors, an accuracy statistic computed as the sum of the integrated square bias and the integrated variance relative to the true density. He concluded that, while there are few differences between the potential kernels, the Epanechnikov kernel is the most efficient among kernels that are themselves probability density functions where efficiency is defined as minimizing mean integrated squared error (MISE). The Epanechnikov kernel function is defined as:

(3.58) $$k\left(z\right) = \frac{3}{4\sqrt{5}}\left(1 - \frac{z^2}{5}\right),\ if\ \left|z\right| \leq \sqrt{5},\ \text{otherwise}\ k\left(z\right) = 0\,.$$

The Gaussian kernel function, also commonly used in empirical literature, is defined as:

(3.59) $$k\left(z\right) = \frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}z^2},\ \text{-}\ \infty < \mathrm{z} < \infty.$$

The smoothness of the kernel distribution depends on the value of h; the larger the value, the smoother the distribution and this may distort the shape of the density. On the other hand, using a very small h could under-smooth the density due to the presence of a large number of observations that fall within the window and produce a low variance that may lead to bias. Therefore, bandwidth choice takes into account the trade-off between the bias and the variance in the measure of the global accuracy of $\hat{f}(x)$ as an estimator of $f(x)$. The mean integrated square error (MSIE) is defined by:

$$\text{(3.60)} \qquad \int E\left[\hat{f}(x)-f(x)\right]^2 dx = \left\{\begin{aligned} &\int\left[E\hat{f}(x)-f(x)\right]^2 dx + \int \operatorname{var}\hat{f}(x)dx \\ &= \int\left[bias\left(\hat{f}(x)\right)^2 + \operatorname{var}\left(f(x)\right)\right]^2 dx. \end{aligned}\right\}.$$

The above expression (equation 3.60) has to be minimized over h to find the optimal width. For the proof of the consistency of $\hat{f}(x)$ in estimating $f(x)$, see Li and Racine (2007, p.9-14). The choice of the optimal bandwidth for a kernel density estimate is typically calculated on the basis of the minimization of the MISE function. Silverman (1986) examined the sensitivity of the window-width to skewness and kurtosis using the lognormal and t families of distributions, and considered the effects of the smoothness parameter on the unimodal and bimodal distributions. He concluded that the optimal smoothing parameter was:

$$\text{(3.61)} \qquad h = 0.9An^{-1/5},$$

where A = min (standard deviation, interquartile range/1.34). Other methods of selecting the optimal bandwidth, including the Sheather-Jones plug-in estimator (Sheather and Jones, 1991) and the adaptive kernel density estimation method, are documented in Jann (2007). Jann (2007) provides a comprehensive review of univariate kernel estimation methods using Stata 9.1.

3.10. Testing for the Number of Modes in a Distribution

The consensus view on the modality of farm size distribution in the U.S. agriculture is that farm numbers follow a bimodal distribution with a large proportion of small and part-time farms, an increasing proportion of large farms, and a declining number of moderately sized farms (U.S. Congress, OTA, 1986). In contrast, Wolf and Summer (2001) tested the number of modes in size distributions of dairy farms in the U.S., where size was measured in terms of herd size, cash sales, and acres. The hypothesis of bimodality was rejected in favor of unimodality for dairy farms size distribution. Hallberg (2001, p.18) also posits that there is little evidence of a bimodal distribution of farm sizes in the U.S. agriculture. This study posits that the distribution of labor productivity has transformed from being unimodal to bimodal. The existence of two modes will indicate that the distribution can be regarded as a mixture of two underlying distributions, each with its own mean and standard deviation and each of which reflect a separate economic population subgroup, which in our case are interpreted as small and large farms.

3.10.1. *Uncalibrated Silverman Test*

The uncalibrated Silverman test is used to test the hypothesis that the distribution of labor productivity has transformed from being unimodal into a bimodal distribution over the sample period. Given a sample realization $X = \{x_1, x_2, ..., x_n\}$ from a population with unknown density f (.), Silverman (1981) developed a method to test the null hypothesis that a density function $f(.)$ has m modes against the alternative that $f(.)$ has more than m modes, where m is a non-negative integer. The test statistics in this case is the critical window width and is well defined when the kernel is Gaussian as:

(3.62) $$\hat{h}_{crit(m)} = \inf\left\{h \mid \hat{f} \text{ has at most } m \text{ modes}\right\}.$$

For $h < \hat{h}_{crit(m)}$, the estimated density has at least m+1 modes. The value of $\hat{h}_{crit(m)}$ is computed through a binary search algorithm, and its significance level can be assessed by the smoothed bootstrap procedure attributable to Efron (1979).[6] Large values of $\hat{h}_{crit(m)}$ are taken as evidence against the null hypothesis that $f(.)$ has only m modes. The value of the $\hat{h}_{crit(m)}$ statistic can be assessed using bootstrap methods.

Henderson et al. (2008) have defined the bootstrap procedure as follows: Let

(3.63) $$y_i = 1 + \left(h^2/\sigma^2\right)\left(X_i + h\varepsilon_i\right),$$

where $h = \hat{h}_{crit(m)}$, σ^2 is the sample variance, ε_i is a random draw from the Gaussian density, and X_i is sampled uniformly with replacement from $\left\{x_1, x_2, ..., x_n\right\}$. Therefore, y_i is a random draw from a smooth conditional distribution. Given a smooth bootstrap sample, $Y = \left\{y_1, y_2, ..., y_n\right\}$, the conditional kernel density to determine the number of modes can be constructed as:

(3.64) $$\hat{f}^*\left(x,h\right) = \left(nh\right)^{-1}\sum_{i=1}^{n} K\left(\frac{y_i - x}{h}\right).$$

Evidence against the null hypothesis is provided if the number of modes found in $\hat{f}^*\left(x,h\right)$ is greater than m modes. A formal test of the size of $\hat{h}_{crit(m)}$ is obtained by generating R bootstrap samples from the data and determining the number of times that $\hat{f}^*\left(x,h\right)$ possesses more than m

[6] I acknowledge the help of Professor Daniel Henderson, Department of Economics, State University of New York at Binghamton, for providing the gauss code for bootstrapping the Silverman test.

modes. As discussed by Silverman (1986), failure to reject the null hypothesis is then based on the bootstrap as follows:

(3.65) $$\hat{P} = P\left(\hat{h}*_{crit(m)} \geq \hat{h}_{crit(m)}\right).$$

This is equivalent to finding:

(3.66) $\hat{P}$ = (# of occurrences in which $\hat{f}*\left(x,h\right)$ has more than m modes)/R.

For additional details, see Henderson et al. (2008), Hall and York (2001), and Bianchi (1997).

3.10.2. *Calibrated Silverman Test*

The uncalibrated Silverman test as described above has been found to be conservative in the sense that the true asymptotic level is less than the nominal one. Hall and York (2001) calibrated the Silverman test to obtain the correct asymptotic level which improved its power of Monte Carlo simulations (see Hall and York, 2001, for details). However, while they show theoretically that the Silverman test can be calibrated for any modality hypothesis, the calibration factor is calculated numerically only for the null hypothesis of unimodality (with multimodality as the alterative hypothesis).

Hall and York (2001) modify the Silverman test by setting $\hat{h}_{crit(m)} = \inf\left\{h \mid \hat{f} \text{ has at most } m \text{ modes}\right\}$ such that $h = \lambda_\alpha \hat{h}_{crit(m)}$, where λ_α is chosen so that the test has asymptotic level α. λ_α is determined from the bootstrap distribution of $\hat{h}*_{crit(m)} \big/ \hat{h}_{crit(m)}$, where $\hat{h}*_{crit(m)}$ is the infinum of all bandwidths h such that equation (3.62) has exactly one mode. They set up the α-level test that rejects the null hypothesis if:

(3.67) $$\hat{P} = P\left(\hat{h}^*_{crit(m)} \big/ \hat{h}_{crit(m)} \le \lambda_\alpha\right) = P\left(\hat{h}^*_{crit(m)} \le \lambda_\alpha \hat{h}_{crit(m)}\right) \ge 1 - \alpha .$$

Therefore, the calibration factor λ_α corrects for the fact that the distribution of

(3.68) $$\hat{U} = P\left(\hat{h}^*_{crit(m)} \le \hat{h}_{crit(m)}\right)$$

is not uniform on the interval (0, 1). Hall and York (2001) show that the following bootstrap distribution function converges in probability to a stochastic process for which the distribution is independent of unknowns:

(3.69) $$\hat{G}_n(\lambda) = P\left(\hat{h}^*_{crit(m)} \big/ \hat{h}_{crit(m)} \le \lambda_\alpha\right).$$

Henderson et al. (2008) have provided a Gauss code that calibrates the Silverman test statistics.

3.10.3. *The Dip Test*

An alternative modality test introduced in the economics literature by Henderson et al. (2008) is the Dip test proposed by Hartigan and Hartigan (1985). This test is appealing because the Silverman test, although frequently used, is more sensitive to spurious modes arising from outlying data values (Hall and York, 2001). The Dip test is much less sensitive than the Silverman test to problems of spurious modes in the tails of nonparametric distributions.

The Dip test, as described by Hartigan (1985), is the maximum difference between the empirical conditional distribution function (ECDF) and the unimodal distribution function that minimizes that maximum difference. The Dip test measures departure of the sample from unimodality. Asymptotically the Dip test for samples from a unimodal distribution approaches zero. For samples from any multimodal distribution, the Dip test approaches a positive constant.

The algorithm for carrying out the test is spelled out in Hartigan and Hartigan (1985) and is now implementable using the Dip package in R.

As described by Henderson et al. (2008), the Dip testing procedure is based on the fact that the CDF corresponding to a single mode population density, *f*, must have a single inflexion point at, say, m_f. This implies convexity of the CDF on the interval $(-\infty, m_f)$ and concavity on (m_f, ∞). Therefore, to describe the computation of the Dip statistic, the greatest convex minorant (GCM) is defined as the supremum of convex functions that are nowhere above the ECDF (i.e., the lower envelope of the ECDF that is everywhere concave) and the least concave majorant (LCM) as the infinum of concave functions that are nowhere below the ECDF (i.e., the upper envelop of the ECDF that is everywhere concave). The Dip statistic is the greater of the maximal distance between the ECDF and the LCM and the maximal distance between the EDCF and the GCM.

The intuition behind the testing procedure is as follows. If the ECDF is characterized by multiple regions of concavity or convexity, the ECDF is stretched just enough for it to take the shape of a uniform CDF. Thus, the Dip statistic determines the amount of stretching needed. If no stretching is required, then the Dip statistic is zero and the conclusion drawn is that the population distribution is unimodal. On the other hand, if a significant amount of stretching is needed, then the distribution is likely multimodal. The severity of the stretching is measured by the Dip statistic, and the testing procedure determines the statistical significance of a positive Dip value. If the Dip statistic is significantly different from zero, the null hypothesis of unimodality is rejected (for computational details about this test, see Hartigan and Hartigan, 1985, and Hartigan, 1985). Figure 3-3 provides an illustration of this concept.

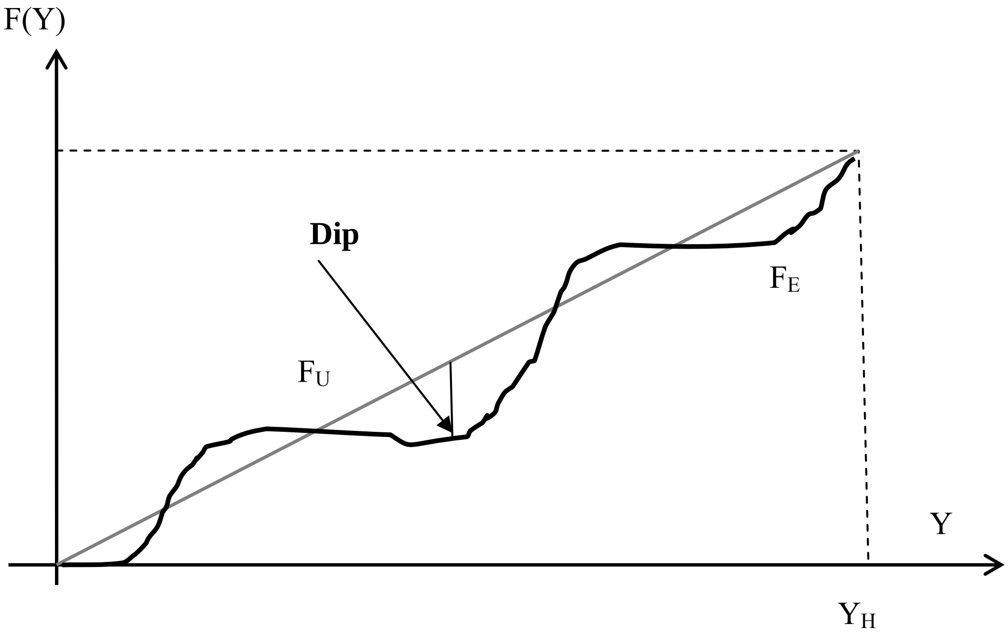

Figure 3-3 DIP test statistic. It is the largest vertical difference between the empirical conditional density distribution F_E and the uniform conditional density distribution F_U.

The significance level of the Dip statistic is assessed using a uniform distribution of the null. Although the Dip test is consistent and asymptotically distinguishes any unimodal distribution from any multimodal distribution, Hartigan and Hartigan (1985) have shown that it is possible for the Dip statistic of a multimodal distribution to be less than the Dip statistic for a unimodal distribution. This implies that unless the Dip statistic is larger than the uniform Dip, nothing can be said about the underlying distribution. Therefore, although the test is attractive on the grounds of ease of implementation, it also leads to conservatism. Thus, Cheng and Hall (1998) proposed the calibration of the Dip statistic to correct for its asymptotic properties (for details on the calibration method, see Cheng and Hall, 1998). Henderson et al. (2008) have provided a Gauss code that implements the calibrated Dip test statistic (for details, see Henderson et al., 2008).

3.11. The Kolmogorov-Smirnov Test

To complement the counterfactual distributions, the two-sample Kolmogorov-Smirnov (KS) test is used to test the null hypothesis of equal distributions against the alternative that the distributions are not equal. The purpose of this test is to determine whether there are changes in the shapes of the actual distributions between two different years (base year and current year), and changes in the shape of the actual distribution in the current year and each of the counterfactual distributions. The KS test is applied directly to the data by using the empirical labor distribution functions. This analysis reveals whether the changes visually observed in the non-parametric kernel density functions are statistically significant or not.

The KS test is based on the maximum absolute difference between the two cumulative distribution functions being compared. For two probability density distributions denoted as *f* (*x*) and *g* (*y*), let the empirical cumulative density functions be denoted as *F* and *G*, respectively. The two sample KS test is used to test the null hypothesis that the two distributions are identical versus the alternative that the two distributions are not identical:

$$
\begin{aligned}
&H_0 : F(z) = G(z) \ \forall \ \mathrm{z} \\
&H_1 : F(z) \neq G(z) \ \forall \ \mathrm{z}.
\end{aligned} \tag{3.70}
$$

Following Gideon and Muellar (1978), the two- sample KS test can be computed as follows: Assume two independent samples of sizes n_1 and n_2 from populations 1 and 2. The cumulative density distributions, *F* and *G*, can be defined as follows:

$$
\begin{aligned}
&F_{n_1}(z) = \text{Number of sample values } \leq \mathrm{z}/n_1 \\
&G_{n_2}(z) = \text{Number of sample values } \leq \mathrm{z}/n_2
\end{aligned} \tag{3.71}
$$

Pool the two samples, order the observations, and let z_j be the *j*th pooled order statistic. Define

$\delta_j = +n_1$ if z_j is from sample 1;

$\delta_j = -n_2$ if z_j is from sample 2.

For each order statistic, define

$$S_j = \sum_{k=1}^{j} \delta_k, \; j = 1, 2, ..., n_1 + n_2 \; .$$

Let, D_{n_1,n_2} denote the usual two-sample KS statistics. Then, this statistic can be computed as follows:

(3.72) $$D_{n_1,n_2} = \sup\left\{| F_{n_1}(z) - G_{n_2}(z) |\right\}, n_1 n_2 D_{n_1,n_2} = \max_j \left\{| S_j |\right\}.$$

The null hypothesis that the two distributions are identical is rejected if D_{n_1,n_2}, the KS test statistic, is greater than c_α, the critical value for the significance level α. For this study, the equality of the following actual versus counterfactual distributions will be tested:

(3.73) $$\begin{aligned} &f(y^c) = g(y^b) \\ &f(y^c) = g((EFF) \times y^b) \\ &f(y^c) = g((TECH) \times y^b) \\ &f(y^c) = g((KACC) \times y^b) \\ &f(y^c) = g((EFF \times TECH) \times y^b) \\ &f(y^c) = g((EFF \times KACC) \times y^b) \\ &f(y^c) = g((TECH \times KACC) \times y^b). \end{aligned}$$

Abadie (2002) has noted that the KS type nonparametric distance tests generally have good power properties. Unfortunately, the asymptotic distributions of the test statistics under the null hypothesis are generally unknown because they depend on the underling distribution of the data. The author proposed a bootstrap strategy to overcome this problem. This strategy is adopted in this study and can be described by the following four steps:

Step 1: Let T_n denote the KS statistic D_{n_1,n_2}. Compute the D_{n_1,n_2} statistics for the original samples $(Y_{1,1}, ..., Y_{1,n_1})$ and $(Y_{1,1}, ..., Y_{1,n_2})$.

Step 2: Resample n observations $\left(\hat{Y}_{1,1},...,\hat{Y}_{1,n}\right)$ from $\left(Y_{1,1},...,Y_{1,n}\right)$ with replacement. Divide $\left(\hat{Y}_{1,1},...,\hat{Y}_{1,n}\right)$ into two samples: $\left(\hat{Y}_{1,1},...,\hat{Y}_{1,n_1}\right)$ given by the n_1 first elements of $\left(\hat{Y}_{1,1},...,\hat{Y}_{1,n}\right)$, and $\left(\hat{Y}_{1,1},...,\hat{Y}_{1,n_2}\right)$ given by the n_2 last elements of $\left(\hat{Y}_{1,1},...,\hat{Y}_{1,n}\right)$. Use those two generated samples to compute the test statistic $\hat{T}_{n.b}$.

Step 3: Repeat Step 2, B times. Note that n_1 and n_2 are constant across bootstrap repetitions.

Step 4: Calculate the p-value of these tests as follows:

p-value $= \sum_{b=1}^{B} 1\left\{\hat{T}_{n.b} > T_n\right\} \Big/ B$. Reject the null hypothesis if the p-value is smaller than some significance level α, 0 < α < 0.5.

3.12. Convergence Tests

Linear regression models have been the workhorse for analyses of the relationship between annual labor productivity growth rates and initial level of productivity in tests for convergence. The linear regression models summarize the relationship between an outcome variable y and a vector (X, Z) through a linear mean regression where the mean of y is modeled as a linear function of both X and Z. In this case, X is a vector of continuous variables and Z is a vector of dummies that represent the categorical variables.

The ordinary least square (OLS) linear regression models the relationship among the dependent variable and K explanatory variables as:

(3.74) $$y_i = X_i\beta + \varepsilon_i ,$$

where y is a vector of a dependent variable, X is a matrix of the levels of independent variables, including dummies, β is a vector of the regression coefficients, and ε is a vector of random errors that are assumed to follow a normal distribution with zero mean and constant variance.

This study examines cross farm convergence by means of linear regression models. This is made possible by the tripartite decomposition of labor productivity into efficiency change, technical change, and capital accumulation. Previous studies relied mostly on estimating the relationship between labor productivity growth rate and the initial labor productivity to detect evidence of convergence in labor productivity growth rates (Kumar and Russell, 2002; Henderson and Russell, 2005). Of interest in this study is to know whether the growth of labor productivity is due to each of the tripartite decomposition components.

From the general parametric regression model in equation (3.74), the following specific regressions are used to estimate evidence of convergence/divergence:

(3.75) $$y_i = \alpha + \beta \ln y_{io} + u_i$$

(3.76) $$y_{EFFi} = \alpha_{EFF} + \beta_{EFF} \ln y_{io} + u_{EFFi}$$

(3.77) $$y_{TECHi} = \alpha_{TECH} + \beta_{TECH} \ln y_{io} + u_{TECHi}$$

(3.78) $$y_{KACCi} = \alpha_{KACC} + \beta_{KACC} \ln y_{io} + u_{KACCi}.$$

The independent variable in the above equations is the natural logarithm of initial labor productivity. The dependent variables for equations 3.75 to 3.78 are annual growth rates of labor productivity, average contribution of efficiency change, average contribution of technical change, and average contribution of capital accumulation, respectively. A significant negative coefficient will indicate convergence and a positive coefficient will indicate divergence. Furthermore, as shown by Delgado-Rodriguez and Álvarez-Ayuso (2008), the total convergence parameter is the sum of the parameters of convergence of the individual cross-sectional estimations:

(3.79) $$\hat{\beta} = \hat{\beta}_{EFF} + \hat{\beta}_{TECH} + \hat{\beta}_{KACC} = \hat{\beta}_{TFP} + \hat{\beta}_{KACC}.$$

Despite the popularity of linear regression models in convergence analyses, a more robust specification is called for in some situations where the imposed linear relationship between (the mean of) y and Z (the categorical variables) is suspect. The semi-parametric specification allows for a regression function that maintains linearity in X (the continuous independent variables) but allows the effect of Z to be nonlinear. Two semi-parametric models are considered: the partial linear model (PLM) and the smooth coefficient model (SCM).

3.12.1. *Partially Linear Model*

Following Li and Racine (2007), a partial linear regression model (PLM) consists of two additive components, a linear parametric part and a nonparametric part:

(3.80) $$y_i = \alpha(Z_i) + X_i^{'}\beta + \varepsilon_i \ .$$

In the above model, $X_i \beta$ is the parametric component, α (.) is the nonparametric component whose functional form is not specified, and ε denotes an error term with zero mean and common variance. Taking the expectation of (3.80) conditional on Z_i, yields:

(3.81) $$E(Y_i \mid Z_i) = E(Y_i \mid Z_i)'\beta + \alpha(Z_i).$$

Subtracting (3.81) from (3.80) to eliminate the unknown function $\alpha(Z_i)$ yields:

(3.82) $$y_i - E(Y_i \mid Z_i) = (X_i - E(Y_i \mid Z_i))'\beta + \varepsilon_i.$$

Define the shorthand notation as $\tilde{Y}_i = Y_i - E(Y_i \mid Z_i)$ and $\tilde{X}_i = X_i - E(Y_i \mid Z_i)$. Applying the least square methods to (3.82), the following estimator of β is obtained:

(3.83) $$\hat{\beta}_{\text{inf}} = \left[\sum_{i=1}^{n} \tilde{X}_i \tilde{X}_i'\right]^{-1} \sum_{i=1}^{n} \tilde{X}_i \tilde{Y}_i.$$

Subtracting (3.81) from (3.80) introduces two new unknown functions, $E(Y_i \mid Z_i)$ and $E(X_i \mid Z_i)$, and therefore the above estimator of $\hat{\beta}_{\text{inf}}$ is *infeasible*. This differencing allows inference to be made on β as if there were no nonparametric components in the model. Nevertheless, the unknown conditional expectations can be consistently estimated using kernel methods. Replacing the unknown conditional expectations that appear in $\hat{\beta}_{\text{inf}}$ with their kernel estimators enables a feasible estimator of β to be obtained. Let:

(3.84) $$\hat{Y}_i \equiv \hat{E}(Y_i \mid Z_i) = n^{-1}\sum_{j=1}^{n} Y_j K_h(Z_i, Z_j) / \hat{f}(Z_i), \hat{X}_i \equiv \hat{E}(Y_i \mid Z_i) = n^{-1}\sum_{j=1}^{n} X_j K_h(Z_i, Z_j) / \hat{f}(Z_i),$$

where

$$\hat{f}(Z_i) = n^{-1}\sum_{j=1}^{n} K_h(Z_i, Z_j), K_h(Z_i, Z_j) = \prod_{s=1}^{q} h_s^{-1} k\left(\frac{z_{is} - z_{js}}{h_s}\right).$$

Therefore, $\tilde{Y}_i = Y_i - E(Y_i \mid Z_i)$ and $\tilde{X}_i = X_i - E(Y_i \mid Z_i)$ in $\hat{\beta}_{\text{inf}}$ can be replaced by $Y_i - \hat{Y}_i$ and $X_i - \hat{X}_i$, respectively. The detailed derivation of the asymptotic distribution of $\hat{\beta}$, the feasible estimator of β, is well documented in Li and Racine (2007) and Yatchew (2003). It is important to note that in the PLM, the intercept cannot be identified separately from the unknown function $\alpha(Z_i)$ because the functional form of the unknown function is not specified.

3.12.2. *Smooth Coefficient Model*

Following Li et al. (2002) and Li and Racine (2007), a smooth coefficient model (SCM) nests a PLM and can be specified as:

(3.85) $$y_i = \alpha\left(Z_i\right) + X_i^{'}\beta\left(Z_i\right) + \varepsilon_i .$$

In the above equation, β (Z_i) is a vector of unspecified smooth functions of Z_i. When β (Z_i) = β, the model reduces to a PLM. The main difference between the PLM and the SCM is that the PLM assumes the slope coefficients, β, are invariant to the nonparametric component, Z_i. In contrast, the SCM allows the nonparametric variable to affect the slope coefficient β. The semi-parametric SCM allows more flexibility in functional forms than the PLM or the parametric OLS models. At the same time it avoids much of the 'curse of dimensionality' problem as the nonparametric functions are restricted only to part of the variable Z. In other words, the SCM lets the marginal effect of a given variable be represented as an unknown function of an observed covariate. Instead of restricting the marginal effect of y with respect to X to be constant and equal to a parameter β, the SCM writes this marginal effect as an unknown of some explanatory variable, say Z (Koop and Tobias, 2006).

The model in equation 5.43 can be expressed more compactly as:

(3.86) $$y_i = \alpha\left(Z_i\right) + X_i^{'}\beta\left(Z_i\right) + \varepsilon_i = (1, x_i^{'})\begin{pmatrix}\alpha\left(Z_i\right)\\ \beta\left(Z_i\right)\end{pmatrix} + \varepsilon_i \equiv X_i^{'}\delta\left(Z_i\right) + \varepsilon_i ,$$

where $\delta\left(Z_i\right) = \left(\alpha\left(Z_i\right), \left(\beta(Z_i)\right)'\right)'$. $\delta\left(Z_i\right)$ is a vector of smooth but unknown functions of Z_i. Li et al. (2002) proposed the following local least square method to estimate $\delta\left(Z_i\right)$:

$$\begin{aligned}\hat{\delta}(Z_i) &= \left[\left(nh^q\right)^{-1} \sum_{j=1}^{n} X_j X_j^{'} K\left(\frac{Z_j - Z}{h}\right)\right]^{-1} \\ &\times \left\{ \left(nh^q\right)^{-1} \sum_{j=1}^{n} X_j y_j K\left(\frac{Z_j - Z}{h}\right)\right\} \equiv \left[D_n(Z)\right]^{-1} A_n(Z).\end{aligned} \tag{3.87}$$

In the above equation,

$D_n(Z) = \left(nh^q\right)^{-1} \sum_{j=1}^{n} X_j X_j^{'} K\left(\frac{Z_j - Z}{h}\right), A_n(Z) = \left\{ \left(nh^q\right)^{-1} \sum_{j=1}^{n} X_j y_j K\left(\frac{Z_j - Z}{h}\right)\right\}$, $K(.)$ is a kernel function, and $h = h_n$. Under certain regularity conditions, the theorem that establishes the consistency and asymptotic normality of $\hat{\delta}(Z_i)$ are proven in Li and Racine (2007) and Li et al. (2002).

3.13. Model Specification Test: Parametric versus Semi-parametric

It is usually more efficient to estimate a correctly specified parametric model than to estimate a semi-parametric model. However, as noted by Li et al. (2002), if a semi-parametric model is a correct specification, and the parametric model is not, the estimation results based on the parametric model will usually lead to inconsistent estimation results. If *Ho* denotes a null hypothesis whose validity we wish to test, a test is said to be consistent if it has asymptotic power equal to one:

(3.89) P (Reject $Ho|Ho$ is false) → 1 as $n \to \infty$.

If the null is rejected and yet there exists alternative models that the test cannot detect, the test is said to be 'inconsistent' since it lacks power in certain directions.

Therefore, in empirical work it is important to test whether the parametric model is an adequate description of the data or not. A variety of methods exist for testing for correctly specified parametric regression models (Härdle and Mammen, 1993; Horowitz and Härdle, 1994; Horowitz and Spokoiny, 2001; Hristache et al., 2001; and Hsiao et al., 2007). This study follows the method by Hsiao et al. (2007) as it admits the mix of both continuous and categorical data types often encountered in applied settings.

Hsiao et al. (2007) propose a nonparametric kernel-based model specification that employs discrete kernel functions and smoothes both the discrete and continuous regresors using least squares cross-validation methods. The test is shown to have an asymptotic normal null distribution and the authors prove the validity of using the wild bootstrap method to approximate the null distribution of the test statistic. Monte Carlo simulations are used to show that the proposed test has significant power advantages over conventional kernel tests which rely upon frequency-based nonparametric estimators that require sample splitting to handle the presence of discrete regresors.

Following Hayfield and Racine (2008), the test proposed by Hsiao et al. (2007) can be summarized as: suppose one wished to test the correctness of a parametric regression model. The null hypothesis that the parametric linear model is the correct specification can be stated as follows:

(3.90) $H_0: E(Y \mid x) = m(x, \gamma_0)$, for almost all x and for some $\gamma_0 \in \mathrm{B} \subset R^p$,

where $m(x, \gamma_0)$ is a known function with γ being a $p \times 1$ vector of unknown parameters and B is a compact subset of R^p. The alternative hypothesis is the negation of the null (H_0) stated as follows:

(3.91) $H_1 : E(Y \mid x) \equiv g(x) \neq m(x, \gamma_0)$, for all $\gamma \in \mathrm{B}$ on a set of x with positive measures.

If $u_i = Y_i - m(X_i, \gamma_0)$, the null hypothesis can be equivalently written as:

(3.92) $E(u_i \mid X_i = x) = 0$ for almost all x.

A consistent model specification test can be constructed by nonparametrically estimating the above equation and averaging over the u_i. Note that $E(u_i \mid X_i = x) = 0$ is equivalent to $\left[E(u_i \mid X_i = x)\right]^2 = 0$. Therefore, by law of iteration it can be seen that $E\left\{\left[E(u_i \mid X_i = x)\right]^2\right\} = E\left\{u_i E(u_i \mid X_i = x)\right\}$. A consistent test statistic can be constructed based on a density weighted version of $E\left\{u_i E(u_i \mid X_i = x)\right\}$, namely $E\left\{u_i E(u_i \mid X_i) f(X_i)\right\}$, where $f(x)$ is the joint PDF of X. Density function is used here to avoid a random denominator that would otherwise appear in the kernel estimator.

The sample analogue of $E\left\{u_i E(u_i \mid X_i) f(X_i)\right\}$ is given by the following formula: $n^{-1}\sum_{i=1}^{n} u_i E(u_i \mid X_i) f(X_i)$. To obtain a feasible test statistic, u_i is replaced by $\hat{u}_i$, where $\hat{u}_i = Y_i - m(X_i, \hat{\gamma})$ is the residual obtained from the parametric null model, and $\hat{\gamma}$ is a $\sqrt{n}$-consistent estimator of γ based on the null model. The $E(u_i \mid X_i) f(X_i)$ is estimated by the leave-one-out kernel estimator $(n-1)^{-1}\sum_{j \neq i}^{n} \hat{u}_j K_{ij}$. Letting X_i be a vector of mixed discrete and continuous variables and using generalized product kernels, the test statistic is based upon:

(3.93) $$I_n \overset{def}{=} \frac{1}{n}\sum_{i=1}^{n} \hat{u}_i \left\{ \frac{1}{n-1} \sum_{j=1, j \neq i}^{n} \hat{u}_j K_{ij} \right\} = \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} \hat{u}_i \hat{u}_j K_{ij}.$$

The studentized version of this test is denoted by J_n. Bootstrap methods can be used to obtain the distribution of $I_n\left(J_n\right)$ under the null which can be used to from a bootstrap p-value (for details, see Hsiao et al., 2007).

CHAPTER 4 - DATA SOURCES AND DECSRIPTION

This chapter provides a description of the source, main variables, and classifications of data used in this study. Frontier analyses using nonparametric approaches are very sensitive to extreme observations. Thus, the procedures used to detect outliers in the data are also discussed.

4.1. Data Sources

Farm-level data used for this study are taken from farm account records of the Kansas Farm Management Association (KFMA) Data Bank. The KFMA Data Bank contains financial and production information for farms and ranches enrolled in the KFMA program (for detailed information about the data bank, see Langemeier, 2003). The Data Bank for the time period studied contains 688 variables per farm for approximately 2,300 to 2,500 farms for years 1993 through 1998, 974 variables per farm for approximately 2,000 to 2,200 farms for years 1999-2001, and 2,370 variables per farm for approximately 2,000 farms beginning in 2002. For the purpose of this study, a balanced panel of continuous data of 583 farms across 15 years (1993-2007) was constructed from the data bank.

4.2. Main Variables

Computation of DEA scores requires the use of output and input variables. The constructed dataset contain the following variables for each farm: two outputs, crops and livestock, and three inputs, assets, labor, and purchased inputs. Crop and livestock outputs are measured in dollar terms and the total output is measured as the total gross farm income (GFI) from both crop and livestock enterprises.

Assets are measured as a flow variable and the following: cost of machinery repairs, irrigation repair, machine hire, auto expenses, building repair, conservation, cash interest, cash farm rent, real estate tax, property tax, general farm insurance, depreciation, and opportunity interest charged on owned equity. Labor is measured by the number of workers employed on each farm for each year. This includes hired, family, and operator labor.

Purchased inputs are measured in dollar terms and include the following items: fuel and oil, seed, fertilizer and lime, dairy expenses, irrigation energy, crop marketing and storage, herbicides and insecticides, feed purchased, veterinarian expenses, livestock marketing and breeding, organizational fees and publications, utilities, and crop insurance. The constructed dataset also contain price indices information for crops, livestock, labor, purchased inputs, and assets for each farm in the entire sample.

As with other studies on productivity decomposition, no attempt was made to account for quality differences in inputs because of lack of such information in the database. However, as noted in the nonparametric efficiency analyses literature (For example, Koop et al., 1999), the DEA approach is very sensitive to outliers in the data. Barnet and Lewis (1995) define an outlier (or set of outliers) as observation(s) which appear to be inconsistent with the remainder of the data. Some outliers are a result of measurement errors and should be eliminated from the dataset. Others are observations associated with a low probability of occurrence and differ greatly from the rest of the dataset. An observation could also be an outlier because it arose from a different data generating process than the others (Simar, 2003). Outliers may affect some characteristics of the entire dataset such as the sample mean and regression lines. In deterministic frontier models, outliers might be highly influential if they distort the enveloping estimator of the frontier and therefore it is very important to develop data analysis tools which detect outliers (Simar, 2003).

There are several outlier observation detection studies on nonparametric efficiency analyses (Dusanskly and Wilson, 1995; Wilson, 1995; and Pastor et al., 1999). However, this study used the graphical analysis approach, i.e., visual inspection of scatter plots, to identity and eliminate extreme values for each pair of output and input combination (i.e., gross farm income versus capital, and gross farm income versus labor) for each year over the entire sample period, 1993-07. Seaver and Triantis (1989) cautioned that it is wise to use more than one outlier detection scheme and the same caveat is applicable in this study. Therefore, the scatter plots were used in conjunction with box plots to identify extreme values for each variable[7]. After the above detection and deletion of extreme values, the remaining dataset provide usable values for 564 farms from the original 583 farms for each year for the entire sample period.

4.3. Data Description for Tripartite Decomposition

Empirical studies on the tripartite decomposition of labor productivity have used one output, measured in real terms, and two inputs, labor and capital (e.g., Kumar and Russell, 2002; Weber and Domazlicky, 2006; Delgado-Rodriguez and Álvarez-Ayuso, 2008). This practice is followed by aggregating the crop and livestock income into gross farm income, and assets and purchased inputs into capital input.

[7] Box plot is a convenient way of graphically depicting groups of numerical data through their five-number summaries: sample minimum, lower quartile, median, upper quartile, and sample maximum. A box plot also indicate which observations, if any, might be considered outliers

The nominal GFI is deflated by the Personal Consumption Expenditure (PCE) Index, with 2007 as the base year. The PCE price index is produced by the Bureau of Economic Analysis (BEA)[8], U.S. Department of Commerce, and is considered to be more comprehensive and theoretically a more compelling measure of consumer prices compared to the Consumer Price Index (CPI) (Hakkio, 2008).

Real capital is calculated in the following manner: *First*, total capital is calculated as the sum of assets and purchased inputs. *Second*, a deflator is constructed using the price indices for purchased inputs (Purinp) and assets (Capp) by farm and year, with 2007 as the base year, and weighted with the total capital:

$$\text{deflator} = \left(\frac{\text{Purchased Inputs}}{\text{Total Capital}}\right) \times \text{Purinp} + \left(\frac{\text{Assets}}{\text{Total Capital}}\right) \times \text{Capp}\,. \tag{4.1}$$

Third, estimates of real capital by farm and year are computed by dividing the nominal capital by the deflator:

$$\text{Real Capital} = \frac{\text{Nominal Capital}}{\text{deflator}}\,. \tag{4.2}$$

Therefore, capital is defined in broad terms to include purchased inputs.

Data are grouped in this format for two main reasons: *first*, because of the problem of jointness in production. It is not possible to disaggregate data in terms of the proportion of capital and purchased inputs that were used in the crop and livestock enterprises. Therefore, due to technical interdependence in production, only one best practice production frontier is estimated rather than a production frontier for each output produced. Shumway et al. (1984, p.78) noted that many agricultural firms produce multiple products and operate subject to at least one allocatable fixed input. Hence, jointness is much more a pervasive problem in agriculture

[8] (www.bea.gov/bea/an/nipaguid.pdf)

than often supposed. Lynne (1988) observed that corn, soybeans, and wheat may exist simultaneously on a farm due to the existence of a nonallocatable input (e.g., tractor) which may suggest jointness in supply and hence, jointness in technology. *Second*, the tripartite decomposition of labor productivity growth is based on the total output per worker rather than output per worker for each enterprise.

To perform the tripartite decomposition, data were grouped into yearly pairs from 1993-1994 to 2006-2007. This grouping is used to distinguish the relative contribution of efficiency change, technical change, and capital accumulation over the entire sample period. Data were also grouped into yearly pairs with 1993 as the base year, i.e., 1993-1994 to 1993-2007, to distinguish the cumulative effect of efficiency change, technical change, and capital accumulation over the sample period. For the purpose of investigating the dynamics of the distribution of labor productivity and convergence, paired yearly data over 10-year and 15-year periods were used (i.e., 1993-2007, 1993-2002, and 1995-2005). The first time period, 1993-2007, captures the labor productivity dynamics between the beginning and end of sample. The second and third time periods captures the productivity dynamics between two comparable years (i.e., 1993 and 2002; 1996 and 2005) when real output was at its lowest and highest, respectively.

Both outputs and inputs are measured in dollar values rather than in quantities because dollar values allows for comparisons between farms which may be heterogeneous given the broad categories of farm sizes and specialization. Table 4.1 provides the descriptive statistics of the outputs and inputs for the sample of 564 farms for 15 years, and Figure 4.1 plots the annual mean of each variable used in the DEA model. In general, the series indicates an upward trend for both real GFI and real capital. Average GFI increased from $196,099 in 1993 to $384,593 by

2007. Real capital increased from $237,324 to $368,311. However, labor input decreased from 1.56 workers to 1.38 workers during the same time period, respectively.

Table 4-1 Mean and Standard Deviation of Output and Inputs

Year	Real Gross Farm Income (in $10,000)	Real Capital (in $10,000)	Labor Inputs (in Persons/Farm)
1993	19.6099	23.7324	1.5600
	(15.0568)	(17.3646)	(1.0100)
1994	19.5660	25.1615	1.5600
	(14.8423)	(18.8407)	(0.9700)
1995	19.7641	25.4157	1.5700
	(16.5134)	(19.3237)	(1.0400)
1996	25.3511	26.2454	1.5600
	(21.2155)	(20.1610)	(1.0000)
1997	27.1713	28.2436	1.5900
	(21.1064)	(20.8474)	(1.1000)
1998	20.8849	28.3949	1.5900
	(16.5206)	(20.9194)	(1.0800)
1999	23.3248	29.1152	1.5500
	(18.9355)	(22.2452)	(1.0200)
2000	23.9256	29.4762	1.4900
	(19.4192)	(22.4727)	(0.9200)
2001	24.2744	30.4581	1.5000
	(20.5756)	(23.8030)	(1.0500)
2002	22.4870	29.8783	1.4800
	(19.2996)	(23.1176)	(1.0000)
2003	26.5078	30.5898	1.4700
	(22.5975)	(23.7453)	(0.9800)
2004	29.3374	31.6818	1.4600
	(26.5719)	(25.1367)	(0.9600)
2005	29.7296	33.5570	1.4400
	(26.7054)	(26.2939)	(0.9500)
2006	30.5322	34.2652	1.4200
	(26.2733)	(26.8308)	(0.9200)
2007	38.4593	36.8311	1.3800
	(34.8205)	(29.1880)	(0.9700)
Pooled Data	25.3950	29.5364	1.5100
	(22.5273)	(23.1488)	(1.0000)

* Figures in brackets are standard deviations. Mean measured in constant dollars (2007=100)

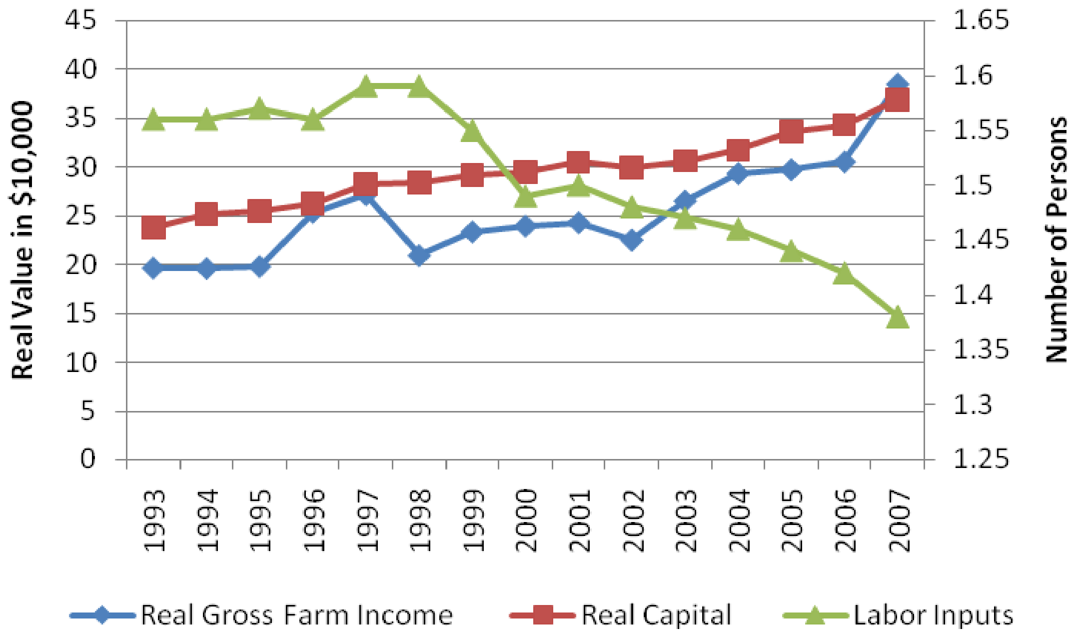

Figure 4-1 Average Farm Outputs and Inputs

4.4. Farm Types Distribution based on Size and Specialization

For the purpose of reporting results, the observations in the sample are grouped according to two farm typologies: farm size and specialization. Distinguishing farm types provides additional insights about differential productivity growth across the Kansas farm sector. Farms are disaggregated into four groups based on size: (1) very small farms (VSF) involve farms with less than $100,000 in GFI; (2) small farms (SF) include farms with GFI between $100,000 and $250,000; (3) medium farms (MF) include farms with GFI between $250,000 and $500,000; and (4) large farms (LF) are farms with GFI above $500,000.

The percentage of time devoted to crop production is used to group the farms based on level of specialization. Farms that devote less than 50 percent of their labor time to crop production are categorized as specialized in livestock production, farms that devote 100 percent of their labor time to crop production are categorized as specialized in crop production, and those that devote between 50 percent and 99 percent of their labor time to crop production are considered to be mixed farms. The justification for this segregation is that the two groups face different constraints likely to affect efficiency and productivity measures.

Table 4-2 Frequency Distribution of Farm by Size and Specialization, 1993 - 2007

	Farm Size (Counts)				Farm Specialization (Counts)		
Year	Very Small Farms	Small Farms	Medium Farms	Large Farms	Livestock	Mixed	Crops
1993	146	284	127	7	134	293	137
1994	142	293	119	10	130	296	138
1995	160	272	121	11	119	295	150
1996	104	263	163	34	113	303	148
1997	80	263	178	43	117	287	160
1998	149	276	120	19	93	309	162
1999	119	267	150	28	92	316	156
2000	119	265	152	28	86	301	177
2001	117	258	158	31	77	301	186
2002	142	262	142	18	79	297	188
2003	118	232	166	48	82	284	198
2004	92	239	171	62	80	277	207
2005	99	235	157	73	81	274	209
2006	93	227	161	83	80	276	208
2007	83	183	167	131	86	266	212

The frequency distribution of the farm types based on size and specialization are reported in Table 4.2 and plotted in Figure 4.2. A visual inspection of the table indicates that there has been a decrease in the number of farms in the lower level typologies (very small and small farms) over the study period and an increase in the number of farms in the upper level typologies (medium sized and large farms). This observation suggests the existence of two separate "centers of attraction" of farm size and lends support to the notion of a "disappearing small" of farm structure in the Kansas farm sector.

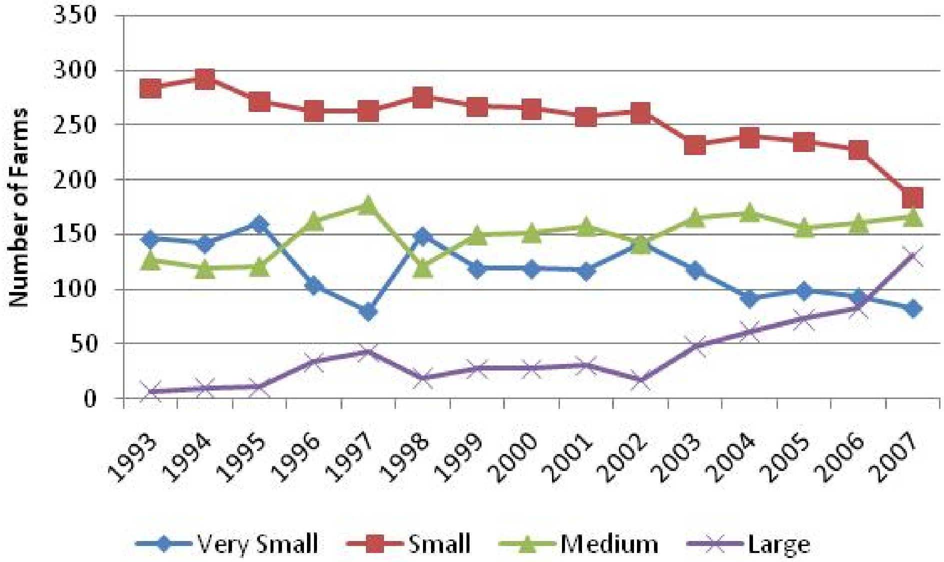

Figure 4-2 Frequency Distribution of Farms in the Lower Level (Very Small and Small Farms) and Upper Level (Medium and Large Farms) Typologies

In 1993, there were 134 livestock farms, 293 mixed farms, and 137 crop farms. By 2007, there were only 86 livestock and 266 mixed farms. Specialized crop farms increased to 212 suggesting that 75 more farms became specialized in crop production compared to 1993. Basic characteristics of the farm categories are reported in Tables 4.3 and 4.4. A cross tabulation between the level of specialization and farm size is reported in Table 4.5.

Livestock farms, on average, use more labor compared to mixed or crop farms, an indication that livestock farms are more labor intensive compared to the other specialties. Livestock farms also use more purchased inputs compared to the other farm types**.** Overall, the sampled farms are predominantly either mixed (51 percent) or crop (31 percent) farms. Livestock farms constitute only 18 percent of farms over the entire study period.

Table 4-3 Mean and Standard Deviation of Inputs and Outputs by Farm Size

Farm Size	Gross Farm Income	Labor	Capital
Very Small Farms	71,682.75	0.90	65,036.81
	(43,206.95)	(0.31)	(29,568.85)
Small Farms	186,317.20	1.24	112,305.70
	(97,185.04)	(0.41)	(43,011.59)
Medium size Farms	368,283.80	1.78	194,143.60
	(185,625.10)	(0.77)	(65,917.20)
Large Farms	683,911.50	3.07	360,579.00
	(450,298.90)	(1.86)	(151,753.00)
Pooled Data	264,867.10	1.51	151,076.40
	(258,059.20)	(1.00)	(108,756.70)

* Figures in brackets are standard deviations. Mean measured in constant dollars (2007=100)

Table 4-4 Mean and Standard Deviation of Inputs and Outputs by Specialization

Specialization	Gross Farm Income	Labor	Capital
Livestock	97,138.58	1.89	147,548.40
	(124,256.70)	(1.50)	(114,653.40)
Mixed	277,788.80	1.46	155,740.40
	(261,111.30)	(0.88)	(114,453.10)
Crops	343,811.00	1.39	145,481.80
	(266,959.30)	(0.77)	(94,202.36)
Pooled Data	264,867.10	1.51	151,076.40
	(258,059.20)	(1.00)	(108,756.70)

* Figures in brackets are standard deviations. Mean measured in constant dollars (2007=100)

Table 4-5 Number of Farms Type by Size and Specialization, Pooled Data

	Livestock	Mixed	Crops	Total
Very Small	338 (19.7)	812 (47.4)	563 (32.9)	1,713 (100.0)
Small	625 (16.5)	2011 (53.1)	1155 (30.5)	3,791 (100.0)
Medium	404 (17.5)	1180 (51.1)	727 (31.5)	2,311 (100.0)
Large	242 (26.0)	442 (47.5)	246 (26.5)	930 (100.0)
Total	1,609 (18.4)	4445 (50.8)	2691 (30.8)	8,745 (100.0)

* Figures reported are counts. Those in brackets are percentages across columns

CHAPTER 5 - EMPIRICAL RESULTS AND DISCUSSION

This section presents and discusses the empirical results of the various analyses conducted to achieve objectives (1) to (4). These results include findings on technical and scale efficiencies of Kansas farms and its variation by farm size and specialization; the tripartite decomposition of labor productivity growth into efficiency change, technical change, and capital deepening; the distributional dynamic of labor productivity growth; and regression analysis results for the test of beta convergence/divergence in labor productivity growth over selected periods (1993-07, 1993-02, and 1996-05).

5.1. Technical and Scale Efficiency of the Kansas Farm Sector, 1993 to 2007

Previous studies on the productive efficiency of Kansas farms ignored the sampling noise in DEA estimates (Featherstone et al., 1997; Rowland et al., 1998). To address this problem, this section used the Simar and Wilson (1998, 2001, and 2002) smoothed bootstrap procedure to investigate the bias, variance, and confidence intervals for technical efficiency scores in the Kansas farm sector. The study investigates whether both technical and scale efficiencies vary by farm size and farm specialization.

5.1.1. *Bootstrapping DEA Efficiency Estimates*

The first objective of this study was to estimate the technical and scale efficiency scores for the Kansas farm sector for the period 1993-2007. The nonparametric production function approach (i.e., data envelopment approach) and the smoothed homogenous bootstrapped procedure introduced in chapter 3 were used to estimate input oriented technical efficiency scores using one output (gross farm income) and two inputs (capital and labor). Working in smaller dimensions (one output, two inputs) tends to provide better estimates of the frontier and helps overcome the *curse of dimensionality*[9] always present in nonparametric estimation (Daraio and Simar, 2007). The input oriented framework aims at reducing the input amount by as much as possible while keeping at least the present output levels. For all the estimates, 2000 bootstrap iterations (i.e., B=2000) were employed. All models were estimated using the FEAR package that is linked to the statistical package R (Wilson, 2008).

Tables 5.1 through 5.3 presents the mean efficiency scores of the 564 farms for the sample period under three assumptions of the technological set: constant returns to scale (CRTS), variable returns to scale (VRTS) and non-increasing returns to scale (NIRTS).[10] For each table, the first through sixth columns represent the mean of the DEA-estimates, the bias corrected DEA estimates, the estimated bias, the estimated standard errors, and the 95-percent confidence lower and upper bounds, respectively. The confidence intervals are based on the bias corrected efficiency scores. Daraio and Simar (2007) note that when the bias is larger than the standard deviation, the bias corrected estimates are preferred to the original estimates. In this case, the original estimates are preferred because the standard deviation is larger than the bias.

Results in Table 5.1 show the mean technical efficiency, across years, under CRTS varied from a maximum of 60 percent (2001) to a minimum of 47 percent (2005). For the bias corrected technical efficiency score, the maximum was 58 percent (2000) and the minimum was

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[9] Convergence rate diminishes as the number of inputs and outputs increases (see Simar and Wilson 2000a for discussion).
[10] Each of those three technological sets are necessary in identifying the nature of returns to scale

42 percent (2005). The lower bound ranged from 40 percent to 56 percent while the upper bound ranged from 46 percent to 60 percent. The mean difference between the lower and upper efficiency interval throughout the study period is 4.8 percent, the highest value is 7.2 percent (2003) and the lowest value is 3.6 percent (1993).

Table 5-1 Input Oriented Technical Efficiency Scores with CRTS model for Kansas Farms

Year	Eff. Score	Eff. Bias Corrected	Bias	Std. Error	Lower Bound	Upper Bound
1993	0.5833	0.5652	0.0181	3.4463	0.5457	0.5812
1994	0.5844	0.5606	0.0237	2.7928	0.5388	0.5816
1995	0.5326	0.5054	0.0271	1.8918	0.4820	0.5297
1996	0.5545	0.5229	0.0316	1.1583	0.4998	0.5502
1997	0.5928	0.5748	0.0179	3.2849	0.5551	0.5911
1998	0.5858	0.5638	0.0220	2.7343	0.5426	0.5831
1999	0.4936	0.4586	0.0349	0.4589	0.4306	0.4900
2000	0.5991	0.5770	0.0221	3.5189	0.5557	0.5963
2001	0.6008	0.5763	0.0245	2.6868	0.5539	0.5980
2002	0.5463	0.5213	0.0249	1.6609	0.4976	0.5441
2003	0.4767	0.4283	0.0484	0.0734	0.3996	0.4719
2004	0.5748	0.5515	0.0232	3.1151	0.5289	0.5717
2005	0.4657	0.4183	0.0474	0.1747	0.3947	0.4606
2006	0.5032	0.4692	0.0340	0.5564	0.4428	0.4998
2007	0.5229	0.5006	0.0222	2.6391	0.4796	0.5210
Total	0.5478	0.5196	0.0281	2.0128	0.4965	0.5447

Notes: the above table reports mean technical efficiency scores bootstrapped with 2000 iterations (B=2000). Confidence intervals are presented at 95 percent confidence level. Total number of farms for each year is 564.

Table 5-2 Input Oriented Technical Efficiency Scores with VRTS model for Kansas Farms

Year	Eff. Score	Eff. Bias Corrected	Bias	Std. Error	Lower Bound	Upper Bound
1993	0.6250	0.5870	0.0379	2.3959	0.5691	0.6200
1994	0.6242	0.5871	0.0370	2.3480	0.5686	0.6182
1995	0.5770	0.5329	0.0440	1.7584	0.5161	0.5705
1996	0.6096	0.5693	0.0403	2.2858	0.5515	0.6027
1997	0.6223	0.5884	0.0338	1.9060	0.5675	0.6175
1998	0.6122	0.5746	0.0376	2.5520	0.5580	0.6070
1999	0.5628	0.5195	0.0433	1.6573	0.4997	0.5564
2000	0.6386	0.6007	0.0378	2.7297	0.5838	0.6329
2001	0.6447	0.6048	0.0398	2.5808	0.5865	0.6387
2002	0.5768	0.5268	0.0500	1.4289	0.5095	0.5696
2003	0.5297	0.4769	0.0528	0.6964	0.4577	0.5215
2004	0.6232	0.5854	0.0378	1.9847	0.5668	0.6172
2005	0.5159	0.4584	0.0575	0.5532	0.4411	0.5061
2006	0.5563	0.5081	0.0481	1.5576	0.4912	0.5492
2007	0.5699	0.5291	0.0407	2.1151	0.5150	0.5591
Total	0.5925	0.5499	0.0426	1.9033	0.5321	0.5858

Notes: the above table reports mean technical efficiency scores bootstrapped with 2000 iterations (B=2000). Total number of farms for each year is 564.

Table 5.2 presents the mean technical efficiency, across years, under VRTS. The efficiency score varied from a minimum of 52 percent (2005) to a maximum of 65 percent (2001). For the bias corrected technical efficiency score, the minimum was 46 percent (2005) and the maximum was 61 percent (2001). The lower bound ranged from 44 percent to 59 percent while the upper bound ranged from 51 percent to 64 percent. The mean difference between the lower and upper bounds throughout the study period is 5.4 percent, with the highest value being 6.5 percent (2005) and the lowest value being 4.4 percent (2007).

Table 5-3 Input Oriented Technical Efficiency Scores with NIRTS model for Kansas Farms

Year	Eff. Score	Eff. Bias Corrected	Bias	Std. Error	Lower Bound	Upper Bound
1993	0.6151	0.5861	0.0289	2.8142	0.5654	0.6105
1994	0.6072	0.5755	0.0316	2.6167	0.5552	0.6015
1995	0.5627	0.5299	0.0328	2.0051	0.5091	0.5576
1996	0.5790	0.5439	0.0351	1.8244	0.5234	0.5728
1997	0.6119	0.5867	0.0251	2.2664	0.5670	0.6083
1998	0.6022	0.5756	0.0266	2.8741	0.5560	0.5983
1999	0.5344	0.4977	0.0367	1.4940	0.4760	0.5291
2000	0.6243	0.5950	0.0292	3.1120	0.5758	0.6191
2001	0.6167	0.5815	0.0351	2.1617	0.5614	0.6107
2002	0.5529	0.5143	0.0386	1.4117	0.4928	0.5475
2003	0.5154	0.4702	0.0452	0.8092	0.4483	0.5089
2004	0.5956	0.5648	0.0308	2.1771	0.5453	0.5899
2005	0.4993	0.4501	0.0491	0.7552	0.4307	0.4907
2006	0.5307	0.4921	0.0386	1.8583	0.4713	0.5249
2007	0.5434	0.5159	0.0274	2.0740	0.4986	0.5399
Total	0.5727	0.5386	0.0340	2.0169	0.5184	0.5673

Notes: the above table reports mean technical efficiency scores bootstrapped with 2000 iterations (B=2000). Total number of farms for each year is 564.

Results for the mean technical efficiency, across years, under NIRTS are presented in Table 5.3. The average efficiency score varied from a minimum of 50 percent (2005) to a maximum of 62 percent (2000). For the bias corrected technical efficiency score, the minimum was 45 percent (2005) and the maximum was 60 percent (2000). The lower bound ranged from 43 percent to 58 percent while the upper bound ranged from 50 percent to 62 percent. The mean difference between the lower and upper efficiency interval throughout the study period is 5.0 percent, with the highest value being 6.1 percent (2003) and the lowest value being 4.1 percent (1997).

Table 5.4 presents the estimated farm-specific technical efficiency measures (VRTS) in the form of frequency distribution within a decile range. The results reveal that, in general, Kansas farms have not been successful in employing best-practice production methods and achieving the maximum possible output from new and existing technologies. The majority of the farms had an efficiency score between 40 percent and 70 percent throughout the sample period. The estimated results reveal that the numbers of farms that operate at efficiency level less than 50 percent are increasing while those operating above the 50 percent efficiency level are decreasing.

In general, the mean technical efficiency scores of all farms for the entire sample period were 55, 57 and 59 percent for the CRTS, NIRTS, and VRTS technology sets, respectively. These results are consistent with production economics theory because VRTS technology set is the least restrictive and the CRTS technology set is the most restrictive, whereas the NIRTS technology set lies in between. The estimated mean confidence intervals for CRTS are narrower (4.8%) than for NIRTS (5.0%) and VRTS (5.4%) because of the greater curvature of the production frontier for the VRTS case. Likewise, the CRTS technology set display smaller bias (2.8%) compared to NIRS (3.4%) and VRTS (4.3%), where larger bias indicates a larger degree of noise.

The empirical results suggest that Kansas farms are technically inefficient and have been facing efficiency deterioration over time. On average, the technical efficiency scores under the three technological sets have been declining over the sample period. This is depicted by the linear prediction graph in Figure 5.1 whereby a linear prediction line with 95 percent confidence level band is fitted for the efficiency scores for each of the three technological sets. All three linear predictions are downward sloping indicating efficiency is deteriorating.

Table 5-4 Frequency Distribution of Input Efficiency Scores with VIRTS model for Kansas Farms, 1993-2007

TE (%)	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
<20	1	1	8	3	1	0	2	1	0	3	3	2	6	5	9
20-30	6	3	18	11	6	9	18	4	2	18	26	7	38	28	33
30-40	24	32	55	39	22	42	61	26	26	42	92	32	106	59	59
40-50	86	76	94	82	69	95	121	70	59	114	133	79	114	114	95
50-60	142	151	154	148	149	121	148	135	135	150	141	119	138	140	127
60-70	152	146	112	130	170	137	109	144	147	121	92	168	90	123	117
70-80	82	79	65	77	90	99	60	107	112	76	49	83	51	58	71
80-90	40	52	34	42	35	31	27	46	50	20	17	37	8	21	26
>90	31	24	24	32	22	30	18	31	33	20	11	37	13	16	27

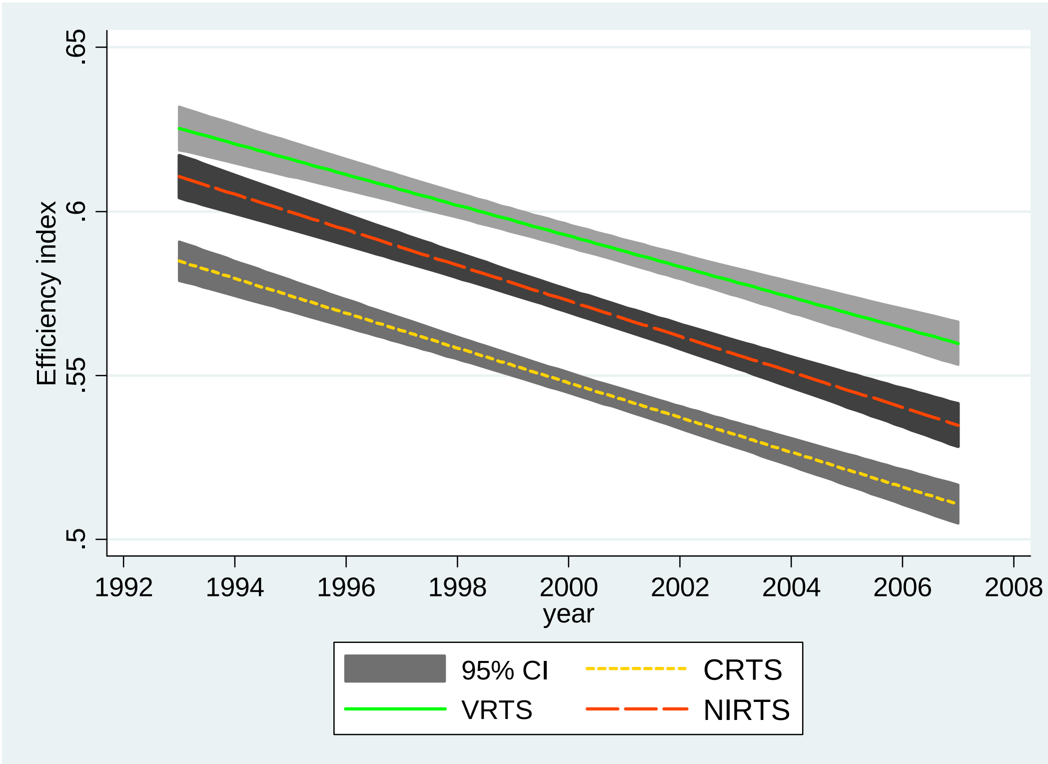


Figure 5-1 Linear Predictions of Technical Efficiency Scores, 1993-2007

In general, the reported results are consistent with what has been reported in literature. Bravo-Ureta et al. (2007) in a meta-regression analysis study of farm level technical efficiency scores found that efficiency scores in North America range from 45.9 percent to 100 percent. Serra et al. (2008) used a stochastic frontier analysis to compute technical efficiency indices for Kansas farms, between 1998 and 2001, and found the mean efficiency scores to range from 70 to 72 percent. Featherstone et al. (1997) indicated that the technical efficiency score for the cow-calf sector was 78 percent in 1995. A meta-analysis study by Bravo-Ureta et al. (2007) on farm level technical efficiency observed that technical efficiency scores are influenced by a number of factors, including the number of variables in the model, number of fixed and variable inputs, and for parametric models, the functional form used to estimate the model.

One interesting outcome from the above analysis is that the ranking of mean technical efficiency scores by year varied slightly depending on the return to scale technology set used and whether the original or bias corrected efficiency scores were used (Table 5.5). The years when the farms seemed to have been efficient under the ranking of the original efficiency (i.e., not corrected for bias) scores ranked lower when the bias corrected efficiency scores are used. Similarly the ranking changes depending on the technology set used although all the technology sets ranked the years 2005 and 2003 as the least efficient years and the years 2001 and 2000 as the most efficient years.

Table 5-5 Ranking of Mean Efficiency Scores by Years

	Original Efficiency Scores			Bias-corrected Efficiency Scores		
Ranking	CRTS	VRTS	NIRTS	CRTS	VRTS	NIRTS
1	2001	2001	2000	2000	2001	2000
2	2000	2000	2001	2001	2000	1997
3	1997	1993	1993	1997	1997	1993
4	1998	1994	1997	1993	1994	2001
5	1994	2004	1994	1998	1993	1998
6	1993	1997	1998	1994	2004	1994
7	2004	1998	2004	2004	1998	2004
8	1996	1996	1996	1996	1996	1996
9	2002	1995	1995	2002	1995	1995
10	1995	2002	2002	1995	2007	2007
11	2007	2007	2007	2007	2002	2002
12	2006	1999	1999	2006	1999	1999
13	1999	2006	2006	1999	2006	2006
14	2003	2003	2003	2003	2003	2003
15	2005	2005	2005	2005	2005	2005

Notes: The table compares the ranking of average annual technical efficiency scores by year for the three technological sets: CRTS, VRTS and NIRTS. Both biased and biased-corrected scores are considered.

Rank correlations were computed between pairs of both original and bias corrected efficiency scores under the three technology sets using two nonparametric methods commonly used in the literature to establish those correlations, the Kendall Tau and Spearman rank correlations.[11]

Table 5-6 Nonparametric Correlations among Efficiency Scores

	CRTS	BC-CRTS	VTRS	BC-VRTS	NIRTS	BC-NIRTS
Spearman's Rank Correlation						
CRTS	1.0000					
BC-CRTS	0.9857	1.0000				
VRTS	0.9357	0.9500	1.0000			
BC-VRTS	0.9643	0.9643	0.9714	1.0000		
NIRTS	0.9643	0.9857	0.9786	0.9786	1.0000	
BC-NIRTS	0.9464	0.9750	0.9286	0.9571	0.9786	1.0000
Kendall Tau's Correlation						
CRTS	1.0000					
BC-CRTS	0.9429	1.0000				
VRTS	0.8286	0.8476	1.0000			
BC-VRTS	0.8857	0.8667	0.9048	1.0000		
NIRTS	0.8667	0.9238	0.9238	0.9048	1.0000	
BC-NIRTS	0.8476	0.9048	0.8286	0.8857	0.9048	1.0000

Notes: All the coefficients are significant at 95 percent significance level. BC is bias corrected.

Table 5.6 shows the results obtained for the correlations of the means of technical efficiencies across years. Both the Spearman and Kendall Tau coefficients are positive and significant for all rank correlations between DEA scores under CRTS, VRTS, and NIRTS. These two statistics indicate that the null hypothesis of no significant rank correlation between any of the two measures is rejected at the 5-percent significance level considering the means of all years. Therefore, although there are slight variations in the ranking of individual efficiency scores, all three models produce comparable rankings for the average efficiency scores.

[11] Spearman's rank correlation tests for an association between two related variables. It is the nonparametric alternative to the Pearson correlation, and its equivalent to ranking the observations and then analyzing the ranks using the Pearson correlations. Kendall's Tau is best described as the difference between the probability that the observation are in the same order for the variables and the probability that the observations are in different order for the variables.

5.1.2. *Technical Efficiency Estimates by Farm Size and Specialization*

Estimates of technical efficiency under VRTS technology set by farm size and specialization are presented in Tables 5.7 and 5.8, respectively. The VRTS technology set is used to report the remaining results because it less restrictive than the NIRTS and CRTS technology sets. Technical efficiency is found to vary by farm size with large farms being more efficient (80%) compared to medium sized farms (67%), small farms (56%), and very small farms (49%). The ranking of efficiency scores by farm size does not change when the bias corrected efficiency scores are used (i.e., 70%, 63%, 54%, and 42% respectively). These results are consistent with the findings of Weersink et al. (1990) that technical efficiency is positively related to farm size for Missouri grains farms.

There was not much variation in technical efficiency scores by farm specialization although crop farms are slightly more efficient (60%) than diversified farms (57%) and livestock farms (57%). Mean technical efficiency decreased over time within each farm size and farm specialization group, as well as over the entire population. This provides evidence for the presence of efficiency degradation within each farm size group and farm specialization group, between the groups and over the entire farm population.

Table 5-7 Input Oriented Technical Efficiency Scores with VIRTS model by Farm Size

Farm Size	Eff. Score	Eff. Bias Corrected	Bias	Std. Error	Lower Bound	Upper Bound
Very Small	0.4872	0.4214	0.0657	2.0021	0.4194	0.4773
Small	0.5631	0.5414	0.0217	2.8421	0.5233	0.5595
Medium	0.6678	0.6245	0.0432	0.7622	0.5977	0.6610
Large	0.7983	0.6958	0.1025	0.0032	0.6677	0.7814
Pooled	0.5925	0.5499	0.0426	1.9033	0.5321	0.5858

Table 5-8 Input Efficiency Scores with VIRTS model by Farm Specialization

Farm Specialization	Eff. Score	Eff. Bias Corrected	Bias	Std. Error	Lower Bound	Upper Bound
Livestock	0.5866	0.5449	0.0417	2.0027	0.5263	0.5802
Mixed	0.5864	0.5480	0.0383	1.9937	0.5294	0.5808
Crops	0.6060	0.5559	0.0501	1.6988	0.5398	0.5984
Pooled	0.5926	0.5499	0.0426	1.9033	0.5321	0.5858

To statistically test technical efficiency differences by farm size and farm specialization, the nonparametric Kruskal-Wallis (KW) test was conducted for all the VRTS efficiency measures.[12] The null hypothesis is that the rank of technical efficiency scores, based on the means, is the same across the different farm sizes and farm specialization groups. Using the KW test, the null hypothesis that the rank of technical efficiency is the same across farm size is rejected at the 1-percent significance level. However, the null hypothesis that the mean rank of technical efficiency is the same across farm specialization groups is not rejected even at 10-percent significance level. This provides evidence that farm size does matter when comparing farm technical efficiency but specialization does not.

5.1.3. *Scale Efficiency*

Results for scale efficiency are presented in Table 5.9. The mean scale efficiency for the farm sector, over the sample period, was 93 percent, with the highest scale efficiency attained in

[12] Kruskal Wallis test is a nonparametric test for the situation where the ANOVA normality assumption may not apply. This test was used instead of ANOVA because normality of efficiency scores in the entire sample was rejected using the Shapiro-Wilk, Shapiro-Francia, and Skewness-Kurtosis tests. However, both the KW and ANOVA give identical results for this case.

1998 (96%) and the lowest in 1999 (89%). Scale efficiency was consistently high in comparison to technical efficiency.

The scale efficiency over the sample period indicates that , on average, small farms are more scale efficient (97%) compared to medium sized farms (93%), very small farms (89%) and large farms (84%). This relationship is maintained throughout the sample period as depicted in Figure 5.2. However, over time, large and medium sized farms are becoming more scale efficient while small and very small farms are becoming scale inefficient. These results are contrary to the results of Paul et al. (2004) who found small family farms to be less efficient in terms of both their scale of operation and technical aspects of production than large farms. The mean difference in scale efficiency by farm specialization is not statistically significant: crop farms (93%), diversified farms (94%), and livestock farms (92%).

Table 5-9 Scale Efficiency Scores

Year	Overall				Farm Size				Farm Specialization		
	Mean	Min	Std. Dev	CV	Very Small	Small	Medium	Large	Livestock	Mixed	Crop
1993	0.9416	0.4131	0.0848	0.0901	0.9528	0.9678	0.8821	0.7211	0.9341	0.9475	0.9361
1994	0.9435	0.4963	0.0772	0.0818	0.9194	0.9826	0.8951	0.7175	0.9403	0.9456	0.9422
1995	0.9329	0.2727	0.0955	0.1023	0.9185	0.9714	0.8827	0.7433	0.9298	0.9351	0.9310
1996	0.9181	0.0826	0.1030	0.1122	0.8119	0.9680	0.9282	0.8079	0.9170	0.9230	0.9088
1997	0.9577	0.5126	0.0776	0.0810	0.9224	0.9857	0.9659	0.8177	0.9513	0.9650	0.9491
1998	0.9610	0.3971	0.0692	0.0720	0.9485	0.9750	0.9549	0.8950	0.9448	0.9655	0.9618
1999	0.8888	0.2811	0.1109	0.1248	0.8318	0.9463	0.8547	0.7643	0.8656	0.8993	0.8810
2000	0.9454	0.3341	0.0850	0.0899	0.9224	0.9765	0.9296	0.8344	0.9302	0.9526	0.9405
2001	0.9364	0.1234	0.0876	0.0936	0.8399	0.9784	0.9528	0.8673	0.9238	0.9423	0.9320
2002	0.9506	0.4558	0.0816	0.0859	0.8838	0.9776	0.9757	0.8854	0.9270	0.9606	0.9446
2003	0.9191	0.2040	0.1212	0.1319	0.9080	0.9862	0.8802	0.7563	0.9030	0.9268	0.9147
2004	0.9311	0.2296	0.0947	0.1017	0.8312	0.9682	0.9643	0.8443	0.9161	0.9363	0.9298
2005	0.9129	0.3136	0.1009	0.1105	0.8447	0.9584	0.9191	0.8459	0.8880	0.9233	0.9090
2006	0.9139	0.2230	0.1009	0.1104	0.8217	0.9611	0.9443	0.8290	0.9037	0.9154	0.9157
2007	0.9255	0.2276	0.1044	0.1128	0.8102	0.9520	0.9837	0.8871	0.9016	0.9310	0.9283
Total	0.9319	0.0826	0.0957	0.1027	0.8846	0.9709	0.9296	0.8355	0.9206	0.9381	0.9278

Notes: The reported values for farm size and farm specialization categories are annual means.

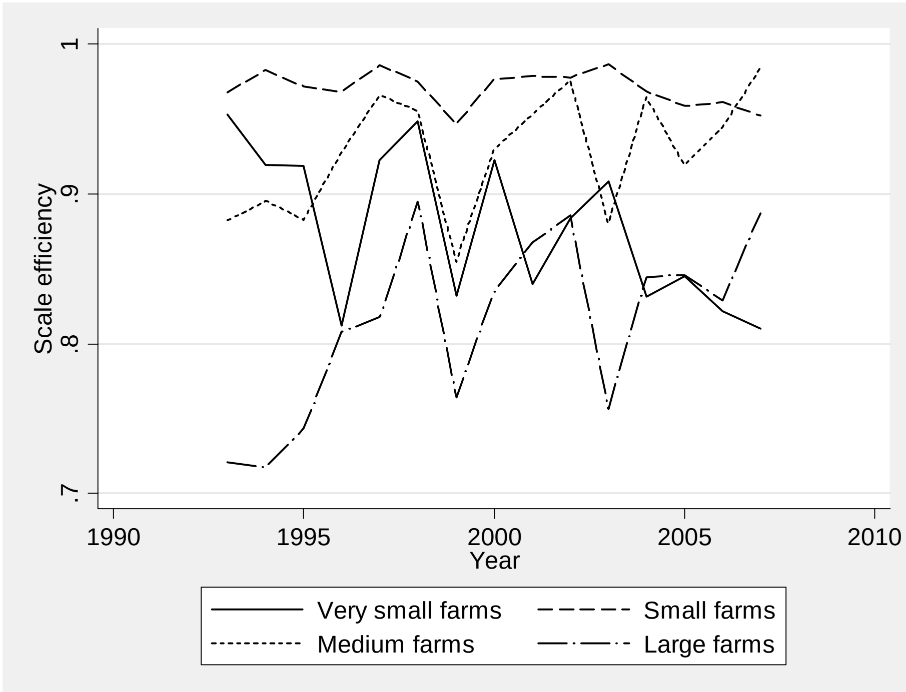


Figure 5-2 Scale Efficiency by Farm Size, 1993 -2007

5.1.4. *Analysis of Returns to Scale*

One can ascertain the returns to scale properties of a farm by comparing the technical efficiency levels with reference to VRTS, NIRTS, and CRTS frontiers. Returns to scale expresses the relationship between a proportional change in inputs and the resulting proportional change in output. Constant returns to scale implies that an *n* percent rise in all inputs produces an *n* percent increase in output. When output rises by a larger percentage than inputs, there are increasing returns to scale (IRTS) and decreasing returns to scale (DRTS) holds when output rises by a smaller percentage than inputs.

A variable returns to scale (VRTS) frontier is one that exhibits CRTS, DRTS, and IRTS. When the NIRTS and CRTS measures are equal but differ from the VRTS measure, increasing returns to scale (IRTS) holds (i.e., $TE^{NIRS} = TE^{CRTS} < TE^{VRTS}$). When VRTS and NIRTS measures are equal but differ from the CRTS measure, diminishing returns to scale (DRTS) holds (i.e., $TE^{VRTS} = TE^{NIRTS} < TE^{CRTS}$). The three measures are equal only at the most productive scale size (MPSS). The MPSS constitute two groups of farms, those that are both technically and scale and those that are technically inefficient but scale efficient. For the purpose of this analysis, the former group is considered to be operating under CRTS (i.e., $TE^{NIRTS}=TE^{CRTS}=TE^{VRTS}=SE=1$) and the latter under MPSS (i.e., $TE^{NIRTS}=TE^{CRTS}=TE^{VRTS}<1$ and SE=1).

Table 5.10 presents the results of the overall number of farms operating under optimal scale (CRTS), sub-optimal scale (IRTS), supra-optimal scale (DRTS), and most productive scale size (MPSS) over the sample period. The data show that the number of farms that operated under supra-optimal scale increased while those that operated sub-optimal scales decreased. This implies that, on average, farms gradually grew larger and became scale inefficient. The overall returns to scale results indicate that only 8 percent of the farms in the sample operated under CRTS and MPSS, 39 percent of the farms operated under sub-optimal scale, and 53 percent operated under supra-optimal scale. The years when the farms predominantly operated under sub-optimal scale are 1993 (52%), 1997 (60%), 2000 (54%), and 2005 (51%).

Table 5.11 presents a breakdown of the number of farms that operated under the four different returns to scale scenarios by farm size. In 1993, 2000, and 2007, the number of very small farms that operated under CRTS and MPSS was 24, 22, and 0, respectively. The number of medium size farms that operated under CRTS and MPSS was 6, 2, and 1, respectively, while that of large farms was 0, 1, and 8, respectively. The observations for the IRTS and DRTS show that very small farms became smaller over the sample period while small and medium sized farms became larger. Results for the large farms are mixed; the number of farms that operate under sub-optimal scale increased over the sample period until year 2007 when 33 farms operated at supra-optimal scale. Similarly, analysis of the returns to scale by specialization shows that both specialized and diversified farms became scale inefficient and grew larger over the sample period.

Table 5-10 Overall Number of Farms Operating under Optimal Scale (CRTS), Sub-optimal Scale (IRTS), and Supra-optimal Scale (DRTS), and Most Productive Scale Size (MPSS)

	CRTS	IRTS	DRTS	MPSS	Total
1993	*6*	295	148	115	564
1994	4	224	325	11	564
1995	3	212	291	58	564
1996	5	256	273	30	564
1997	2	336	224	2	564
1998	4	261	298	1	564
1999	2	230	287	45	564
2000	4	307	197	56	564
2001	3	193	324	44	564
2002	3	101	453	7	564
2003	2	186	323	53	564
2004	5	155	362	42	564
2005	3	289	113	159	564
2006	2	188	373	1	564
2007	2	98	457	7	564

Notes: values reports are actual number of farms operating under each of the four technological sets for 15 years. MPSS are farms that are scale efficient (SE = 1) but technically inefficient (TE < 1).

Table 5-11 Number of Farms Operating under Optimal Scale (CRTS), Sub-optimal Scale (IRTS), and Supra-optimal Scale (DRTS), and Most Productive Scale Size by Farm Size, 1993-2007

	Optimal Scale CRTS				Sub-optimal Scale IRTS				Supra-optimal Scale DRTS				Most Productive Scale Size MPSS			
Year	VS	S	M	L	VS	S	M	L	VS	S	M	L	VS	S	M	L
1993	0	2	4	0	9	170	109	7	113	23	12	0	24	89	2	0
1994	0	1	3	0	3	103	108	10	139	182	4	0	0	7	4	0
1995	0	0	3	0	3	97	101	11	152	136	3	0	5	39	14	0
1996	0	0	3	2	0	83	141	32	104	163	6	0	0	17	13	0
1997	0	1	0	1	8	145	146	37	71	116	32	5	1	1	0	0
1998	0	1	1	2	25	131	88	17	124	143	31	0	0	1	0	0
1999	0	0	1	1	0	77	126	27	119	165	3	0	0	25	20	0
2000	0	2	1	1	8	144	128	27	89	86	22	0	22	33	1	0
2001	0	0	2	1	0	36	127	30	117	204	3	0	0	18	26	0
2002	0	0	2	1	0	6	78	17	142	254	57	0	0	2	5	0
2003	0	0	1	1	0	18	122	46	117	196	10	0	1	18	33	1
2004	0	1	1	3	0	6	91	58	92	223	47	0	0	9	32	1
2005	0	0	1	2	7	100	119	63	76	36	1	0	16	99	36	8
2006	0	0	0	2	0	9	98	81	93	218	62	0	0	0	1	0
2007	0	0	0	2	0	0	8	90	83	183	158	33	0	0	1	6

Notes: The farm sizes are represented as follows: VS = Very small, S = Small, M = Medium, and L = Large. Values reported are counts.

5.1.5. *Analysis of Efficiency Distributions*

Nonparametric kernel density estimation techniques have become common in graphically illustrating various results in nonparametric production efficiency analysis (Henderson and Zelenyuk, 2007; Simar and Zelenyuk, 2006). Compared to histograms, kernel densities have the advantage of providing smoother density estimates and do not depend on the width and number of bins (Wand and Jones, 1995). This method is useful in the context of this study because no distributional assumptions were imposed on the efficiency scores across farms. When using kernel density estimation, Simar and Zelenyuk (2006) note that one has to take care of at least three things. First, the random variable whose density is to be estimated has a bounded support with many observations close to the bound. Second, only the consistent estimate of the true random variable (efficiency scores) is observed, not the true realization of the efficiency scores. Therefore, the consistent estimates are biased downwards, as reflected in the biased corrected estimates. Third, some farms are on the frontier (having an efficiency score equal to unity) and, hence, there is always a strictly positive probability of observing at least one farm with efficiency score of unity. This is a violation of the continuity assumption that is needed to ensure consistency of the density estimation.

The suggestions of Simar and Zelenyuk (2006) are followed to address the above cited problems. First, the Silverman reflection method is used to correct for the bounded support. Second, bootstrap DEA is used to compute the efficiency scores and the density is estimated using the bias corrected efficiency scores. Third, densities are estimated using the reflection method, with a Gaussian kernel, and bandwidth selected is done via the Silverman (1986) rule of thumb.

Kernel densities for the bias corrected technical efficiency scores, under the assumption of NIRTS, are estimated for an interval of five years, i.e., 1993, 1997, 2002, and 2007. The results are presented in Figure 5.3, where panel A to D depicts the univariate kernel estimate of the efficiency scores with a 95-percent confidence level band.

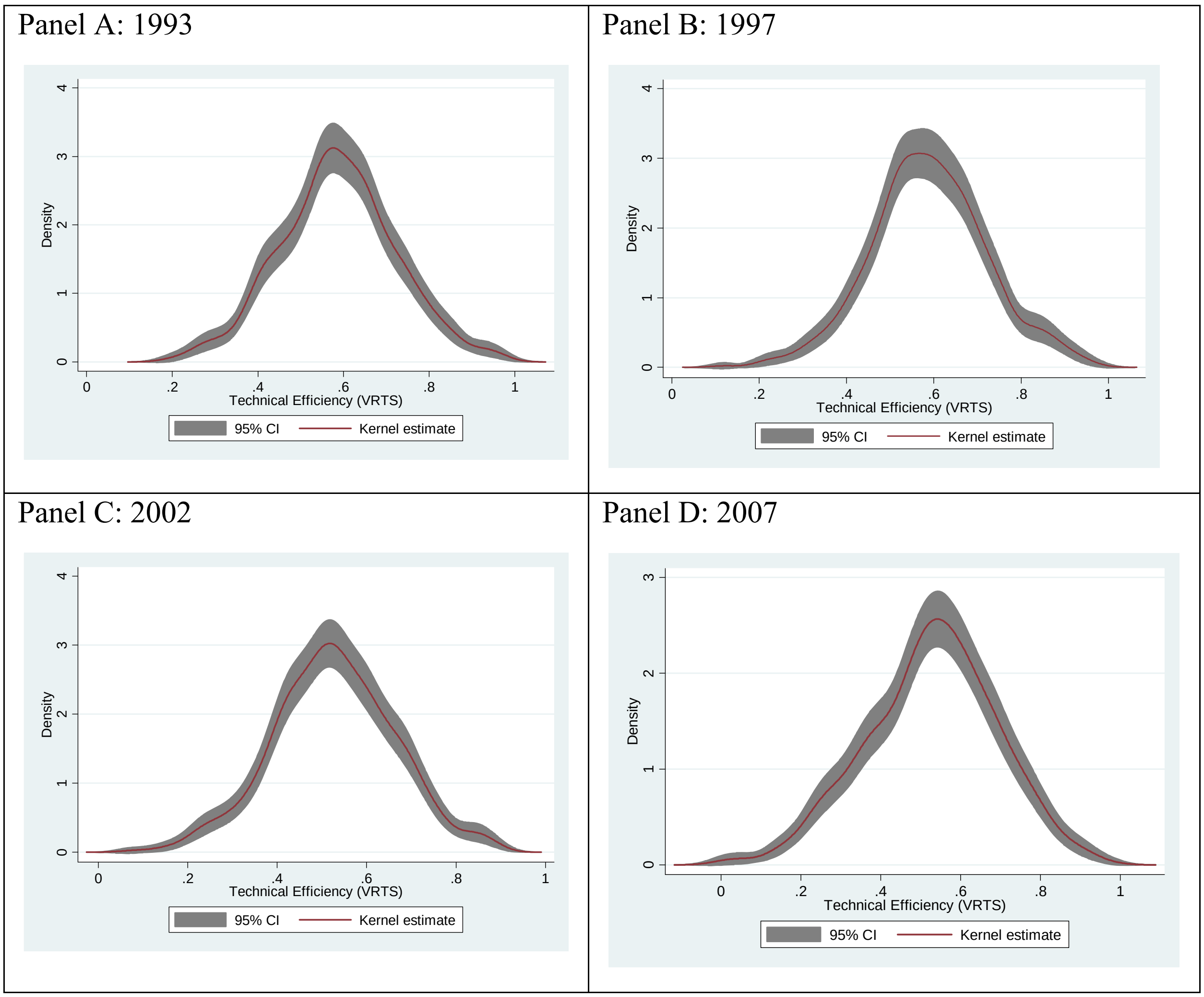


Figure 5-3 Kernel density distributions of input oriented technical efficiency scores (VRTS) for 1993, 1997, 2002, and 2007

As is expected, most of the probability density mass lies close to the efficiency boundary (i.e., above efficiency level of 50%) with diminishing tails toward greater inefficiency. By comparing the densities, effects of a decrease in efficiency can be noted, since there is evidence of a shift of the probability mass towards the left, from 1993 to 2007. The densities exhibit a single peak suggesting that the distribution of efficiency has remained unimodal over the sample period.

Figure 5.4 reports the kernel destiny estimates of the technical efficiency scores for 1993 (solid line) and 2007 (dashed line) on one graph. The figure shows a shift of the entire distribution of efficiency scores for 2007 towards the left, indicating that Kansas farms did not move closer to the frontier. The shift is more prominent in the left tail, an indication that farms that had low efficiency scores in 1993 moved further away from the frontier relative to farms that had high efficiency scores.

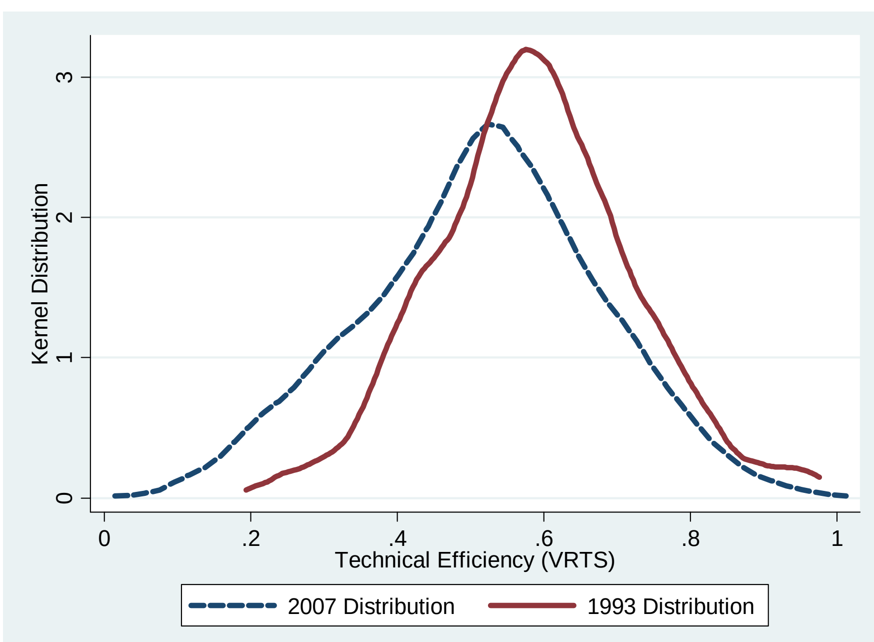


Figure 5-4 Distributions of Input Efficiency Scores, 1993 and 2007

5.1.6. *Concluding Remarks*

This section introduced recent advances in bootstrapping and data envelopment analysis to investigate technical and scale efficiency indices of the Kansas farm sector using three different technology sets: CRTS, VRTS and NIRTS. The data consisted of a balanced panel of 564 farms for the sample period 1993-07. The input oriented approach was used to compute technical efficiency scores, bias corrected efficiency scores, and the 95 percent confidence interval. Further, the sample was separated into farm size and farm specialization categories. Kernel estimation methods were used to investigate the distribution of efficiency scores over an interval of five years. It is important to note that the objective was not to investigate sources of technical efficiency, which could be a subject of further research. The following conclusions may be drawn from the analysis.

First, the study reveals that there is substantial room for improvement in technical efficiency in the sample of farms analyzed. The mean technical efficiency over the sample period, assuming NIRTS technology, was 57 percent, with a maximum of 62 percent and a minimum of 50 percent. More farms operated under VRTS rather than CRTS.

Second, technical efficiency scores differ by farm size but not by specialization. Larger farms are more technically efficient than smaller farms. Statistical difference in means of technical efficiency by specialization category was not significant.

Third, the results indicate that ranking of the mean efficiency scores depends on the type of technological set being used and whether the ranking is based on original efficiency scores or bias corrected efficiency scores. The implication of these results is that interpretation of the relative performance of DEA scores needs to be handled with care. As observed by Gocht and Balcombe (2006), researchers should guard against making definitive judgment about individual decision making units on the basis of efficiency scores alone.

Fourth, scale efficiency analysis reveals that farms are more scale efficient than technically efficient, indicating that inefficiency emanates from poor managerial practices rather than scale of operation. The analyzed farms are, on average, scale inefficient (93%). Small farms (97%) and medium sized farms (93%) are more scale efficient compared to very small farms (89%) and large farms (84%). However, large and medium sized farms are becoming more scale efficient over time while small and very small farms are becoming scale inefficient. The difference in scale efficiency by specialization is not significant.

Fifth, the study finds no evidence of improvement in technical efficiency (catching-up) over the sample period. Farms that had lower efficiency scores in 1993 moved further away from the frontier by 2007 compared to farms that initially had high efficiency scores.

In general, the results indicate deterioration in technical efficiency implying that most Kansas farms have not been able to keep up with technological leaders in the sector. Smaller farms are becoming both technically and scale inefficient compared to larger farms that are less inefficient over time. From a policy viewpoint, the results indicate that any policy to address inefficiency in the farm sector should take into account the relationship between farm size and efficiency. Farms that get both technically and scale efficient by increasing in size should be encouraged to grow larger while those that become both technically and scale inefficient by getting smaller should be allowed to exit. An extension of this study would be to identify the determinants of efficiency, especially how the input-output configuration and different managerial practices affects efficiency.

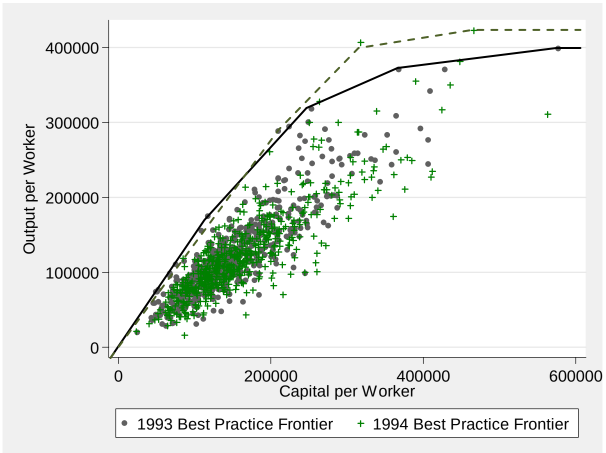
5.2. Tripartite Decomposition of Labor Productivity Growth

The second objective of this study was to decompose labor productivity into components attributed to efficiency change, technical change, and capital deepening, following the approach by Kumar and Russell (2002). The purpose of this exercise is to gain a more detailed understating of how each of these three factors have contributed to the growth of labor productivity in the Kansas farm sector in the entire sample period, 1993 to 2007. Two approaches are used to present the results on productivity changes: average annual changes and cumulative change in productivity relative to the base year, 1993. For both approaches, changes in productivity are computed using percentage changes and growth rates (equations 3.14 and 3.56). Given the large number of farms (564 in this case), the averages of the annual performance of all the farms are used to present the results rather than the disaggregated results for each farm.

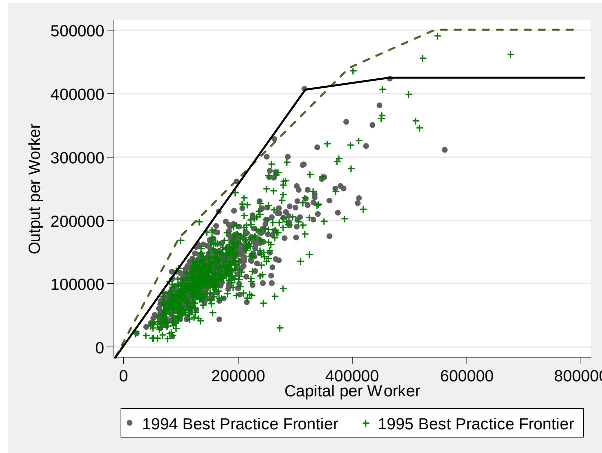
5.2.1. *Best-Practice Frontiers*

The Kansas farm sector production frontiers for the sample period, 1993-07, along with scatter plots for the output per worker vs. capital per worker, are presented in Figure 5.5. The figure contains 14 panels whereby the estimated best-practice frontiers for two consecutive years, starting from 1993-94 to 2006-07, are superimposed on one graph, thus tracing out the sequential shift of the frontiers. The upward shift of the frontier indicates technological progress and a downward shift indicates technological regression. The kinks on each curve indicate technically efficient farms for the specified year.

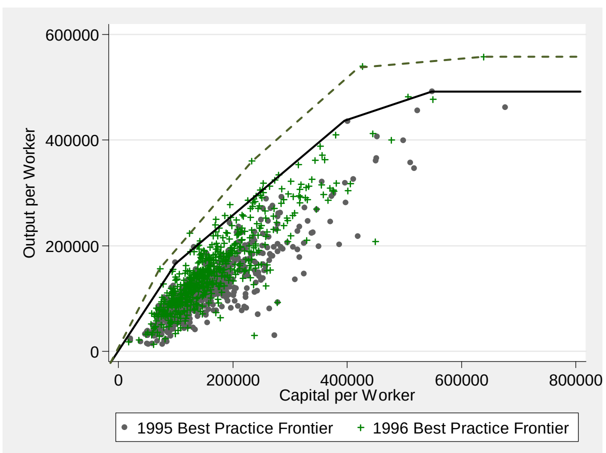
Panel A: Best Practice Frontiers 1993-94



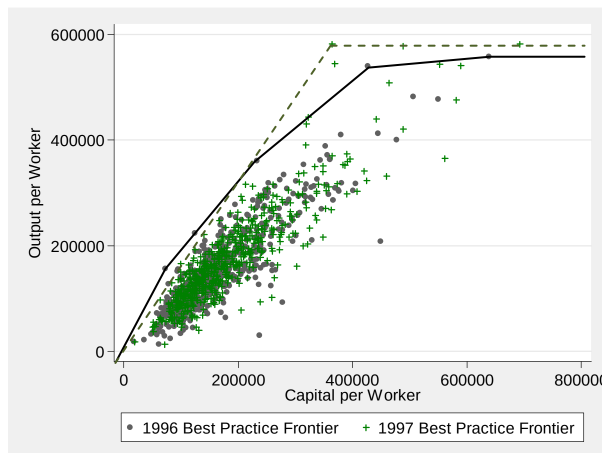
Panel B: Best Practice Frontiers 1994-95



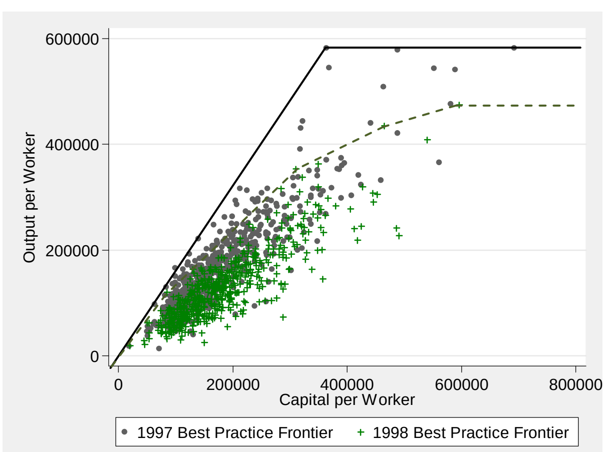
Panel C: Best Practice Frontiers 1995-96



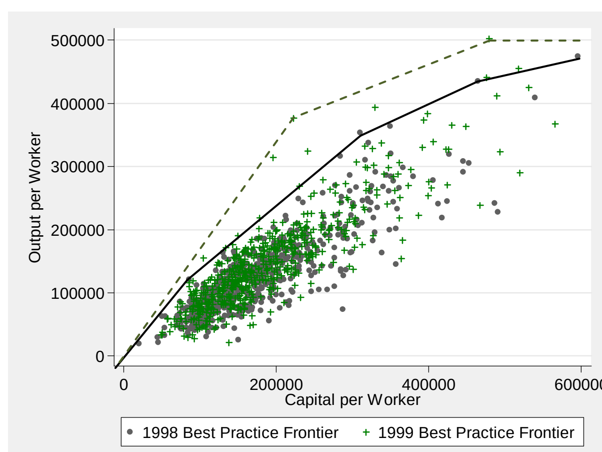
Panel D: Best Practice Frontiers 1996-97



Panel E: Best Practice Frontiers 1997-98

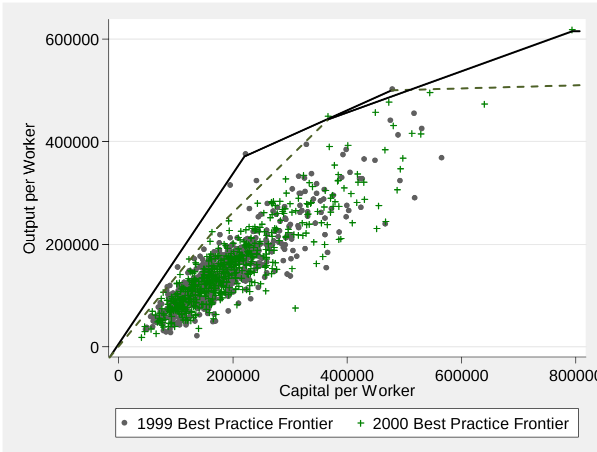


Panel F: Best Practice Frontiers 1998-99

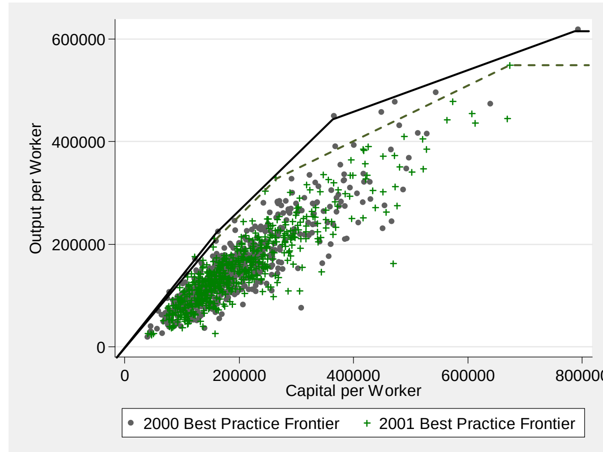


(*Continued*)

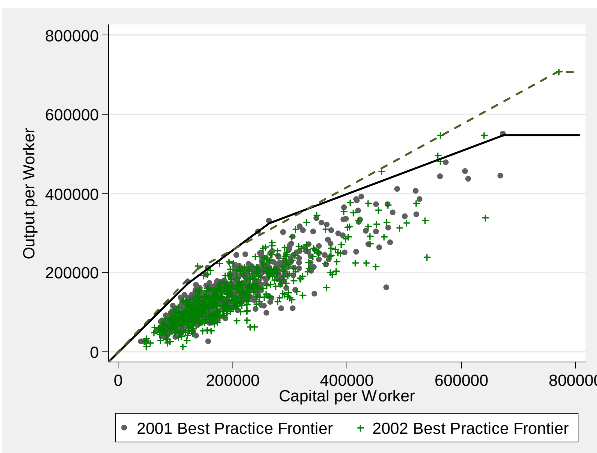
Panel G: Best Practice Frontiers 1999-00



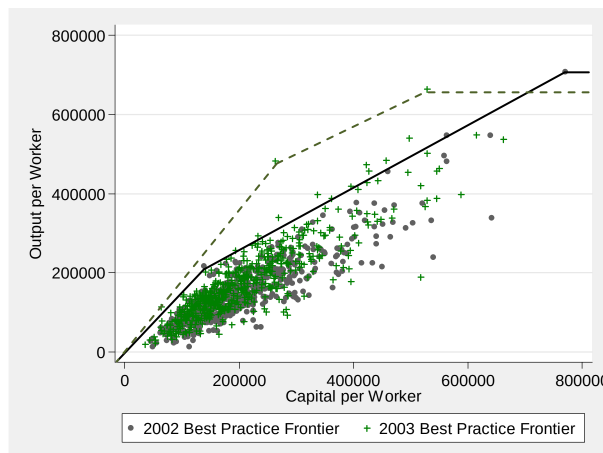
Panel H: Best Practice Frontiers 2000-01



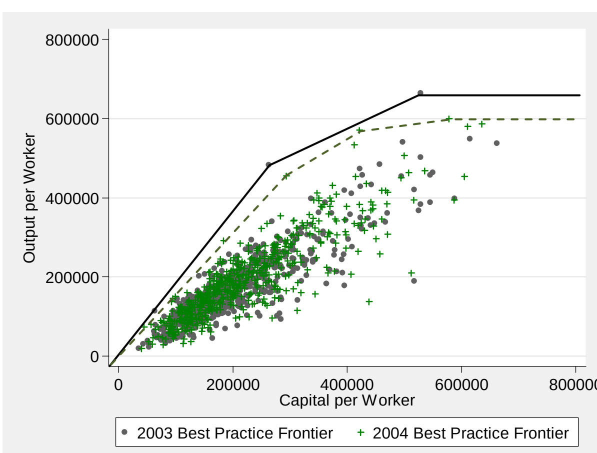
Panel I: Best Practice Frontiers 2001-02



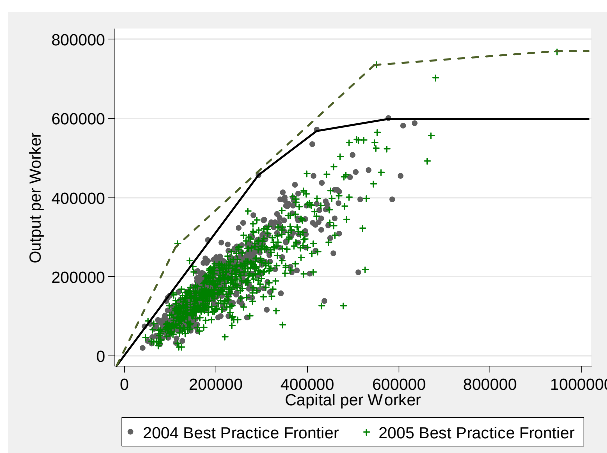
Panel J: Best Practice Frontiers 2002-03



Panel K: Best Practice Frontiers 2003-04



Panel L: Best Practice Frontiers 2004-05



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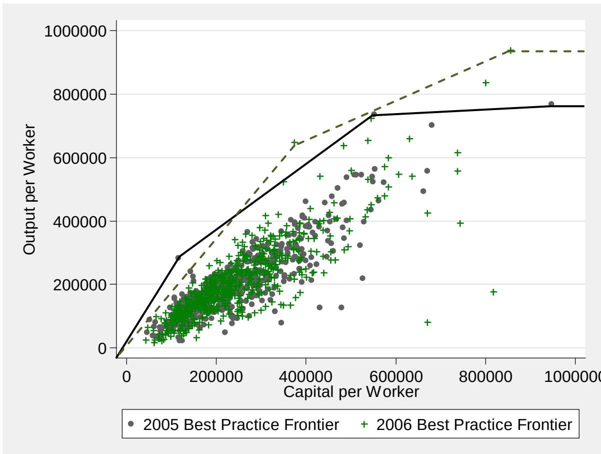
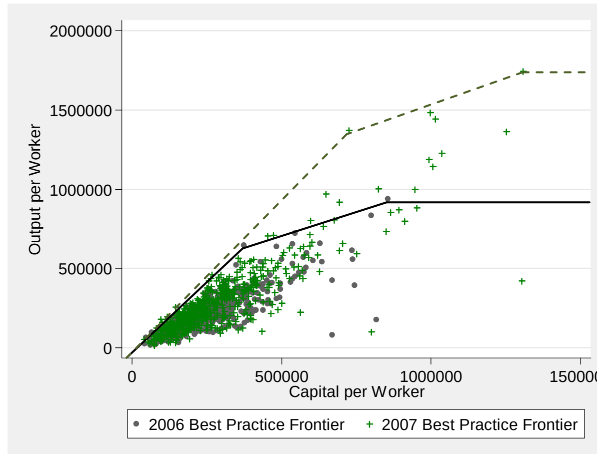
Panel G: Best Practice Frontiers 2005-06



Panel H: Best Practice Frontiers 2006-07



Note: The above panels contain the empirically constructed best practice frontiers along with scatter plots of labor productivity and the capital-labor ratio. Each kink is an actual observation and depicts farms that are 100 percent efficient. Two best practice frontiers are superimposed sequentially from 1993/94 to 2006/07.

Figure 5-5 Estimated Year to Year Sequential Shift of the Best Practice Frontier, 1993/94- 2006/07

It is evident from these graphs that technology change is non-neutral. The best-practice frontiers shifted upwards in several periods but not by the same proportion for every value of the capital-labor ratio. For example, for the period 1993-94, the lower part of the best practice frontiers remained the same (Figure 5.5 Panel A) whereas for the period 2004-5 the frontier for 2005 strictly dominated that of 2004 with larger shifts of the frontier at high levels of capital per worker (Figure 5.5 Panel L). This suggests that technological progress has not been Hicks-neutral. A large upward shift of the frontiers occurred in the periods 1995-96, 1998-99, 2002-03, 2004-05, and 2006-07. Visual inspection of the graphs indicates that technological regression occurred in the periods 1997-98, 1999-00, 2000-01 and 2003-04. The largest shift of the frontier occurred at higher levels of capital per worker, an indication that technological progress is partly embodied in capital deepening. For example, the frontier shifted upwards dramatically in 2007 at high levels of capital per worker (Figure 5.5 Panel H).

5.2.2. ***Tripartite Decomposition - Overall***

To determine the factors that played the most important role in productivity growth, the Kumar and Russell (2002) approach is used to decompose productivity into efficiency change, technical change, and capital deepening. Table 5.12 shows the estimates of the percentage changes in labor productivity and each of the three components for the entire sample period. The first two columns report the average output per worker for the base period and current period. The third column reports the average percentage change in output per worker and the subsequent columns show the percentage changes of the tripartite decomposition components and their relative contribution to the percentage change in labor productivity.

Table 5-12 Average Percentage Change of Tripartite Decomposition Indexes, 1993-94 to 2006-07

Period	Output per worker, base	Output per worker, current	Percentage change in output per worker	Contribution to percentage change in output per worker of:		
				Change in efficiency	Change in technology	Capital deepening
1993-94	124,997	124,174	4.96	4.34	-4.55	6.49
1994-95	124,174	122,792	2.06	-6.34	8.30	1.04
1995-96	122,792	156,811	37.96	9.46	20.35	4.24
1996-97	156,811	171,763	16.51	13.39	-3.86	8.05
1997-98	171,763	129,744	-19.89	2.70	-23.51	2.35
1998-99	129,744	147,662	20.48	-12.34	31.41	4.79
1999-00	147,662	154,776	9.86	26.84	-16.65	4.36
2000-01	154,776	156,797	6.34	3.21	-1.67	4.86
2001-02	156,798	147,854	-3.16	-7.21	3.92	0.26
2002-03	147,854	174,306	25.41	-8.22	32.52	3.71
2003-04	174,306	192,162	15.96	24.95	-11.91	5.45
2004-05	192,162	197,206	5.84	-17.53	21.82	7.02
2005-06	197,206	208,152	9.02	14.22	-5.14	3.33
2006-07	208,152	282,596	38.14	7.33	12.28	13.64
Yearly Average			12.11	3.91	4.52	4.97

Notes: The values listed for efficiency change, technical change and capital accumulation change are geometric means. The last four columns show the average productivity change and the contributions to productivity change of the three factors, efficiency change ([EFF-1] ×100), technical change ([TECH-1] ×100), and physical capital deepening ([KACC-1] ×100). For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).

The results in the table suggest that, on average, capital accumulation was the main source of the increase in labor productivity. The average annual percentage change in productivity is 12.11 percent of which 4.97 percent is accounted for by capital deepening, 4.52 percent by technological progress, and 3.91 percent by efficiency change. The highest percentage change in labor productivity was 38 percent and occurred in the periods 1995-96 and 2006-07. The main source of productivity growth in 1995-96 was technological progress (20.35%) while in 2006-07 the main source was capital accumulation (13.64%). Productivity declined in the periods 1997-98 due to technological regression (-23.51%) and in 2001-02 due to degradation in efficiency (-7.21%). Technological progress was more prominent in the periods 1998-99 and 2002-03. In these periods, percentage change due to technological progress was 32.5 percent and 31.4 percent, respectively. However, in the same periods, efficiency declined by 8.22 percent and 12.3 percent, respectively.

Table 5.13 reports the annual growth rates of output per worker and the decomposition of the contribution of efficiency, technology, and capital deepening to productivity growth. Note that the growth rate of labor productivity between two consecutive years can be broken down as the sum of the growth rate of efficiency, the rate of technical progress, and the contribution of the increase in capital deepening.

On average, productivity grew at an annual average rate of 5.00 percent of which 3.18 percent is accounted for by capital deepening and 2.81 percent by technical change. Efficiency change fell by an average of 0.98 percent, suggesting that the farm sector did not experience efficiency catch-up in the sample period. Consistent with results reported in Table 5.12, productivity growth declined dramatically in the period 1997-98 mainly due to technological regress and low capital deepening. The results indicate that a decline in the growth rate of capital deepening, as evident in the periods 1994-95 and 2001-02, always led to a decline in productivity. The periods that received the highest growth rates in productivity were 2006-07, 1995-96, and 2002-03. In these periods, productivity grew by 24, 26, and 17 percent, respectively and the main source of the growth was technological progress. In general, efficiency growth declined in 6 out of the 14 periods and technological regress occurred in 7 out of the 14 periods.

Table 5-13 Decomposition of Labor Productivity Growth

Period	Annual Growth Rate of Change in: Output per Worker (g_y)	Efficiency (g_{eff})	Technology (g_{tech})	Capital Deepening (g_{cap})
1993-94	-0.52	0.37	-4.79	3.89
1994-95	-4.44	-11.23	7.56	-0.76
1995-96	25.67	4.67	18.49	2.51
1996-97	9.63	7.89	-4.41	6.15
1997-98	-28.00	-1.94	-26.95	0.89
1998-99	12.81	-17.40	27.14	3.06
1999-00	4.41	20.32	-18.40	2.49
2000-01	1.64	0.12	-1.77	3.30
2001-02	-7.75	-10.74	3.74	-0.75
2002-03	16.96	-12.86	27.74	2.08
2003-04	9.82	18.91	-12.72	3.62
2004-05	1.42	-23.02	18.91	5.54
2005-06	4.41	8.55	-6.50	2.36
2006-07	24.00	2.59	11.30	10.11
Average	5.00	-0.98	2.81	3.18

Notes: The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap}$. The first three columns show the year to year growth rate in output per worker and the contribution to that growth due to efficiency change, technical change and capital deepening. For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).

The periods 1998-99, 2002-03, and 2004-05 are worth noting because of the dramatic increases in the growth rates of technology (27.14, 27.74, and 18.91, respectively) and decline in the growth rates of efficiency (-17.40, -12.86, and -23.02, respectively). These observations are consistent with the notion that as technological progress occurs, being driven by a few technological innovators, a majority of the other farms fail to adopt the best available technology and, therefore, become more inefficient by operating far below the best-practice frontier. This explains partly why the average growth rate in efficiency declined over the entire sample period.

It is worth noting that the figures reported in the previous analysis for the overall farm sector conceal some large differences between the productivity growth rates of the different farm typologies based on farm size and farm specialization.

5.2.2.1 *Tripartite Decomposition by Farm Size*

Tables 5.14 to 5.17 show the percentage change in labor productivity and the three decomposition components for the very small farms, small farms, medium sized farms, and large farms, respectively. Comparisons across the different farm sizes indicate that labor productivity varies by farm size. The average percentage change in productivity were statistically different and high for large farms (25.50%) compared to medium sized farms (16.43%), small farms (11.61%), and very small farms (4.29%). Capital deepening was the main source of productivity growth in each of the farm size categories. Large farms experienced a high increase in capital deepening (7.81%) as compared to medium sized farms (5.63%), small farms (4.59%), and very small farms (4.17%). The average percentage change in capital deepening for very small farms (4.17%) was below the average for the entire farm sector (4.97%).

Very small farms experienced a decline in efficiency (-0.89%) while large farms experienced a higher gain in efficiency (11.09%), compared to medium sized farms (6.47%)

and small farms (4.47%). Both very small farms and small farms had an almost equal percentage change in technology (approximately 4.00%) but different percentage changes in capital deepening. Technical change for the medium sized and large farms was 4.64 and 5.51 percent, respectively. Very small farms experienced a decline in productivity in 4 out of the 14 periods (1994-95, 1997-98, 2001-02, and 2004-5) compared to small farms and medium sized farms that experienced a decline in productivity in two periods (1997-98 and 2001-2) and one period (1997-98), respectively.

Table 5-14 Average Percentage Change of Tripartite Decomposition Indexes for Very Small Farms, 1993-94 to 2006-07

Period	Output per worker, base	Output per worker, current	Percentage change in output per worker	Contribution to percentage change in output per worker of:		
				Change in efficiency	Change in technology	Capital deepening
1993-94	80,452	74,162	0.61	2.33	-6.38	7.83
1994-95	82,917	69,154	-11.95	-23.15	15.31	-0.23
1995-96	70,958	81,403	35.72	8.06	19.98	4.89
1996-97	87,190	84,918	12.08	25.29	-12.21	4.82
1997-98	111,305	71,389	-28.67	-12.63	-20.23	3.13
1998-99	75,955	75,307	6.76	-15.62	28.45	-1.27
1999-00	82,298	80,575	5.15	25.36	-17.49	2.48
2000-01	85,093	82,204	6.40	-3.61	1.39	6.82
2001-02	91,614	78,774	-8.58	-14.53	6.96	-0.60
2002-03	83,551	88,881	18.02	-3.74	23.56	1.43
2003-04	92,296	95,944	9.84	15.50	-11.80	7.56
2004-05	105,670	97,227	-2.33	-31.63	34.88	7.99
2005-06	101,041	100,089	2.29	19.22	-15.88	4.71
2006-07	104,980	110,164	14.65	-3.37	11.00	8.85
Yearly Average			4.29	-0.89	4.11	4.17

Notes: The values listed for efficiency change, technical change and capital accumulation change are geometric means. The last four columns show the average productivity change and the contributions to productivity change of the three factors, efficiency change ([EFF-1] ×100), technical change ([TECH-1] ×100), and physical capital deepening ([KACC-1] ×100). For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).

Table 5-15 Average Percentage Change of Tripartite Decomposition Indexes for Small Farms, 1993-94 to 2006-07

Period	Output per worker, base	Output per worker, current	Percentage change in output per worker	Contribution to percentage change in output per worker of:		
				Change in efficiency	Change in technology	Capital deepening
1993-94	130,945	123,457	2.08	4.09	-5.06	4.03
1994-95	124,949	122,454	4.09	-3.32	7.25	0.96
1995-96	108,968	139,625	36.48	10.64	19.91	2.83
1996-97	132,662	146,751	18.70	17.69	-6.30	8.27
1997-98	178,301	132,442	-19.38	4.34	-24.05	1.63
1998-99	123,075	136,495	20.45	-14.74	33.54	5.98
1999-00	141,081	142,674	8.94	26.40	-18.29	5.69
2000-01	144,069	143,643	4.57	3.21	-1.07	2.98
2001-02	152,266	139,478	-4.61	-7.31	3.24	-0.43
2002-03	130,976	150,763	25.36	-7.75	31.53	4.01
2003-04	149,021	157,871	15.10	25.49	-12.60	5.00
2004-05	163,003	161,804	4.47	-21.09	23.99	8.01
2005-06	161,286	165,996	9.68	20.57	-8.81	3.07
2006-07	157,718	191,927	28.15	4.40	9.89	12.21
Yearly Average			11.01	4.47	3.80	4.59

Notes: The values listed for efficiency change, technical change, and capital accumulation change are geometric means. The last four columns show the average productivity change and the contributions to productivity change of the three factors, efficiency change ([EFF-1] ×100), technical change ([TECH-1] ×100), and physical capital deepening ([KACC-1] ×100). For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).

Table 5-16 Average Percentage Change of Tripartite Decomposition Indexes for Medium Sized Farms, 1993-94 to 2006-07

Period	Output per worker, base	Output per worker, current	Percentage change in output per worker	Contribution to percentage change in output per worker of:		
				Change in efficiency	Change in technology	Capital deepening
1993-94	161,897	181,307	15.79	6.75	-1.23	10.37
1994-95	174,536	186,058	12.08	6.74	1.91	1.59
1995-96	164,089	211,251	40.39	7.56	21.08	6.30
1996-97	202,117	220,762	14.92	4.33	1.48	8.89
1997-98	221,178	179,456	-13.66	12.81	-25.87	2.93
1998-99	168,526	203,524	28.60	-7.54	31.17	6.65
1999-00	190,841	211,483	14.46	29.26	-14.55	4.04
2000-01	204,773	215,047	9.70	7.44	-4.08	6.83
2001-02	220,434	216,891	2.27	-1.36	2.22	1.35
2002-03	191,901	230,650	27.42	-12.14	38.40	4.22
2003-04	223,193	249,680	17.09	26.69	-11.55	4.89
2004-05	240,025	243,834	6.29	-9.89	14.86	3.37
2005-06	235,498	248,768	9.97	7.61	0.65	2.90
2006-07	227,229	309,359	44.65	12.30	10.46	14.43
Yearly Average			16.43	6.47	4.64	5.63

Notes: The values listed for efficiency change, technical change, and capital accumulation change are geometric means. The last four columns show the average productivity change and the contributions to productivity change of the three factors, efficiency change ([EFF-1] ×100), technical change ([TECH-1] ×100), and physical capital deepening ([KACC-1] ×100). For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).

Table 5-17 Average Percentage Change of Tripartite Decomposition Indexes for Large Farms, 1993-94 to 2006-07

Period	Output per worker, base	Output per worker, current	Percentage change in output per worker	Contribution to percentage change in output per worker of:		
				Change in efficiency	Change in technology	Capital deepening
1993-94	144,135	175,476	22.21	11.47	-3.27	13.12
1994-95	151,115	215,411	45.26	19.69	2.55	15.70
1995-96	190,294	259,427	44.61	13.66	21.46	3.19
1996-97	246,500	283,490	17.96	2.43	4.48	9.26
1997-98	238,828	234,204	2.08	35.14	-26.57	3.07
1998-99	214,173	262,384	35.55	-1.29	25.05	9.09
1999-00	253,340	276,831	13.69	24.26	-8.95	1.39
2000-01	252,061	250,917	3.80	7.43	-5.90	3.14
2001-02	234,950	270,111	17.82	5.82	3.21	8.48
2002-03	235,177	303,245	36.82	-7.99	38.98	6.06
2003-04	258,637	308,488	25.19	32.05	-10.41	5.62
2004-05	300,393	346,473	20.38	-3.42	12.08	10.33
2005-06	328,914	365,740	12.94	4.07	5.71	3.29
2006-07	319,653	484,388	58.65	11.87	18.76	17.65
Yearly Average			25.50	11.09	5.51	7.81

Notes: The values listed for efficiency change, technical change, and capital accumulation change are geometric means. The last four columns show the average productivity change and the contributions to productivity change of the three factors, efficiency change ([EFF-1] ×100), technical change ([TECH-1] ×100), and physical capital deepening ([KACC-1] ×100). For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).

Overall, very small farms moved further away from the best-practice frontier while the rest of the farm size categories moved closer to the frontier. While capital deepening was the main source of productivity for very small farms (4.17%) and small farms (4.59%), efficiency gains were the main source of productivity growth for medium sized farms (6.47%) and large farms (11.09%). For example, in the period 2002-03, there was a dramatic increase in the percentage change in technology (40%) accompanied by a decline in efficiency (8%), a clear indication that many farms within the large farms subcategory operated below the best-practice frontier in 2003 relative to the year 2002.

5.2.2.2 *Tripartite Decomposition by Growth Rates*

Tables 5.18 to 5.21 summarize the results for the average annual growth rates for labor productivity, efficiency change, technical change, and capital deepening for very small farms, small farms, medium sized farms, and large farms respectively. On average, the labor productivity growth rate for very small farms declined over the sample period (-4.50%) with the main source of the decline being a fall in the growth of efficiency (-8.86%). Productivity growth for small farms (4.73%) and medium sized farms (9.98%) was primarily driven by capital deepening (2.94% and 3.94%, respectively) while productivity growth on large farms (17.14%) was primarily driven by gains in efficiency (7.53%). The decline in productivity growth, degradation in efficiency, and slow growth rate in capital deepening in the very small farms category supports the conventional hypothesis of declining small farms and increasing large farms in the farm sector.

Table 5-18 Decomposition of Labor Productivity Growth for Very Small Farms

Period	Annual Growth Rate of Change in: Output/ Worker (gy)	Efficiency (geff)	Technology (gtech)	Capital Deepening (gcap)
1993-94	-6.19	-3.55	-6.62	3.98
1994-95	-20.11	-31.92	13.93	-2.11
1995-96	18.36	-2.34	18.15	2.55
1996-97	2.64	12.61	-13.48	3.52
1997-98	-40.33	-19.29	-22.71	1.67
1998-99	0.10	-22.09	24.91	-2.72
1999-00	-1.95	17.40	-19.25	-0.10
2000-01	-2.79	-8.43	1.33	4.30
2001-02	-15.51	-20.59	6.69	-1.61
2002-03	8.68	-11.84	20.88	-0.35
2003-04	2.61	10.51	-12.57	4.67
2004-05	-7.86	-43.22	29.03	6.34
2005-06	-4.24	11.12	-18.93	3.57
2006-07	3.57	-12.41	10.20	5.78
Average	-4.50	-8.86	2.25	2.11

Notes: The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap.}$ The first three columns show the year to year growth rate in output per worker and the contribution to that growth due to efficiency change, technical change and capital deepening.

Table 5-19 Decomposition of Labor Productivity Growth for Small Farms

Period	Annual Growth Rate of Change in: Output/ Worker (gy)	Efficiency (geff)	Technology (gtech)	Capital Deepening (gcap)
1993-94	-3.19	0.43	-5.29	1.67
1994-95	-0.38	-6.73	6.66	-0.31
1995-96	26.38	6.54	18.12	1.72
1996-97	11.65	12.02	-6.77	6.41
1997-98	-26.97	0.50	-27.61	0.14
1998-99	12.85	-20.12	28.80	4.17
1999-00	3.67	20.28	-20.27	3.66
2000-01	1.12	0.40	-1.11	1.83
2001-02	-8.55	-10.21	3.09	-1.42
2002-03	17.40	-11.99	27.01	2.38
2003-04	8.44	18.92	-13.48	3.00
2004-05	0.57	-26.62	20.84	6.34
2005-06	4.54	12.73	-10.26	2.07
2006-07	18.64	-0.23	9.38	9.49
Average	4.73	-0.29	2.08	2.94

Notes: The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap.}$ The first three columns show the year to year growth rate in output per worker and the contribution to that growth due to efficiency change, technical change and capital deepening.

Table 5-20 Decomposition of Labor Productivity Growth for Medium Sized Farms

Period	Annual Growth Rate of Change in: Output/ Worker (gy)	Efficiency (geff)	Technology (gtech)	Capital Deepening (gcap)
1993-94	11.45	4.25	-1.50	8.70
1994-95	3.99	3.52	1.62	-1.15
1995-96	27.92	4.86	19.10	3.96
1996-97	9.18	1.52	1.10	6.56
1997-98	-19.29	9.39	-30.06	1.38
1998-99	20.69	-11.20	26.90	4.98
1999-00	9.80	22.94	-16.06	2.92
2000-01	5.88	4.80	-4.28	5.35
2001-02	-1.07	-3.74	2.09	0.58
2002-03	20.07	-15.06	32.20	2.94
2003-04	12.08	20.86	-12.33	3.55
2004-05	3.04	-12.85	13.27	2.63
2005-06	6.65	4.58	0.05	2.03
2006-07	29.29	8.65	9.86	10.78
Average	9.98	3.04	3.00	3.94

Notes: The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap.}$ The first three columns show the year to year growth rate in output per worker and the contribution to that growth due to efficiency change, technical change and capital deepening.

Table 5-21 Decomposition of Labor Productivity Growth for Large Farms

Period	Annual Growth Rate of Change in: Output/ Worker (g_y)	Efficiency (g_{eff})	Technology (g_{tech})	Capital Deepening (g_{cap})
1993-94	15.47	8.30	-3.46	10.63
1994-95	30.61	16.21	2.29	12.12
1995-96	31.79	10.78	19.42	1.60
1996-97	12.05	0.15	4.08	7.83
1997-98	-1.26	27.17	-31.01	2.58
1998-99	24.14	-4.67	22.09	6.73
1999-00	9.28	18.95	-9.78	0.11
2000-01	1.18	6.13	-6.21	1.27
2001-02	12.35	4.01	3.03	5.30
2002-03	24.39	-11.93	32.68	3.65
2003-04	19.61	26.00	-11.07	4.68
2004-05	13.28	-5.94	11.10	8.11
2005-06	9.42	1.93	5.04	2.45
2006-07	37.67	8.30	16.52	12.85
Average	17.14	7.53	3.91	5.71

Notes: The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap.}$ The first three columns show the year to year growth rate in output per worker and the contribution to that growth due to efficiency change, technical change and capital deepening.

5.2.2.3 *Tripartite Decomposition by Farm Specialization*

Tables 5.22 to 5.24 shows the percentage change in productivity and the three components for livestock, diversified, and crop farms, respectively. Crop farms experienced a higher percentage change in productivity (14.13%) compared to livestock farms (9.31%) and diversified farms (11.62%). Capital deepening was the main source of productivity change for all the three specializations. Crops farms moved closer to the best-practice frontier over the sample period (5.07%) compared to diversified farms (3.47%), and livestock farms (2.69%). Technological change was not statistically different across the farm specializations: crop farms (4.60%), diversified farms (4.54%), and livestock farms (4.31%).

Table 5-22 Average Percentage Change of Tripartite Decomposition Indexes for Livestock Farms, 1993-94 to 2006-07

Period	Output per worker, base	Output per worker, current	Percentage change in output per worker	Contribution to percentage change in output per worker of:		
				Change in efficiency	Change in technology	Capital deepening
1993-94	124,581	124,787	5.66	2.26	-4.08	9.14
1994-95	122,684	116,444	-2.12	-9.43	8.27	0.92
1995-96	117,419	143,147	28.64	4.09	20.16	0.88
1996-97	150,013	164,002	20.28	21.31	-4.34	4.81
1997-98	150,809	117,955	-18.39	5.02	-22.13	0.57
1998-99	114,762	147,576	34.95	-4.14	29.00	9.78
1999-00	147,935	140,535	-2.38	17.38	-16.65	0.86
2000-01	137,905	140,170	5.53	2.26	-0.77	4.61
2001-02	133,572	129,357	1.91	-5.33	4.94	1.10
2002-03	122,589	134,909	11.20	-13.06	27.21	0.26
2003-04	137,692	155,981	18.70	30.33	-12.18	3.87
2004-05	159,194	159,622	1.05	-24.25	30.84	3.86
2005-06	177,004	175,199	3.71	14.61	-12.63	7.99
2006-07	172,130	206,657	21.65	-3.35	12.71	12.46
Yearly Average			9.31	2.69	4.31	4.36

Notes: The values listed for efficiency change, technical change, and capital accumulation change are geometric means. The last four columns show the average productivity change and the contributions to productivity change of the three factors, efficiency change ([EFF-1] ×100), technical change ([TECH-1] ×100), and physical capital deepening ([KACC-1] ×100). For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).

Table 5-23 Average Percentage Change of Tripartite Decomposition Indexes for Diversified Farms

Period	Output per worker, base	Output per worker, current	Percentage change in output per worker	Contribution to percentage change in output per worker of:		
				Change in efficiency	Change in technology	Capital deepening
1993-94	123,243	120,029	2.61	4.90	-4.91	3.68
1994-95	121,950	120,194	0.92	-7.00	8.41	0.81
1995-96	120,649	153,942	37.14	9.28	20.32	4.31
1996-97	151,555	170,870	19.73	15.16	-4.22	9.31
1997-98	173,908	125,168	-23.51	-1.79	-23.68	2.15
1998-99	126,395	145,826	22.36	-11.33	32.05	4.57
1999-00	144,091	154,810	12.68	29.48	-16.66	4.88
2000-01	155,277	159,507	6.26	3.75	-1.71	4.68
2001-02	161,628	147,826	-5.57	-8.75	3.95	-0.48
2002-03	150,856	179,445	25.00	-9.53	33.52	4.24
2003-04	185,339	203,551	15.82	23.35	-11.91	6.61
2004-05	198,585	202,791	5.47	-16.66	19.98	7.41
2005-06	201,374	209,312	7.49	10.29	-3.64	3.33
2006-07	211,238	283,340	36.22	7.48	12.02	12.19
Yearly Average			11.62	3.47	4.54	4.84

Notes: The values listed for efficiency change, technical change, and capital accumulation change are geometric means. The last four columns show the average productivity change and the contributions to productivity change of the three factors, efficiency change ([EFF-1] ×100), technical change ([TECH-1] ×100), and physical capital deepening ([KACC-1] ×100). For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).

Table 5-24 Average Percentage Change of Tripartite Decomposition Indexes for Crop Farms

Period	Output per worker, base	Output per worker, current	Percentage change in output per worker	Contribution to percentage change in output per worker of: Change in efficiency	Change in technology	Capital deepening
1993-94	129,150	132,487	9.34	5.09	-4.24	10.01
1994-95	129,729	132,938	7.61	-2.59	8.11	1.60
1995-96	131,281	173,119	46.77	13.91	20.56	6.66
1996-97	171,210	179,040	7.98	4.42	-2.87	8.17
1997-98	179,702	145,237	-13.86	9.92	-23.98	3.77
1998-99	145,361	151,430	8.13	-19.22	31.54	2.28
1999-00	153,600	161,637	11.02	26.96	-16.63	5.15
2000-01	160,950	159,296	6.82	2.74	-1.97	5.27
2001-02	158,926	155,671	-1.48	-5.57	3.44	1.07
2002-03	154,011	183,252	31.88	-4.34	33.28	4.37
2003-04	173,694	190,906	15.08	25.00	-11.81	4.51
2004-05	196,520	204,449	8.18	-16.08	20.74	7.72
2005-06	199,445	219,286	13.09	19.29	-4.25	1.52
2006-07	218,892	312,467	47.23	11.48	12.44	15.94
Yearly Average			14.13	5.07	4.60	5.57

Notes: The values listed for efficiency change, technical change, and capital accumulation change are geometric means. The last four columns show the average productivity change and the contributions to productivity change of the three factors, efficiency change ([EFF-1] ×100), technical change ([TECH-1] ×100), and physical capital deepening ([KACC-1] ×100). For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).

The annual growth rates of productivity and the three components for livestock, diversified, and crop farms are reported in Tables 5.25 to 5.27, respectively. On average, livestock farms slipped further from the best-practice frontier over the sample period (-2.07%) compared to diversified (-0.98%) and crop farms (-0.63%). Average productivity growth was higher for crop farms (5.75%) than for diversified (5.09%) or livestock farms

(3.05%). Out of the 14 periods, livestock farms experienced a decline in the growth of capital deepening in 7 periods compared to diversified farms and crop farms that experienced a decline in capital deepening in 2 and 1 periods, respectively. Similarly, livestock farms experienced a decline in the growth of productivity in 6 periods compared to the other farms that experienced a decline in only 4 periods.

Table 5-25 Decomposition of Labor Productivity Growth for Livestock Farms

Period	Annual Growth Rate of Change in:			
	Output/ Worker (g_y)	Efficiency (g_{eff})	Technology (g_{tech})	Capital Deepening (g_{cap})
1993-94	1.21	-0.61	-4.34	6.15
1994-95	-7.67	-13.58	7.51	-1.61
1995-96	17.56	-0.30	18.32	-0.45
1996-97	11.56	13.32	-5.00	3.24
1997-98	-25.68	0.80	-25.20	-1.29
1998-99	24.74	-8.20	25.31	7.63
1999-00	-5.65	13.22	-18.38	-0.49
2000-01	3.10	0.57	-0.85	3.39
2001-02	-5.11	-9.59	4.74	-0.26
2002-03	5.87	-16.44	23.72	-1.41
2003-04	14.38	24.75	-13.02	2.65
2004-05	-2.84	-31.63	26.05	2.73
2005-06	-0.92	7.33	-14.82	6.57
2006-07	12.13	-8.61	11.58	9.16
Average	3.05	-2.07	2.54	2.57

Notes: The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap.}$ The first three columns show the year to year growth rate in output per worker and the contribution to that growth due to efficiency change, technical change and capital deepening.

Table 5-26 Decomposition of Labor Productivity Growth for Diversified Farms

Period	Output/ Worker (gy)	Efficiency (geff)	Technology (gtech)	Capital Deepening (gcap)
	Annual Growth Rate of Change in:			
1993-94	-2.51	0.96	-5.13	1.66
1994-95	-4.19	-11.37	7.67	-0.50
1995-96	26.97	5.89	18.46	2.61
1996-97	12.04	9.66	-4.74	7.12
1997-98	-32.46	-6.18	-27.17	0.89
1998-99	13.94	-16.49	27.63	2.80
1999-00	7.20	22.50	-18.42	3.13
2000-01	2.44	0.74	-1.82	3.51
2001-02	-9.40	-11.77	3.77	-1.40
2002-03	18.38	-12.92	28.48	2.83
2003-04	9.93	17.71	-12.72	4.93
2004-05	2.01	-21.39	17.40	5.99
2005-06	3.29	5.63	-4.79	2.45
2006-07	23.69	3.32	11.09	9.28
Average	5.09	-0.98	2.84	3.24

Notes: The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap.}$ The first three columns show the year to year growth rate in output per worker and the contribution to that growth due to efficiency change, technical change and capital deepening.

Table 5-27 Decomposition of Labor Productivity Growth for Crop Farms

Period	Annual Growth Rate of Change in: Output/ Worker (g_y)	Efficiency (g_{eff})	Technology (g_{tech})	Capital Deepening (g_{cap})
1993-94	2.12	0.04	-4.48	6.56
1994-95	-2.35	-9.10	7.37	-0.62
1995-96	29.21	5.97	18.67	4.57
1996-97	3.89	0.74	-3.40	6.54
1997-98	-20.83	4.59	-27.54	2.13
1998-99	3.47	-24.66	27.24	0.89
1999-00	4.56	20.08	-18.37	2.85
2000-01	-0.24	-1.08	-2.08	2.92
2001-02	-6.26	-9.60	3.28	0.06
2002-03	19.51	-11.29	28.34	2.46
2003-04	7.92	18.27	-12.60	2.25
2004-05	2.31	-21.83	18.11	6.02
2005-06	7.95	12.89	-5.57	0.63
2006-07	29.19	6.21	11.45	11.53
Average	5.75	-0.63	2.89	3.49

Notes: The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap}$. The first three columns show the year to year growth rate in output per worker and the contribution to that growth due to efficiency change, technical change and capital deepening.

5.2.3. *Number of Farms with Productivity Changes*

Table 5.28 reports productivity changes, relative to the base year 1993, by percentage of farms. Columns 1 to 4 are a summary of the percentage of farms whose productivity growth was primarily due to efficiency change, technical change, or capital deepening. Columns 5 and 6 report the percentage of farms that experienced an increase and decrease in productivity, respectively. Columns 7 and 8 report the percentage of farms that experienced efficiency gains or losses, respectively. Columns 9 and 10 are the percentage of farms that experienced technological progress or regress, respectively and columns 10 and 11 are the percentage of farms that experienced gains or losses in capital deepening, respectively.

Overall, 70.00 percent of the farms experienced increases in productivity while 30.00 percent experienced declines in productivity for the entire period. On average, the main source of productivity growth was capital deepening for 47.35 percent of the farms, technological progress for 35.03 percent of the farms, and efficiency gains for 17.62 percent of the farms. More than half of the farms (58.71%) slipped further away from the best-practice frontier over the sample period while 41.29 percent moved closer to the best-practice frontier. More than half of the farms experienced both technological progress (70.40%) and an increase in capital deepening (72.94%).

By 2007, 100 percent of the farms had experienced cumulative technological progress and 87.23 percent of the farms had experienced increases in capital deepening. However, only 38.38 percent of the farms were catching up (i.e., moved closer to the best practice frontier in 2007 relative to 1993). Focusing on the main source of productivity growth, only 3.17 percent of the farms had efficiency gains as their main source of productivity growth compared to technological progress (43.63%) and capital deepening (53.19%). By 2007, only 12.59 percent of the farms had not increased their productivity relative to the base year 1993.

Table 5-28 Kansas Farms Productivity Characteristics over Sample Period, Relative to the Base Year 1993

	Tripartite Decomposition Gains			Productivity Change		Efficiency Change		Technology Change		Capital Deepening	
	EFF	TECH	KACC	Gain	Loss	Positive	Negative	Progress	Regress	Gain	Loss
1993-94	42.55	13.30	44.15	49.29	50.71	49.65	50.35	13.83	86.17	60.64	39.36
1993-95	24.11	38.12	37.77	45.57	54.43	36.52	63.48	61.35	38.65	55.32	44.68
1993-96	12.77	68.97	18.26	70.74	29.26	42.53	57.47	100.00	0.00	58.16	41.84
1993-97	23.94	39.01	37.06	81.38	18.62	54.26	45.74	100.00	0.00	68.44	31.56
1993-98	33.16	8.87	57.98	51.60	48.40	51.95	48.05	3.72	96.28	68.09	31.91
1993-99	7.45	49.65	42.91	65.78	34.22	26.29	73.71	100.00	0.00	71.99	28.01
1993-00	28.37	11.52	60.11	70.39	29.61	56.48	43.52	21.99	78.01	73.76	26.24
1993-01	30.14	10.46	59.40	71.10	28.90	55.95	44.05	12.77	87.23	76.77	23.23
1993-02	15.07	20.74	64.18	62.41	37.59	41.49	58.51	71.99	28.01	76.60	23.40
1993-03	3.37	53.90	42.73	78.01	21.99	21.31	78.69	100.00	0.00	77.48	22.52
1993-04	15.25	27.66	57.09	81.91	18.09	51.51	48.49	100.00	0.00	79.96	20.04
1993-05	1.06	67.55	31.38	80.50	19.50	20.39	79.61	100.00	0.00	82.09	17.91
1993-06	6.21	37.06	56.74	83.16	16.84	31.21	68.79	100.00	0.00	84.57	15.53
1993-07	3.19	43.62	53.19	87.41	12.59	38.48	61.52	100.00	0.00	87.23	12.77
Average	17.62	35.03	47.35	69.95	30.05	41.29	58.71	70.40	29.60	72.94	27.07

Note: Figures indicate the percentage of farms exhibiting specified productivity characteristic over the sample period 1993/94 to 1993/07. Total number of farms for each period is 564.

5.2.4. *Scale Effects on the Decomposition*

Malmquist productivity indices were computed to isolate the scale effects in the tripartite decomposition presented. Following Fare et al. (1994), Wheelock and Wilson (1999), and Zofio (2007), the efficiency change (EFF) component calculated relative to constant returns to scale technology can be decomposed into pure efficiency change (P.Eff) (calculated relative to variable returns to scale technology) and a residual scale component (S.Eff) which captures changes in the deviation between the two technologies. The technical change (TECH) component can be decomposed into pure technical change (P.Tech) and scale technical change (S.Tech). The product of the residual scale component (S.Eff) and scale technical change (S.Tech) gives a measure of the scale effects (Scale) due to changes in the location of farm with respect to the frontier. A value of unity (100%) indicates no change in scale (see Wheelock and Wilson, 1999, for details). A value greater than unity (>100%) indicates the farms moved closer to optimal scale while a value less than unity (<100%) indicates the farms moved further away from the optimal scale.

The main results of this decomposition are reported in Table 5.29 and plotted in Figure 5.6. Columns 5 and 6 indicate that, on average, the farms became both technically and scale inefficient. Relative to the year 1993, the farms in 2007 were further away from the CRTS frontier (optimal scale). However, the changes in scale efficiency were relatively small. Column 7 shows that pure technical change was positive in 11 out of the 14 periods[13]. Column 8 indicates very small changes in the scale of technology, with technology moving away from optimal scale in 11 out of the 14 periods. Overall, column 9 indicates that the

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[13] The shift of the VRTS frontier

scale effects were very small and tended to move the farms further away from the CRTS frontier. This is also depicted in Figure 5.6 where the scale effects remained close to zero.

Table 5-29 Cumulative Decomposition of Malmquist Productivity Index with Scale Effects

	Malm	Eff	Tech	P.Eff	S.Eff	P.Tech	S.Tech	Scale
1993-94	-0.74	4.34	-4.55	4.25	0.60	-4.26	-0.10	0.26
1993-95	-3.89	-6.64	3.36	-5.69	-0.63	1.92	1.61	0.55
1993-96	20.70	-2.33	24.05	0.60	-2.25	20.52	3.92	0.86
1993-97	23.42	5.56	17.54	3.89	2.20	20.15	-1.87	-0.06
1993-98	-6.41	3.61	-9.57	1.79	2.78	-7.66	-1.33	0.62
1993-99	3.46	-12.66	18.49	-6.57	-5.38	11.49	7.67	1.23
1993-00	4.16	6.00	-1.63	5.74	0.85	-0.41	-0.89	-0.12
1993-01	4.38	6.76	-2.26	7.62	0.10	-2.33	1.38	0.19
1993-02	-1.42	-3.76	2.40	-4.57	1.67	3.57	1.02	2.81
1993-03	11.88	-15.38	32.38	-12.50	-2.19	31.45	1.23	-1.53
1993-04	19.40	2.42	16.91	3.94	-0.57	17.69	0.26	-1.14
1993-05	21.87	-17.92	48.69	-15.17	-2.56	46.04	2.85	-0.17
1993-06	16.56	-10.56	30.80	-7.43	-2.543	29.90	1.22	-1.22
1993-07	36.86	-7.74	49.29	-5.61	-1.02	50.40	-0.23	-1.15

Note: The values reported for each period are geometric means for 564 farms. Malm is Malmquist productivity index, Eff is efficiency change, Tech is technical change, P.Eff is pure technical efficiency change, S.Eff is scale efficiency change, P.Tech is pure technical change, S.Tech is scale technical change, and Scale is scale effect. The decomposition is as follows: Eff = P.Eff × S.Eff; Tech = P.Tech × S.Tech; Scale = S.Eff × S.Tech; and Malm = Eff ×Tech. This implies that Malm = (P.Eff × S.Eff) × (P.Tech × S.Tech). This is also equivalent to Malm = P.Eff × P.Tech × Scale.

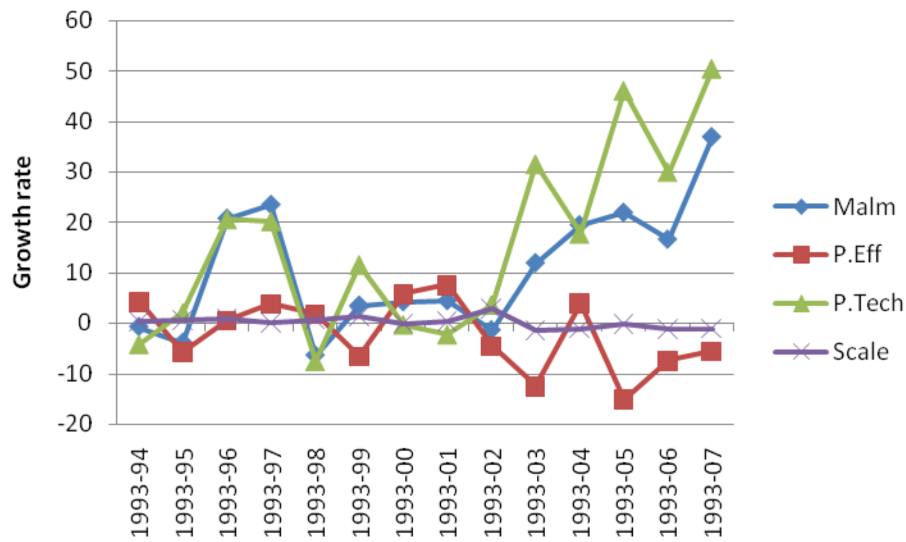


Figure 5-6 Annual Growth Rate of Malmquist Index (Malm), Pure Efficiency Change (P.Eff), Pure Technical Change (P.Tech), and Scale Effects (Scale), relative to Base Year 1993

5.2.5. *Tripartite Decomposition relative to the Base Year 1993*

To gain deeper insight on the changes in productivity, each subsequent year can be compared with the base year (1993 in this case) to compute the cumulative productivity changes over the sample period, expressed on an annual basis. This approach is different from the earlier approach that focused on annual average changes between two adjacent pair of years over the sample period.

The findings reported in Tables 5.30 and 5.31 confirm the results of the previous analysis, namely that labor productivity change is primarily driven by changes in capital deepening and technological progress. Specifically, between 1993 and 2007, productivity across the whole farm sector increased by an average of 145 percent which comprised of an increase in capital deepening and technological progress of 73 percent and 49 percent, respectively, and a decline in efficiency by 7.74 percent. Productivity growth slowed in 1995, 1998, and 2002, relative to the base year, mainly due to a combination of technological regress and/or decline in efficiency.

Table 5-30 Cumulative Percentage Change of Tripartite Decomposition Indexes, 1993-2007

Period	Output per worker, base	Output per worker, current	Percentage change in output per worker	Contribution to percentage change in output per worker of:		
				Change in efficiency	Change in technology	Capital deepening
1993-94	124,997	124,174	4.96	4.34	-4.55	6.49
1993-95	124,997	122,792	3.29	-6.64	3.36	6.19
1993-96	124,997	156,811	32.61	-2.33	24.05	9.09
1993-97	124,997	171,763	46.98	5.56	17.54	19.30
1993-98	124,997	129,744	12.10	3.61	-9.57	18.71
1993-99	124,997	147,662	27.51	-12.66	18.49	23.26
1993-00	124,997	154,776	33.29	6.00	-1.63	27.69
1993-01	124,997	156,797	36.43	13.05	-4.37	57.97
1993-02	124,997	147,854	28.68	-3.76	2.40	28.05
1993-03	124,997	174,306	51.68	-15.38	32.38	35.25
1993-04	124,997	192,162	68.07	2.42	16.91	39.60
1993-05	124,997	197,206	72.55	-17.92	48.69	38.28
1993-06	124,997	208,152	83.43	-10.56	30.80	55.45
1993-07	124,997	282,596	145.07	-7.74	49.29	72.59

Notes: The values listed for efficiency change, technical change, and capital accumulation change are geometric means. The last four columns show the average productivity change and the contributions to productivity change of the three factors, efficiency change ([EFF-1] ×100), technical change ([TECH-1] ×100), and physical capital deepening ([KACC-1] ×100). For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).

Table 5.31 reports the cumulative average growth rates in productivity between 1993 and 2007. The results are consistent with what is reported in the previous analysis (Table

5.13). Productivity grew at an annual rate of 5 percent with capital deepening and technological progress accounting for 3.21 and 2.77 percent of the growth rate, respectively, while efficiency change contributed to a decline in productivity of 0.98 percent.

Table 5-31 Decomposition of Labor Productivity Growth relative to Base Year 1993

Period	Annual Growth Rate of Change in: Output/ Worker (gy)	Efficiency (geff)	Technology (gtech)	Capital Deepening (gcap)
1993-94	-0.52	0.37	-4.79	3.89
1993-95	-2.48	-5.43	1.55	1.40
1993-96	6.91	-2.06	7.13	1.84
1993-97	7.59	0.43	3.97	3.19
1993-98	0.47	-0.05	-2.03	2.55
1993-99	2.52	-2.94	2.82	2.64
1993-00	2.79	0.38	-0.26	2.67
1993-01	2.65	0.35	-0.29	2.59
1993-02	1.49	-0.88	0.25	2.12
1993-03	3.04	-2.08	2.79	2.33
1993-04	3.66	-0.17	1.40	2.43
1993-05	3.47	-2.08	3.29	2.26
1993-06	3.54	-1.26	2.02	2.78
1993-07	5.00	-0.98	2.77	3.21

Notes: The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap.}$ The first three columns show the year to year growth rate in output per worker and the contribution to that growth due to efficiency change, technical change and capital deepening.

5.2.5.1 *Tripartite Decomposition by Farm Size Relative to the Base Year 1993*

Tables 5.32 to 5.35 provide a summary of the cumulative percentage changes in productivity and the three components for very small farms, small farms, medium sized farms, and large farms, respectively. Between 1993 and 2007, productivity for large farms increased by 239 percent compared to that of medium sized farms (165%), small farms (106%), and very small farms (43%). However, increases in capital deepening were not that different. Large farms increased their capital per worker by 90.23 percent, medium sized farms by 81.69 percent, small farms by 63.10 percent, and very small farms by 47.41 percent.

Table 5-32 Cumulative Percentage Change of Tripartite Decomposition Indexes for Very Small Farms, 1993-2007

Period	Output per worker, base	Output per worker, current	Percentage change in output per worker	Contribution to percentage change in output per worker of:		
				Change in efficiency	Change in technology	Capital deepening
1993-94	80,452	74,162	0.61	2.33	-6.38	7.83
1993-95	86,006	69,154	-11.81	-20.32	8.16	1.49
1993-96	79,013	81,403	12.35	-18.71	30.30	5.69
1993-97	77,497	84,918	22.54	0.50	12.96	9.84
1993-98	85,599	71,389	-4.43	-7.80	-9.50	13.48
1993-99	84,647	75,307	2.27	-20.77	15.49	12.40
1993-00	81,610	80,575	10.10	-0.43	-4.75	17.06
1993-01	84,018	82,204	10.06	-5.34	-6.11	31.92
1993-02	88,929	78,774	0.53	-16.22	3.60	14.35
1993-03	87,678	88,881	11.97	-22.50	26.99	16.19
1993-04	86,151	95,944	25.61	-10.09	12.25	24.24
1993-05	89,272	97,227	24.68	-37.81	54.51	27.47
1993-06	89,439	100,089	24.71	-26.37	24.21	36.48
1993-07	87,069	110,164	43.07	-29.30	39.14	47.41

Notes 1: The values listed for efficiency change, technical change, and capital accumulation change are geometric means. The last four columns show the average productivity change and the contributions to productivity change of the three factors, efficiency change ([EFF-1] ×100), technical change ([TECH-1] ×100), and physical capital deepening ([KACC-1] ×100). For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).
Notes 2: The output per worker in the base year (1993) is not constant across the periods because the current year is used to define farm size based on real gross farm income.

Table 5-33 Cumulative Percentage Change of Tripartite Decomposition Indexes for Small Farms

Period	Output per worker, base	Output per worker, current	Percentage change in output per worker	Contribution to percentage change in output per worker of:		
				Change in efficiency	Change in technology	Capital deepening
1993-94	130,945	123,457	2.08	4.09	-5.06	4.03
1993-95	127,855	122,454	3.84	-4.91	1.74	7.26
1993-96	118,310	139,625	30.07	-2.83	23.34	8.60
1993-97	110,551	146,751	46.07	8.84	14.50	18.67
1993-98	129,192	132,442	12.97	5.74	-10.42	19.56
1993-99	118,027	136,495	27.47	-13.17	18.25	25.57
1993-00	120,085	142,674	32.44	5.62	-2.98	30.47
1993-01	120,218	143,643	35.68	11.82	-6.04	62.33
1993-02	122,467	139,478	28.39	-3.46	1.45	30.37
1993-03	117,285	150,763	47.38	-16.99	30.32	38.39
1993-04	115,303	157,871	56.72	2.17	14.24	35.74
1993-05	113,454	161,804	62.09	-21.51	48.13	38.52
1993-06	112,873	165,996	72.73	-10.43	26.47	55.90
1993-07	108,959	191,927	105.88	-10.00	39.90	63.10

Notes 1: The values listed for efficiency change, technical change, and capital accumulation change are geometric means. The last four columns show the average productivity change and the contributions to productivity change of the three factors, efficiency change ([EFF-1] ×100), technical change ([TECH-1] ×100), and physical capital deepening ([KACC-1] ×100). For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).
Notes 2: The output per worker in the base year (1993) is not constant across the periods because the current year is used to define farm size based on real gross farm income.

Table 5-34 Cumulative Percentage Change of Tripartite Decomposition Indexes for Medium Sized Farms, 1993-2007

Period	Output per worker, base	Output per worker, current	Percentage change in output per worker	Contribution to percentage change in output per worker of:		
				Change in efficiency	Change in technology	Capital deepening
1993-94	161,897	181,307	15.79	6.75	-1.23	10.37
1993-95	168,303	186,058	17.76	5.78	0.87	8.10
1993-96	156,147	211,251	44.09	5.82	21.64	10.79
1993-97	154,892	220,762	53.73	3.10	21.66	23.33
1993-98	158,422	179,456	23.56	9.54	-7.98	21.02
1993-99	159,860	203,524	42.91	-8.44	20.72	28.49
1993-00	156,868	211,483	48.16	10.47	1.67	30.40
1993-01	154,283	215,047	54.08	23.26	-1.50	72.34
1993-02	159,573	216,891	53.61	5.85	2.67	37.32
1993-03	150,314	230,650	74.32	-11.73	36.49	44.35
1993-04	146,336	249,680	91.49	4.90	20.61	51.55
1993-05	147,401	243,834	92.05	-10.81	46.23	42.60
1993-06	146,659	248,768	93.53	-8.96	33.98	59.08
1993-07	136,514	309,359	165.21	-1.57	49.57	81.69

Notes 1: The values listed for efficiency change, technical change, and capital accumulation change are geometric means. The last four columns show the average productivity change and the contributions to productivity change of the three factors, efficiency change ([EFF-1] ×100), technical change ([TECH-1] ×100), and physical capital deepening ([KACC-1] ×100). For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).
Notes 2: The output per worker in the base year (1993) is not constant across the periods because the current year is used to define farm size based on real gross farm income.

Table 5-35 Cumulative Percentage Change of Tripartite Decomposition Indexes for Large Farms, 1993-2007

Period	Output per worker, base	Output per worker, current	Percentage change in output per worker	Contribution to percentage change in output per worker of: Change in efficiency	Change in technology	Capital deepening
1993-94	144,135	175,476	22.21	11.47	-3.27	13.12
1993-95	145,110	215,411	50.04	12.68	1.07	27.10
1993-96	168,043	259,427	59.18	12.52	21.95	15.16
1993-97	177,974	283,490	70.08	5.03	27.54	23.99
1993-98	161,915	234,204	56.57	24.69	-7.67	32.86
1993-99	176,177	262,384	52.56	4.09	21.59	19.46
1993-00	182,860	276,831	59.19	12.80	6.49	31.84
1993-01	170,165	250,917	52.30	40.55	1.50	46.70
1993-02	173,589	270,111	58.16	14.47	4.60	29.09
1993-03	166,459	303,245	91.77	-2.69	41.39	35.46
1993-04	161,153	308,488	110.21	15.06	23.92	44.31
1993-05	162,423	346,473	129.19	5.34	47.89	42.93
1993-06	155,976	365,740	158.91	3.70	43.90	68.44
1993-07	156,749	484,388	238.76	1.22	68.47	90.23

Notes 1: The values listed for efficiency change, technical change, and capital accumulation change are geometric means. The last four columns show the average productivity change and the contributions to productivity change of the three factors, efficiency change ([EFF-1] ×100), technical change ([TECH-1] ×100), and physical capital deepening ([KACC-1] ×100). For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).
Notes 2: The output per worker in the base year (1993) is not constant across the periods because the current year is used to define farm size based on real gross farm income.

Looking at the cumulative average annual growth rates reported in Tables 5.36 to 5.39, the results indicate that productivity for large farms grew at a rate of 7.53 percent with capital deepening contributing 4.01 percent and technology 3.60 percent. Medium sized farms productivity grew at a rate of 6.02 percent with the highest contribution coming from capital deepening (2.58%) and technical change (2.82%). Small farms productivity grew at an annual rate of 4.08 percent with capital deepening contributing 2.91 percent and technical change 2.36 percent. While capital deepening was the main source of growth of large, medium, and small farms, technological progress was the main source of productivity growth for very small farms. On average, productivity grew at a rate of 0.99 percent for very small farms, with technological progress contributing 2.30 percent and capital deepening 1.88 percent. However, gains from technological progress and capital deepening were eroded by a decline in efficiency of 2.19 percent. The key finding of the comparison across farm sizes is that capital deepening and technological progress are the main sources of productivity growth. Efficiency change is a source of regression in productivity growth.

Table 5-36 Decomposition of Labor Productivity Growth for Very Small Farms

Period	Annual Growth Rate of Change in: Output/ Worker (g_y)	Efficiency (g_{eff})	Technology (g_{tech})	Capital Deepening (g_{cap})
1993-94	-6.19	-3.55	-6.62	3.98
1993-95	-11.40	-14.57	3.82	-0.64
1993-96	0.50	-8.88	8.75	0.63
1993-97	2.64	-1.48	3.03	1.08
1993-98	-2.89	-2.62	-2.01	1.74
1993-99	-1.52	-4.97	2.39	1.06
1993-00	-0.05	-0.72	-0.70	1.37
1993-01	-0.19	-1.00	-0.40	1.22
1993-02	-1.33	-2.61	0.39	0.89
1993-03	0.16	-3.09	2.38	0.87
1993-04	0.83	-1.53	1.04	1.32
1993-05	0.55	-4.54	3.61	1.48
1993-06	0.34	-2.94	1.63	1.65
1993-07	0.99	-3.19	2.30	1.88

Notes: The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap.}$ The first three columns show the year to year growth rate in output per worker and the contribution to that growth due to efficiency change, technical change and capital deepening.

Table 5-37 Decomposition of Labor Productivity Growth for Small Farms

Period	Annual Growth Rate of Change in: Output/ Worker (g_y)	Efficiency (g_{eff})	Technology (g_{tech})	Capital Deepening (g_{cap})
1993-94	-3.19	0.43	-5.29	1.67
1993-95	-0.98	-3.55	0.79	1.78
1993-96	6.40	-2.11	6.95	1.56
1993-97	7.60	1.24	3.36	2.99
1993-98	0.94	0.52	-2.22	2.63
1993-99	2.85	-2.93	2.79	3.00
1993-00	2.85	0.37	-0.44	2.92
1993-01	2.70	0.33	-0.40	2.77
1993-02	1.69	-0.76	0.15	2.30
1993-03	2.86	-2.26	2.64	2.48
1993-04	3.15	-0.26	1.20	2.21
1993-05	3.17	-2.34	3.26	2.24
1993-06	3.24	-1.24	1.78	2.71
1993-07	4.08	-1.19	2.36	2.91

Notes: The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap.}$ The first three columns show the year to year growth rate in output per worker and the contribution to that growth due to efficiency change, technical change and capital deepening.

Table 5-38 Decomposition of Labor Productivity Growth for Medium Sized Farms

Period	Annual Growth Rate of Change in: Output/ Worker (g_y)	Efficiency (g_{eff})	Technology (g_{tech})	Capital Deepening (g_{cap})
1993-94	11.45	4.25	-1.50	8.70
1993-95	4.22	1.45	0.34	2.43
1993-96	10.30	1.20	6.51	2.60
1993-97	9.02	0.00	4.81	4.20
1993-98	2.48	1.21	-1.70	2.97
1993-99	4.46	-1.96	3.13	3.28
1993-00	4.34	1.06	0.20	3.08
1993-01	4.26	1.03	-0.11	3.34
1993-02	3.58	0.35	0.27	2.96
1993-03	4.59	-1.55	3.09	3.05
1993-04	5.05	0.22	1.68	3.15
1993-05	4.49	-1.18	3.15	2.52
1993-06	4.37	-0.97	2.21	3.13
1993-07	6.03	-0.37	2.82	3.58

Notes: The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap.}$ The first three columns show the year to year growth rate in output per worker and the contribution to that growth due to efficiency change, technical change and capital deepening.

Table 5-39 Decomposition of Labor Productivity Growth for Large Farms

Period	Annual Growth Rate of Change in: Output/ Worker (gy)	Efficiency (geff)	Technology (gtech)	Capital Deepening (gcap)
1993-94	15.47	8.30	-3.46	10.63
1993-95	16.32	5.43	0.47	10.41
1993-96	14.08	3.53	6.58	3.97
1993-97	10.78	0.71	5.93	4.14
1993-98	7.25	3.99	-1.63	4.89
1993-99	6.26	0.40	3.25	2.61
1993-00	5.96	1.55	0.85	3.57
1993-01	4.74	2.17	0.08	2.49
1993-02	4.45	1.30	0.47	2.69
1993-03	5.63	-0.58	3.44	2.76
1993-04	5.98	1.09	1.92	2.96
1993-05	6.21	0.18	3.24	2.79
1993-06	6.34	0.03	2.75	3.57
1993-07	7.53	-0.08	3.60	4.01

Notes: The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap.}$ The first three columns show the year to year growth rate in output per worker and the contribution to that growth due to efficiency change, technical change and capital deepening.

5.2.5.2 *Tripartite Decomposition by Farm Specialization Relative to the Base Year 1993*

Tables 5.40 to 5.42 report the cumulative percentage changes in productivity and the three components for livestock, diversified, and crop farms, respectively. Crop farms increased productivity by 161.38 percent between 1993 and 2007. The main source of that increase was capital deepening (77.52%) and technology progress (51.02%). Diversified farms increased productivity by 147.24 percent of which capital deepening contributed 72.44 percent and technological progress 49.38 percent. Livestock farms increased productivity 98.15 percent with capital deepening contributing 60.92 percent, and technological progress 44.74 percent.

Table 5-40 Cumulative Percentage Change of Tripartite Decomposition Indexes for Livestock Farms, 1993-2007

Period	Output per worker, base	Output per worker, current	Percentage change in output per worker	Contribution to percentage change in output per worker of:		
				Change in efficiency	Change in technology	Capital deepening
1993-94	124,581	124,787	5.66	2.26	-4.08	9.14
1993-95	123,744	116,444	-0.18	-9.72	3.30	6.43
1993-96	124,930	143,147	16.57	-8.83	24.76	1.97
1993-97	128,307	164,002	38.71	3.31	18.08	15.50
1993-98	120,986	117,955	5.99	4.69	-8.96	12.75
1993-99	124,403	147,576	27.03	-4.79	17.86	13.62
1993-00	121,291	140,535	28.63	9.21	-2.05	19.10
1993-01	123,092	140,170	25.70	16.74	-4.93	36.22
1993-02	116,039	129,357	23.96	-2.47	2.75	23.48
1993-03	110,553	134,909	29.28	-17.39	29.45	20.54
1993-04	115,006	155,981	45.93	7.07	14.02	21.29
1993-05	115,227	159,622	48.57	-21.57	51.82	23.34
1993-06	116,733	175,199	57.75	-11.82	27.93	37.88
1993-07	115,854	206,657	98.15	-17.53	44.74	60.92

Notes 1: The values listed for efficiency change, technical change, and capital accumulation change are geometric means. The last four columns show the average productivity change and the contributions to productivity change of the three factors, efficiency change ([EFF-1] ×100), technical change ([TECH-1] ×100), and physical capital deepening ([KACC-1] ×100). For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).
Notes 2: The output per worker in the base year (1993) is not constant across the periods because the current year is used to define farm size based on real gross farm income.

Table 5-41 Cumulative Percentage Change of Tripartite Decomposition Indexes for Diversified Farms, 1993-2007

Period	Output per worker, base	Output per worker, current	Percentage change in output per worker	Contribution to percentage change in output per worker of:		
				Change in efficiency	Change in technology	Capital deepening
1993-94	123,243	120,029	2.61	4.90	-4.91	3.68
1993-95	123,252	120,194	0.89	-5.96	3.02	3.97
1993-96	123,599	153,942	33.12	-1.54	23.68	8.95
1993-97	120,638	170,870	50.03	9.45	16.93	17.46
1993-98	123,080	125,168	9.98	2.82	-9.86	17.42
1993-99	121,969	145,826	29.83	-11.90	18.60	24.49
1993-00	121,872	154,810	35.44	8.49	-1.69	27.43
1993-01	120,712	159,507	42.09	19.89	-4.41	61.70
1993-02	122,453	147,826	30.15	-1.92	2.35	28.01
1993-03	124,383	179,445	56.94	-12.97	32.77	36.65
1993-04	125,014	203,551	77.39	4.57	17.72	43.27
1993-05	121,585	202,791	82.06	-14.50	47.83	42.70
1993-06	119,434	209,312	92.98	-8.37	30.96	62.87
1993-07	122,401	283,340	147.24	-4.57	49.38	72.44

Notes 1: The values listed for efficiency change, technical change and capital accumulation change are geometric means. The last four columns show the average productivity change and the contributions to productivity change of the three factors, efficiency change ([EFF-1] ×100), technical change ([TECH-1] ×100), and physical capital deepening ([KACC-1] ×100). For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).
Notes 2: The output per worker in the base year (1993) is not constant across the periods because the current year is used to define farm size based on real gross farm income.

Table 5-42 Cumulative Percentage Change of Tripartite Decomposition Indexes for Crop Farms, 1993-2007

Period	Output per worker, base	Output per worker, current	Percentage change in output per worker	Contribution to percentage change in output per worker of:		
				Change in efficiency	Change in technology	Capital deepening
1993-94	129,150	132,487	9.34	5.09	-4.24	10.01
1993-95	129,423	132,938	10.76	-5.54	4.09	10.36
1993-96	127,910	173,119	43.79	1.01	24.26	14.81
1993-97	130,394	179,040	47.56	0.22	18.23	25.37
1993-98	130,955	145,237	19.65	4.50	-9.36	24.60
1993-99	131,481	151,430	23.09	-18.84	18.64	26.47
1993-00	132,112	161,637	31.90	0.22	-1.33	32.31
1993-01	132,720	159,296	31.72	0.43	-4.07	60.93
1993-02	132,780	155,671	28.33	-7.20	2.32	30.02
1993-03	131,859	183,252	53.40	-18.00	33.04	39.33
1993-04	128,837	190,906	64.14	-2.27	16.95	41.77
1993-05	133,256	204,449	69.37	-20.98	48.60	38.28
1993-06	135,557	219,286	80.64	-12.97	31.70	52.36
1993-07	131,962	312,467	161.38	-7.74	51.02	77.52

Notes 1: The values listed for efficiency change, technical change and capital accumulation change are geometric means. The last four columns show the average productivity change and the contributions to productivity change of the three factors, efficiency change ([EFF-1] ×100), technical change ([TECH-1] ×100), and physical capital deepening ([KACC-1] ×100). For each period, e.g., 1993-94, the beginning year is the base year (1993) and the ending year is the current year (1994).
Notes 2: The output per worker in the base year (1993) is not constant across the periods because the current year is used to define farm size based on real gross farm income.

In terms of average cumulative growth rates, reported in Tables 5.43 to 5.45, diversified farms experienced a high growth rate in productivity (5.43%) compared to crop farms (5.19%) and livestock farms (3.23%). The main source of productivity growth for all the specialization categories was capital deepening (3.34%, 3.30%, and 2.61%, respectively) and technical progress (2.78%, 2.85%, and 2.55%, respectively). Growth rates in efficiency deteriorated for each specialization category.

Table 5-43 Decomposition of Labor Productivity Growth for Livestock Farms

Period	Annual Growth Rate of Change in: Output/ Worker (g_y)	Efficiency (g_{eff})	Technology (g_{tech})	Capital Deepening (g_{cap})
1993-94	1.21	-0.61	-4.34	6.15
1993-95	-4.48	-7.21	1.51	1.22
1993-96	2.74	-4.35	7.32	-0.24
1993-97	5.81	0.03	4.06	1.71
1993-98	-0.64	0.19	-1.90	1.07
1993-99	2.84	-1.29	2.73	1.40
1993-00	1.99	0.87	-0.32	1.44
1993-01	1.82	0.67	-0.33	1.47
1993-02	1.26	-0.60	0.30	1.56
1993-03	1.48	-2.18	2.56	1.10
1993-04	2.71	0.32	1.17	1.22
1993-05	2.39	-2.40	3.46	1.33
1993-06	2.54	-1.30	1.85	1.99
1993-07	3.23	-1.93	2.55	2.61

Notes: The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap.}$ The first three columns show the year to year growth rate in output per worker and the contribution to that growth due to efficiency change, technical change and capital deepening.

Table 5-44 Decomposition of Labor Productivity Growth for Diversified Farms

Period	Annual Growth Rate of Change in: Output/ Worker (g_y)	Efficiency (g_{eff})	Technology (g_{tech})	Capital Deepening (g_{cap})
1993-94	-2.51	0.96	-5.13	1.66
1993-95	-2.53	-4.68	1.38	0.76
1993-96	7.22	-1.69	7.03	1.88
1993-97	8.37	1.36	3.85	3.15
1993-98	0.17	-0.19	-2.10	2.46
1993-99	2.74	-2.85	2.83	2.75
1993-00	3.21	0.76	-0.27	2.72
1993-01	3.28	0.81	-0.30	2.76
1993-02	1.80	-0.63	0.25	2.17
1993-03	3.53	-1.78	2.81	2.50
1993-04	4.23	0.06	1.46	2.71
1993-05	4.09	-1.68	3.24	2.53
1993-06	4.15	-1.06	2.03	3.17
1993-07	5.43	-0.69	2.78	3.34

Notes: The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap.}$ The first three columns show the year to year growth rate in output per worker and the contribution to that growth due to efficiency change, technical change and capital deepening.

Table 5-45 Decomposition of Labor Productivity Growth for Crop Farms relative to Base Year 1993

Period	Annual Growth Rate of Change in: Output/ Worker (g_y)	Efficiency (g_{eff})	Technology (g_{tech})	Capital Deepening (g_{cap})
1993-94	2.12	0.04	-4.48	6.56
1993-95	-0.78	-5.49	1.90	2.81
1993-96	9.44	-1.07	7.19	3.32
1993-97	7.49	-0.96	4.11	4.34
1993-98	1.68	0.10	-1.98	3.56
1993-99	1.90	-4.10	2.84	3.16
1993-00	2.48	-0.48	-0.21	3.17
1993-01	1.98	-0.53	-0.27	2.78
1993-02	1.11	-1.40	0.24	2.28
1993-03	2.98	-2.46	2.84	2.61
1993-04	3.26	-0.67	1.40	2.53
1993-05	3.07	-2.47	3.28	2.26
1993-06	3.13	-1.51	2.08	2.56
1993-07	5.19	-0.96	2.85	3.30

Notes: The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap.}$ The first three columns show the year to year growth rate in output per worker and the contribution to that growth due to efficiency change, technical change and capital deepening.

5.2.6. *Concluding Remarks*

The purpose of this section was to use nonparametric production frontier methods to decompose labor productivity in the Kansas farm sector into three components: efficiency change (movements towards or away from the best-practice frontier), technical change (shifts in the best-practice frontier), and capital deepening (movement along the best-practice frontier). The conclusions from this analysis are as follows:

(1) The Kansas farm sector has experienced growth in labor productivity over the sample period but the productivity growth dynamics varied by farm typologies. Productivity growth also varied widely from year to year, a reflection of the stochastic nature of agricultural production that is dependent on factors beyond the control of the producers.

(2) On average, the main sources of labor productivity growth are capital deepening and technological progress. Productivity growth is tied to capital deepening and is bound to decline with a decline in the growth rate of capital deepening. The high contribution of capital deepening to productivity growth in the Kansas farm sector is consistent with findings from studies on other regions in the world. For instance, Salinas-Jime´nez (2003) found capital deepening to be the main source of productivity growth in the Spain and Enflo and Hjertsrand (2006) found capital deepening to be the main source of labor productivity growth in Europe.

(3) It is encouraging to observe the role played by technological progress in productivity growth because changes in efficiency alone cannot sustain productivity growth. Once the farms are able to achieve technical efficiency productivity can only be increased

by innovation (i.e., upward shift of the frontier). Technological progress was remarkably high across the farms and occurred at high levels of capital per worker.

(4) Technological progress has not been Hicks-neutral. This result is consistent with the observations by Managi and Karemera (2004) that rejected Hicks neural technological change in the U.S. agriculture.

(5) Very small farms experienced a decline in productivity over the sample period. In contrast, large farms experienced high growth rates in productivity mainly due to gains in efficiency.

(6) Farm typologies matter and influence productivity growth. Large farms experienced high productivity growth rates compared to medium sized farms, small farms, and very small farms. Except for technological progress where very small farms experienced higher growth rates in technical change than small farms, growth in efficiency change, technical change, and capital deepening also vary by farm size. Conversely, scale efficiency was inversely related to farm sizes. Very small farms were more scale efficient compared to large farms.

(7) The results for the entire period indicate very small changes in the scale of technology, a clear indication that the observed changes in capital deepening and technical change are not attributable to scale effects.

(8) Diversified farms experienced high productivity growth rates compared to crop farms and livestock farms. However, there was more technological innovation in the crop farms than in diversified or livestock farms.

The overall picture indicates improvement in productivity in the Kansas farm sector. Capital deepening and technological progress are the principle factors responsible for productivity growth. Technological innovation is embodied in capital deepening and is primarily driven by a small number of farms. Therefore, the majority of the farms are lagging behind rather than catching up in the technological front. Specifically, very small farms are not able to adopt the available technology and consequently are experiencing a decline in productivity while large farms are experiencing high productivity growth by catching up with technological leaders.

The techniques used in this section do not provide reasons for the phenomena that are measured, that is, efficiency change, technical change, and capital deepening. This is left as a subject for further research. It would be interesting to investigate institutional factors that have contributed to the high growth rates in capital deepening and technological progress. Analysis of the factors that have contributed to decline in efficiency across the Kansas farms would also be interesting. The key researchable questions to address are: (1) what is hindering farms from moving towards the frontier? (2) Is it the case whereby the available best-practice technology is not appropriate? (3) How can the technology be made appropriate or accessible to majority of the farms?

5.3. Analysis of Productivity Distribution Dynamics

The third objective of this study was to analyze the distribution dynamics of labor productivity. Specifically, the contribution of efficiency change, technical change, and capital deepening to the evolution of the entire labor productivity distributions between two years, from a base year (y_b) to a current year (y_c) was examined. This follows the critique of Quah (1990; 1993; 1996a and 1996b) that analyses based on standard parametric regression methods cannot adequately address convergence issues related to the entire distribution, especially when the distribution is multimodal. Particular emphasis is given to whether the labor productivity distribution displays more than one peak[14].

For this analysis, three different periods were considered: 1993-07, 1993-03, and 1996-05. The first period (1993-07) was considered because it captures labor productivity for the entire sample period. The second period (1993-02) was considered because it depicts two comparable years when productivity was low relative to the other years. The third period (1996-05) captures two comparable years when productivity was high relative to the other years.

The distributions employed are Gaussian kernel-based density estimates. Silverman rule of thumb was used in choosing the optimum bandwidth. Analysis based on kernel density relies heavily on visual impressions of the productivity distribution. Detection of modes by visual inspection can be deceiving because some modes could be anomalies attributable to measurement error or other stochastic phenomena. Specific aspects of the shape that otherwise would be undetected by visual impression can be highlighted using non-

[14] Single peak implies unimodality, i.e., the difference in labor productivity growth rates are narrowing over time across the whole cross-section of farms.

parametric statistical tests. Therefore, the uncalibrated bootstrap Silverman (1986) multimodality test is applied. The existence of two modes indicates that the distribution can be regarded as a mixture of two underlying distributions, each with its own mean and standard deviation, and each of which reflect a separate economic subgroup.

Following the work of Henderson et al. (2008), the study also uses a refinement of the Silverman test that corrects for its incorrect asymptotic level: the calibrated Silverman test. An alternative modality test is also used, the Dip statistic of Hartigan and Hartigan (1985), because it is less sensitive than the calibrated Silverman test to problems of spurious modes in the tails of nonparametric distributions. Again, following Henderson et al. (2008), the calibration of Cheng and Hall (1998) is employed to correct for the incorrect asymptotic level of the Dip statistic. Finally, the standard Kolmogorov-Smirnov (KS) test is used to test whether the shape of the distributions have changed over the sample periods, between the specified periods, and as a result of the effect of each of the tripartite decomposition components.

5.3.1. *Tripartite Decomposition Summary*

The tripartite decomposition approach of Kumar and Russell (2002) was applied to the three periods. Table 5.46 shows the mean growth rates of labor productivity and its three components - efficiency change, technical change, and capital deepening- for the three periods considered (1993-07, 1993-02, 1996-05), broken down by farm size.

Table 5-46 Growth of Labor Productivity and the Tripartite Decomposition Components for Selected Periods

	Productivity Growth (g_y)			Efficiency Change (g_{eff})			Technical Change (g_{tech})			Capital Deepening (g_{cap})		
Period	**93-07**	**93-02**	**96-05**	**93-07**	**93-02**	**96-05**	**93-07**	**93-02**	**96-05**	**93-07**	**93-02**	**96-05**
All	4.67	1.34	2.09	-0.92	-0.79	-1.87	2.59	0.29	1.79	3.00	1.91	2.18
VSF	0.92	-1.20	-0.27	-2.98	-2.35	-4.04	2.14	0.35	1.97	1.75	0.80	1.81
SF	3.81	1.52	1.85	-1.11	-0.69	-2.06	2.20	0.14	1.86	2.72	2.07	2.06
MF	5.63	3.23	3.01	-0.34	0.32	-0.97	2.63	0.25	1.64	3.34	2.66	2.33
LF	7.03	4.01	4.07	-0.07	1.17	-0.28	3.36	0.42	1.61	3.75	2.42	2.74

Notes: “All” stands for all farms, “VSF” is very small farms, “SF” is small farms, “MF” is medium sized farms, and “LF” is large farms. The reported estimates are growth rates and the following equality holds: $g_y = g_{eff} + g_{tech} + g_{cap}$.

By comparing the results for each sub-period, it is evident that productivity growth was high in the 1996-05 sub-period (2.09%) due to the high rate of advancement in technology (1.79%) and the high rate of capital deepening (2.18%). In contrast, productivity growth was low (1.34%) in the sub-period 1993-02 mainly due to slow rate of technological advancement (0.29%) and capital deepening (1.91%). A breakdown of the results by farm size provides strong evidence that productivity growth varies by farm size. While deterioration in efficiency was the norm in the three periods, medium sized and large farms achieved efficiency gains in the low productivity period 1993-02. The annual rate of growth in productivity was high in the 1993-07 period (4.67%) compared to the 1993-02 period (1.34%) and the 1996-05 (2.09%) period. This indicates that productivity growth occurred between 2003 and 2007 to drive up the average annual growth rates from the average of 1.34 percent in the 1993-02 period to 4.67 percent in the 1993-07 period. Very small farms achieved higher growth rates in technical change in the 1993-02 and 1996-05 periods (0.35% and 1.97%) compared to small farms (0.14% and 1.86%) and medium sized farms (0.25% and 1.64%).

5.3.2. ***Kernel Density Distributions***

The tripartite decomposition of labor productivity (Kumar and Russell, 2002) can be written as follows:

(5.31) $$y_c = \left(EFF \times TECH \times KACC\right) \times y_b .$$

In the above equation y_c is the current period labor productivity (for example, 2007) and y_b is the base period labor productivity (for example, 1993). Accordingly, labor productivity in the current period can be constructed by multiplying the labor productivity in the base period by each of the three components: efficiency change (EFF), technical change (TECH), and capital deepening (KACC). Thus, the impact of each of the components can be isolated by introducing each component in sequence. For instance, holding constant the impact of technical change and capital deepening, the shift of the labor productivity distribution due solely to efficiency change can be isolated by examining the counterfactual distribution of the variable:

(5.32) $$y^E = EFF \times y_b .$$

Similarly, one can construct counterfactual distributions by introducing the other components. The counterfactual distribution variable that isolates the impact of technical change to the current productivity distribution, *ceteris paribus*, is:

(5.33) $$y^T = TECH \times y_b .$$

The impact of capital deepening to the current productivity distribution can be isolated using the following variable:

(5.34) $$y^K = KACC \times y_b .$$

In the same vein, the joint effect of efficiency change and technical change on the base period distribution can be isolated by the following counterfactual distribution variable:

(5.35) $$y^{ET} = \left(EFF \times TECH\right) \times y_b = TECH \times y^E$$

Similarly, the joint effect of efficiency change and capital deepening on the base period distribution can be isolated as follows:

(5.36) $$y^{EK} = \left(EFF \times KACC\right) \times y_b = KACC \times y^E$$

Finally, the following counterfactual distribution variable isolates the joint effect of technical change and capital deepening on the base period distribution:

(5.37) $$y^{TK} = \left(TECH \times KACC\right) \times y_b = KACC \times y^T$$

For ease of interpretation of the counterfactual distributions, it is important to note that if any of the components or the joint effect of two or more of the components does not have any impact of the base year labor productivity distribution, then the respective counterfactual distribution would be identical to the actual distribution in the base year.

5.3.2.1 *Distribution Dynamics in the Period 1993-07*

The labor productivity distributions of the beginning and end of the period 1993-07 are shown in Figure 5.7. The solid (dashed) curve is the estimated 1993 (2007) distribution of output per worker. The first thing to note is that the distributions in both years are unimodal. Unimodality here implies tendency of growth rates in output per worker to converge to a single steady state across the farm sector. There is a remarkable shift of the probability mass towards the right with a long tail from the 1993 distribution to the 2007 distribution. In 1993, a majority of the farms were concentrated around a relatively low value of output per worker but this situation changed by 2007. The densities, however, remained skewed to the left of the probability mass. This suggests that productivity has increased over the sample period with a few farms achieving remarkable growth.

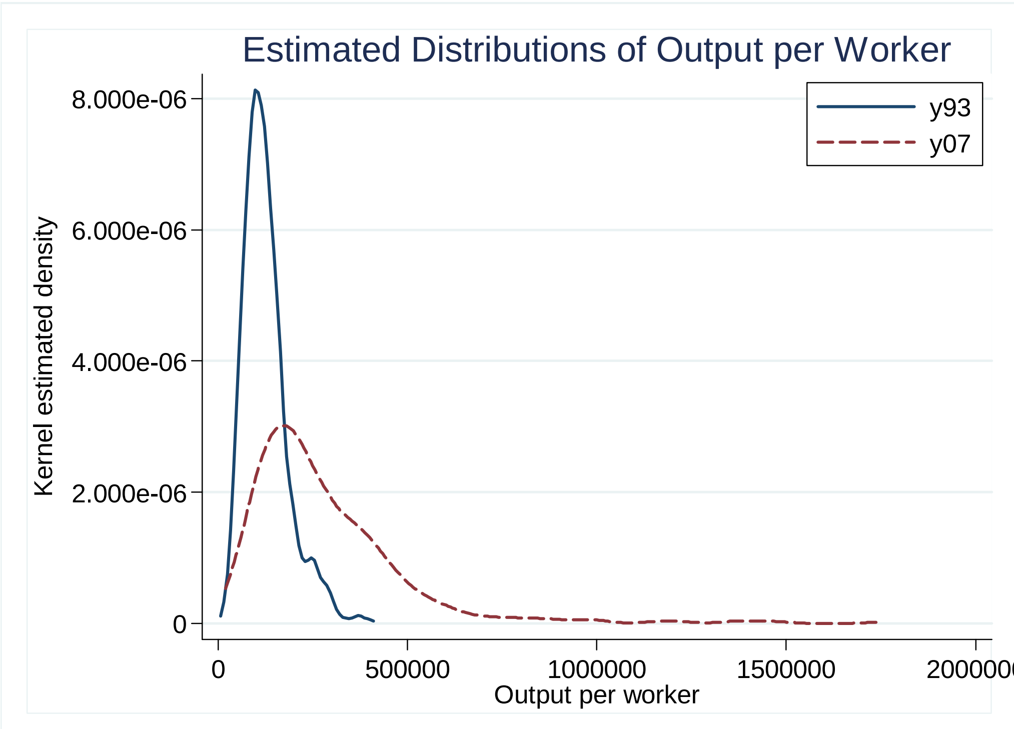


Figure 5-7 Actual Distributions of Output per Worker, 1993 and 2007

The 2007 distribution is widely spread compared to the 1993 distribution, suggesting an increase in the variance of output per worker. The shape of the 2007 distribution, relative to the 1993 distribution, indicates that labor productivity growth is not uniform across the sampled farms. Some farms achieved a high growth in productivity, many others achieved significant growth, and a few farms experienced very slow growth.

Figure 5.8 shows the counterfactual distribution of efficiency change as a tight dotted curve superimposed on the 1993 and 2007 distributions. Although this counterfactual distribution is almost identical to the 1993 distribution, there is a very moderate shift of the probability mass to the left on the lower tail of the distribution.

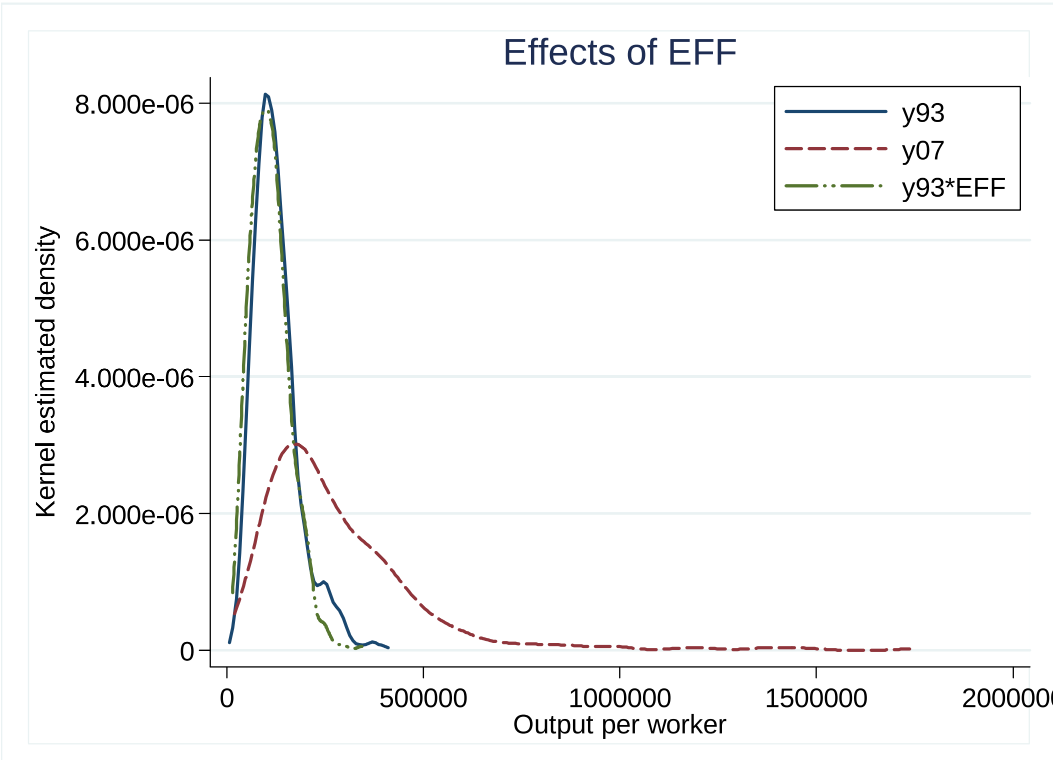


Figure 5-8 Counterfactual distribution of the effect of efficiency change imposed on actual distributions of output per worker, 1993 and 2007

The effect of technological change is shown in Figure 5.9. Technical change shifted the probability mass of the initial productivity distribution to the right, indicating that technological change contributed positively to the growth of productivity. This shift is more pronounced in the right tail of the distribution, suggesting that farms with high output per worker levels in 1993 experienced higher growth in productivity due to technical change compared to those that had low output per worker levels.

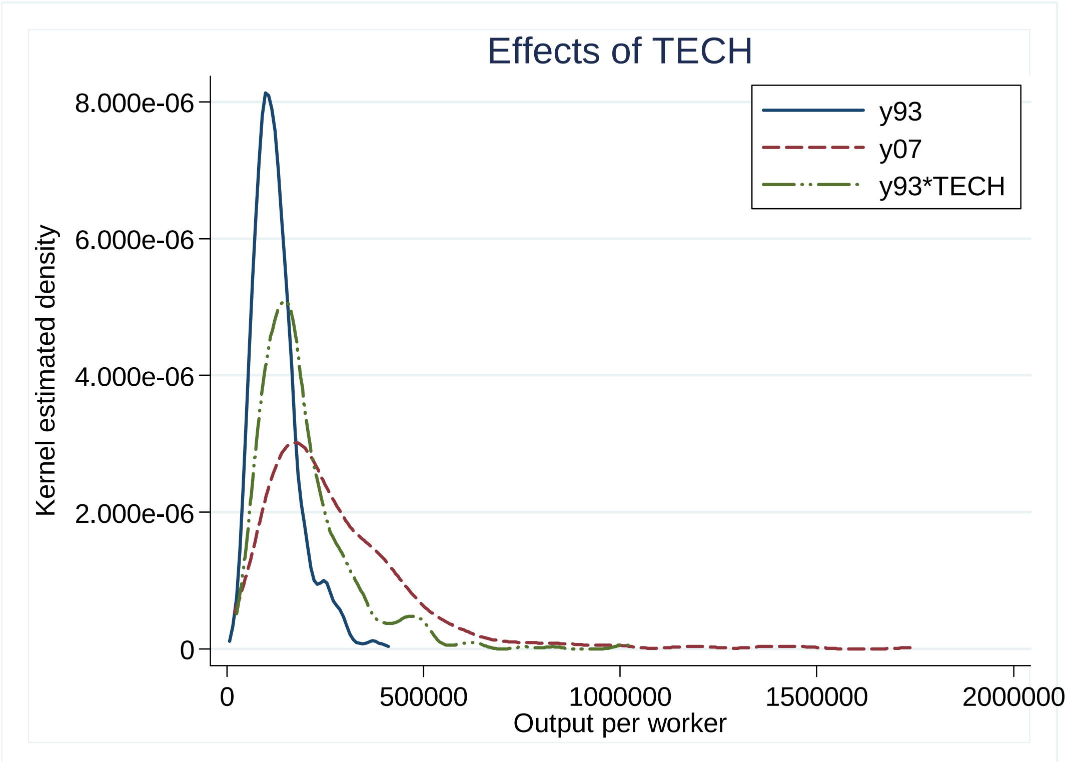


Figure 5-9 Counterfactual distribution of the effect of technical change imposed on actual distributions of output per worker, 1993 and 2007

Figure 5.10 shows the impact of capital deepening on the labor productivity distribution. The shift of the probability mass towards the upper tail is higher in this case compared to that caused by the impact of technical change, a clear indication that capital deepening played a major role in the growth of productivity relative to the other two components. The fact that the counterfactual distribution of capital deepening does not completely map the labor productivity distribution in 2007 provides evidence that productivity growth is primarily driven by a combination of two components, capital deepening and technical change, with the former having the largest effect. Efficiency change contributed to a reduction in productivity.

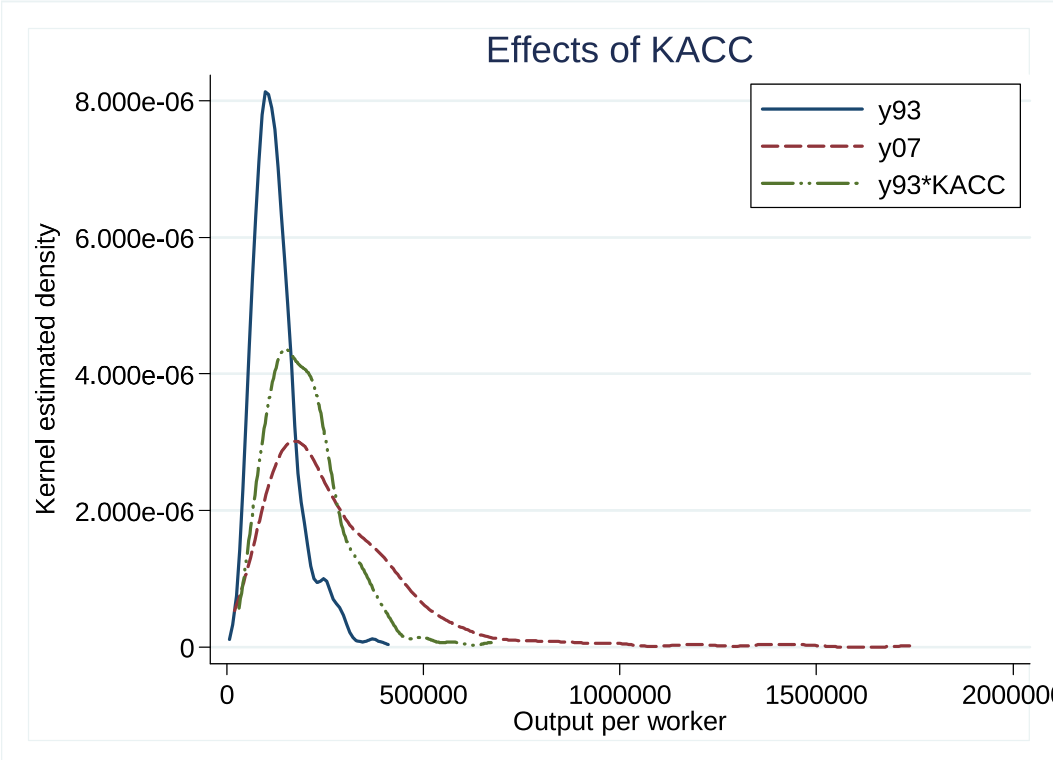


Figure 5-10 Counterfactual distribution of the effect of capital deepening change imposed on actual distributions of output per worker, 1993 and 2007.

5.3.2.2 *Distribution Dynamics in the Period 1993-02*

Figure 5.11 shows the actual productivity distributions for the years 1993 (solid curve) and 2002 (dashed curve). A perceptible shift of the density in the upper tail towards high output per worker levels can be observed between the two years, indicating that productivity improvement. Both distributions remained unimodal.

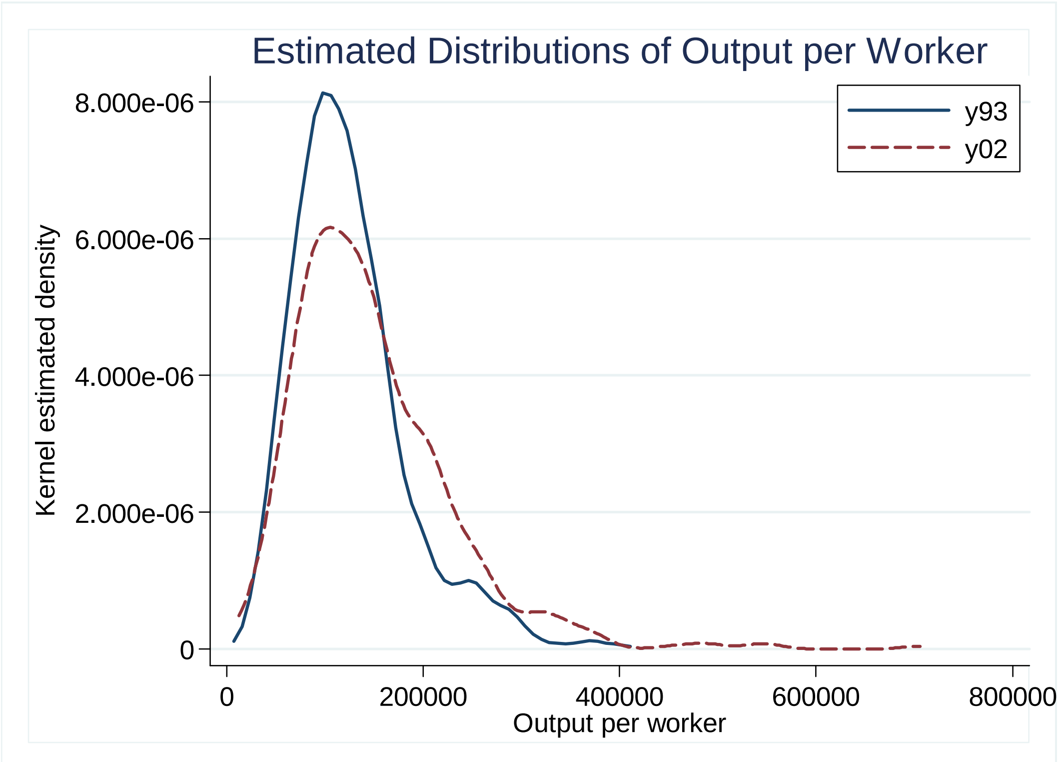


Figure 5-11 Actual distribution of output per worker, 1993 and 2002

The effects of efficiency change, depicted in Figure 5.12, suggest that a decline in efficiency slowed down productivity growth across the whole farm sector. The distributional effects due to efficiency change are not very different from those of productivity in 1993 except for the slight shift of the density to the left. Likewise, technical change had almost negligible effect on the 1993 productivity distribution. Figure 5.13 shows an almost perfect mapping between the two distributions.

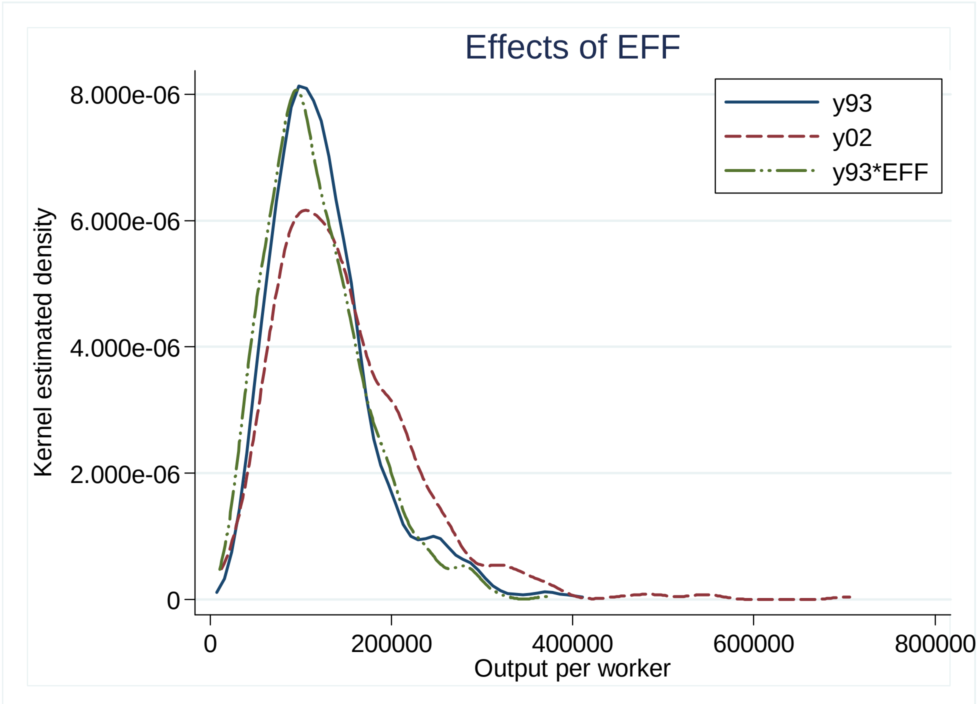


Figure 5-12 Counterfactual distribution of the effect of efficiency change imposed on actual distributions of output per worker, 1993 and 2002

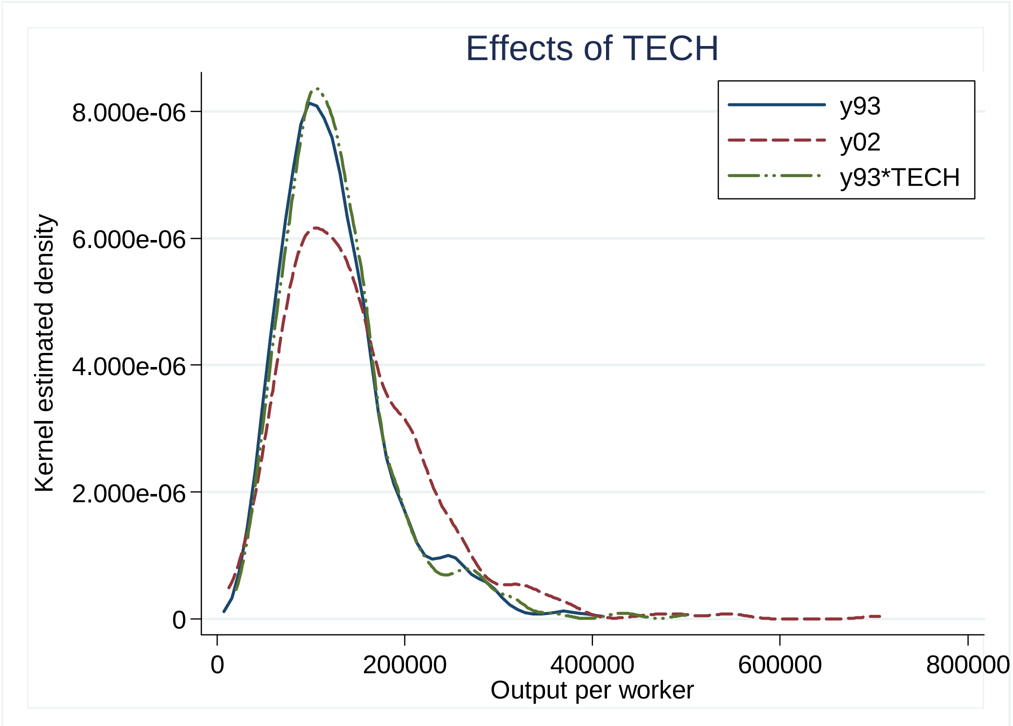


Figure 5-13 Counterfactual distribution of the effect of technical change imposed on actual distributions of output per worker, 1993 and 2002

Figure 5.14 depicts the effects of capital deepening on the 1993 productivity distribution. As shown in the figure, there is a great shift of the density towards the 2002 distribution as compared to the counterfactual distributions of efficiency change and technical change that mapped the 1993 distribution closely. This lends support to the observation that capital deepening is the key factor driving productivity growth. Considering the fact that the years chosen (1993 and 2002) happen to be when productivity was low, the results suggest that high capital per worker is more important in sustaining productivity growth in low productivity years.

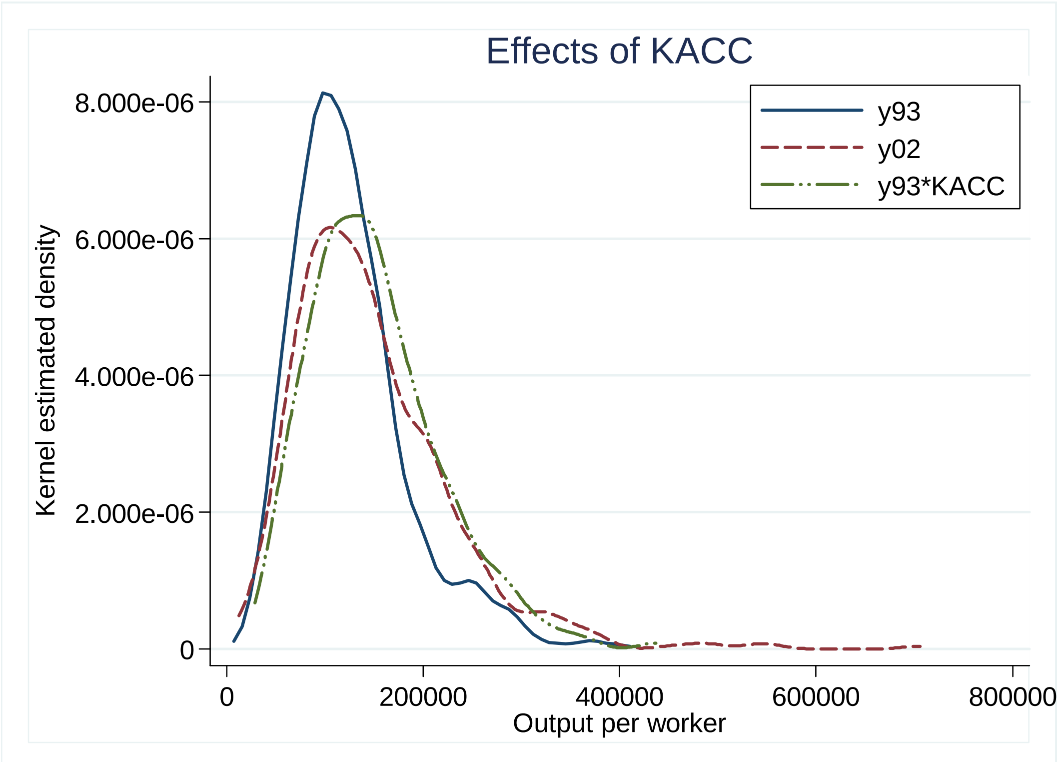


Figure 5-14 Counterfactual distribution of the effect of capital deepening change imposed on actual distributions of output per worker, 1993 and 2002

5.3.2.3 *Distribution Dynamics in the Period 1996-05*

Figure 5.15 shows the actual productivity distributions for the years 1996 (solid curve) and 2005 (dashed curve). The 1996 distributions appear to have two modes. Bimodality seems to persist in the 2005 distribution although the location of the second mode is towards the end of the upper tail. The moderate shift of the probability mass to the right suggests improvement in productivity. Compared to the earlier two periods examined, the negative impact of efficiency change to productivity growth is more prominent as evidenced by the leftwards shift of the probability mass in Figure 5.16. Bimodality of the distribution also persists but at a higher output per worker level.

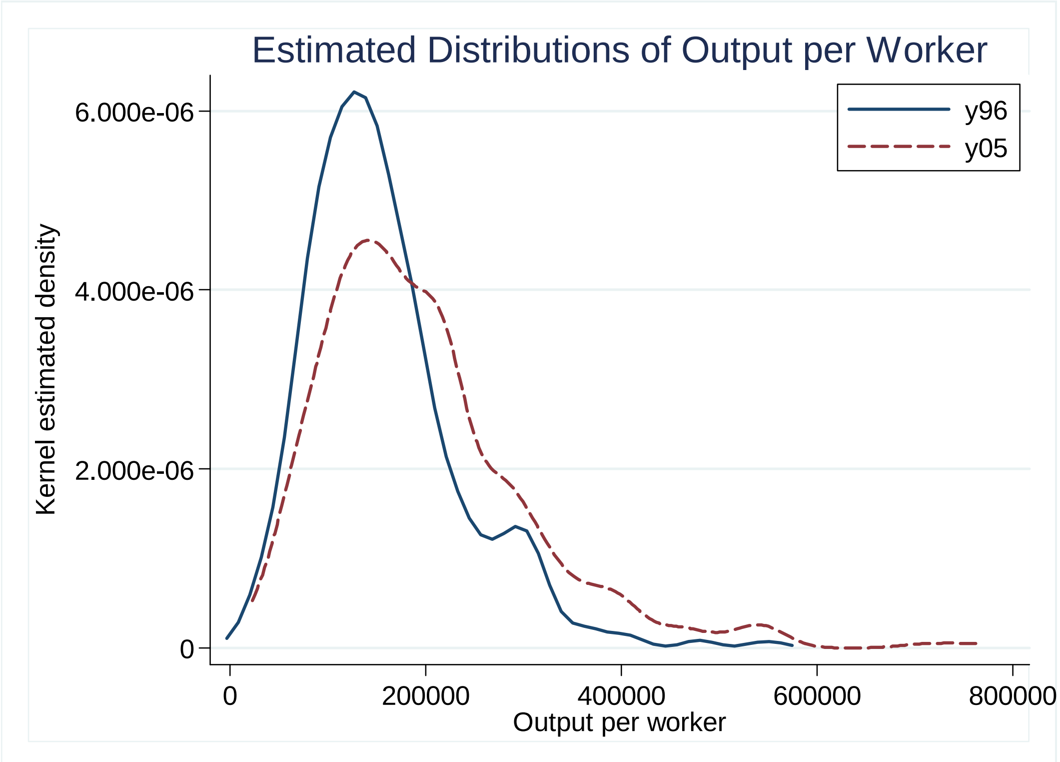


Figure 5-15 Actual distribution of output per worker, 1996 and 2005

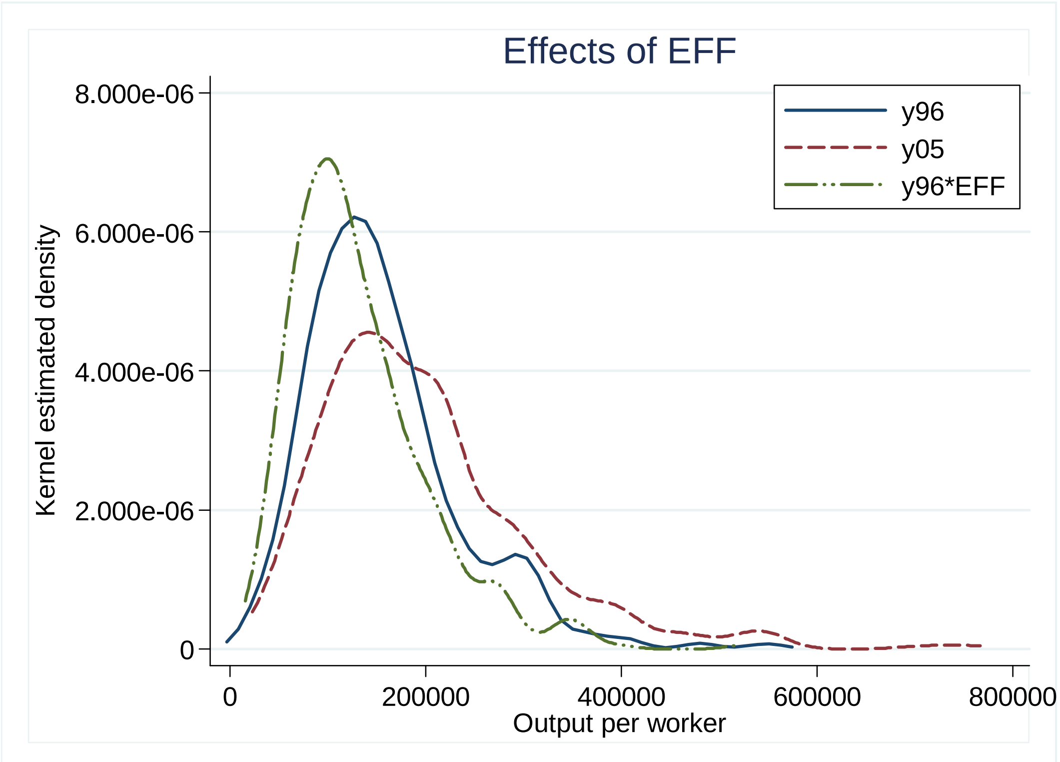


Figure 5-16 Counterfactual distribution of the effect of efficiency change imposed on actual distributions of output per worker, 1996 and 2002

The impact of technical change and capital deepening to the productivity distributions are depicted in Figures 5.17 and 5.18, respectively. In both cases, the probability mass shifted towards the upper tail with the counterfactual distribution due to capital deepening significantly mapping that of the 2005 distribution. Bimodality also seems to disappear in both cases.

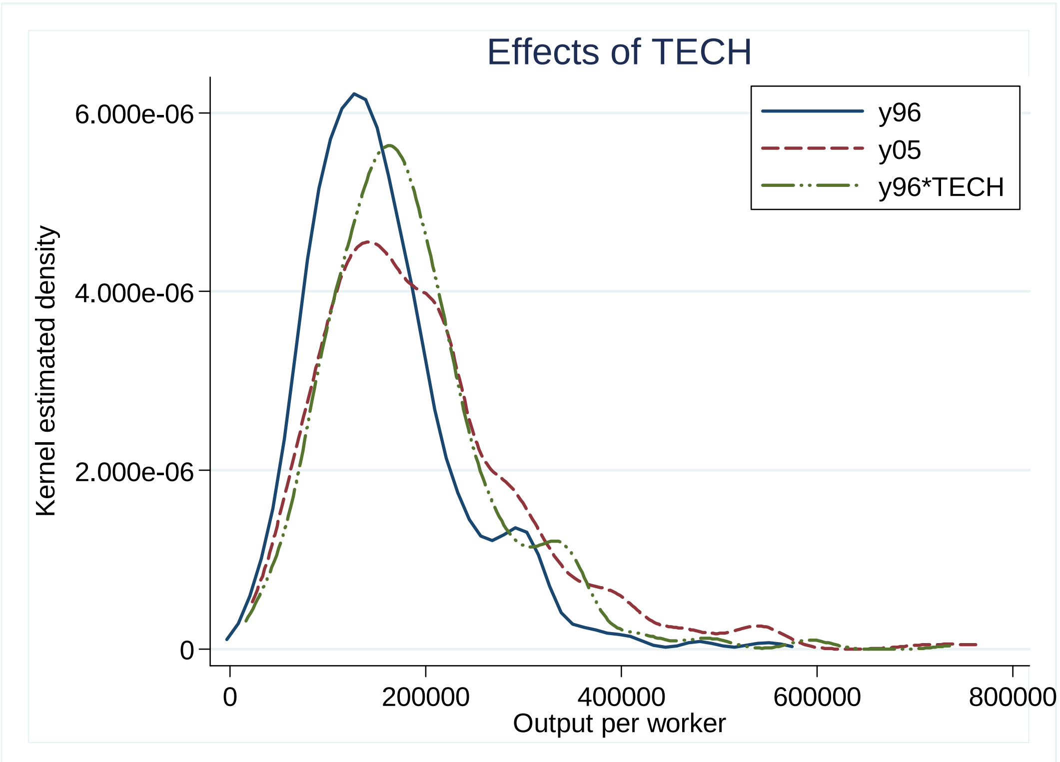


Figure 5-17 Counterfactual distribution of the effect of technical change imposed on actual distributions of output per worker, 1996 and 2005

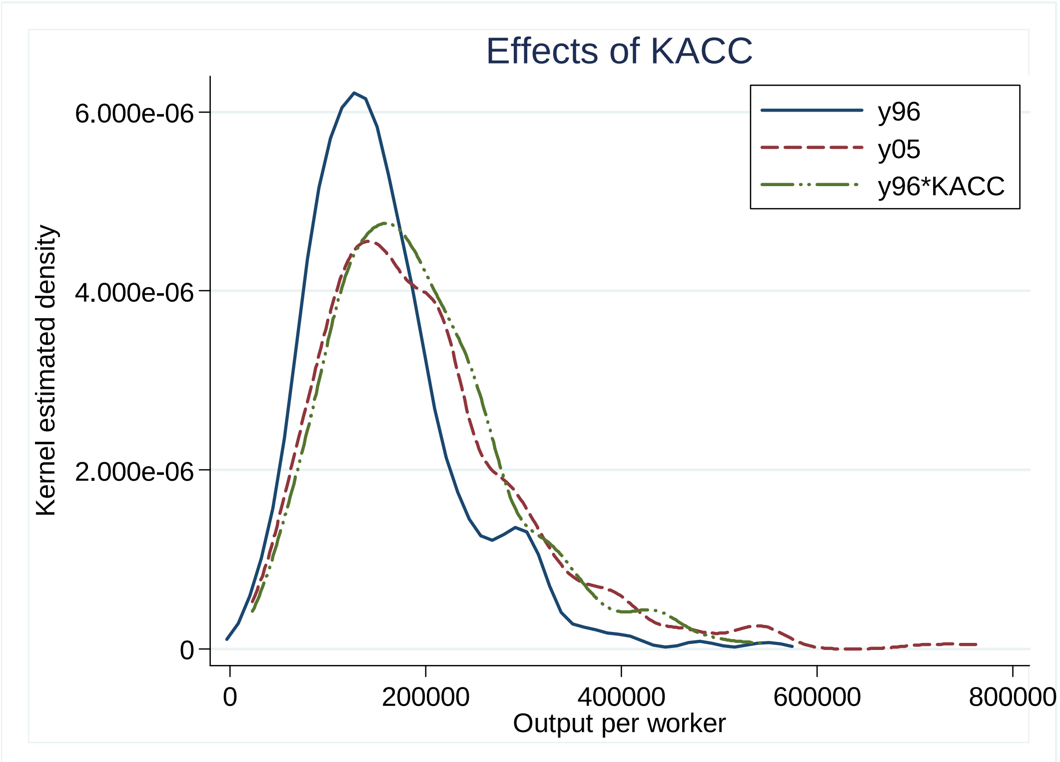


Figure 5-18 Counterfactual distribution of the effect of capital deepening change imposed on actual distributions of output per worker, 1996 and 2002

The foregoing analyses provide strong evidence that capital deepening is the primary driving force in increasing output per worker for the sampled farms followed by technical change. The impact of efficiency change has been that of decreasing the growth in output per worker. Overall, the results may indicate that as farms adopt new technologies, they suffer setbacks in applying it. The effects of technical change are also realized over a long period, suggesting that it takes time for new innovations to be assimilated.

5.3.3. ***Bootstrap Multimodality Tests***

The bootstrap test proposed by Silverman (1986) is used to statistically assess the presence of more than *m* modes in the distributions[15]. The null hypothesis is that there are *m* modes and the alternative is the presence of more than *m* modes. A mode is defined as a point at which the gradient of the density changes from positive to negative (Pittau and Zelli, 2001). In Table 5.47, the p-values of the Silverman test of multimodality of the counterfactual distributions generated by the sequential introduction of the tripartite decomposition components for the three periods (1993-07, 1993-02, and 1996-05) are presented. The Silverman test is computationally demanding and therefore only 1000 bootstrap replications were used. Taking the suggestion of Silverman, the test is conducted for an increasing number of modes until the null hypothesis cannot be rejected.

As the results indicate, the presence of one mode is not rejected in all the actual and counterfactual distributions for the 1993-07 and 1993-02 periods, except for the technical change distribution in the 1993-07 period where two modes are detected (the null hypothesis of one mode is rejected at the 10-percent significance level while the null hypothesis of two modes is not rejected). Visual inspection of the density distribution in Figure 5.9 confirms the existence of two modes in the technical change counterfactual distribution.

[15] A key concept in density estimation is the concept of critical bandwidth (i.e., the smallest possible bandwidth producing a density with at most *m* modes. The critical bandwidth can be used as a statistic to test the null hypothesis that a distribution has *m* modes verses the alternative of more than *m* modes. Thus a 'larger' value of the critical bandwidth indicates more than m modes, thus rejecting the null. How large is large in this context is assessed by the bootstrap (Bianchi, 1997).

Table 5-47 Bootstrap test for Multimodality using the Silverman Test

Hypotheses:	Ho: $m = 1$ Ha: $m > 1$	Ho: $m = 2$ Ha: $m > 2$	Ho: $m = 3$ Ha: $m > 3$	
	p-value	*p-value*	*p-value*	*Mode*
1993-2007				
$g(y_{93})$	0.372	0.350	0.656	1
$g(y_{93}\times EFF)$	0.356	0.436	0.274	1
$g(y_{93}\times TECH)$	0.064	0.142	0.136	2
$g(y_{93}\times KACC)$	0.560	0.418	0.070	1
$g(y_{93}\times EFF\times TECH)$	0.772	0.494	0.804	1
$g(y_{93}\times EFF\times KACC)$	0.414	0.478	0.752	1
$g(y_{93}\times TECH\times KACC)$	0.420	0.480	0.730	1
$g(y_{93}\times EFF\times TECH\times KACC)$	0.512	0.158	0.038	1
1993-2002				
$g(y_{93})$	0.356	0.369	0.637	1
$g(y_{93}\times EFF)$	0.178	0.149	0.794	1
$g(y_{93}\times TECH)$	0.378	0.140	0.175	1
$g(y_{93}\times KACC)$	0.170	0.450	0.747	1
$g(y_{93}\times EFF\times TECH)$	0.177	0.362	0.783	1
$g(y_{93}\times EFF\times KACC)$	0.380	0.040	0.490	1
$g(y_{93}\times TECH\times KACC)$	0.340	0.032	0.506	1
$g(y_{93}\times EFF\times TECH\times KACC)$	0.189	0.046	0.098	1
1996-2005				
$g(y_{96})$	0.616	0.042	0.036	1
$g(y_{96}\times EFF)$	0.086	0.066	0.162	3
$g(y_{96}\times TECH)$	0.300	0.046	0.188	1
$g(y_{96}\times KACC)$	0.374	0.752	0.332	1
$g(y_{96}\times EFF\times TECH)$	0.034	0.042	0.178	3
$g(y_{96}\times EFF\times KACC)$	0.072	0.346	0.592	2
$g(y_{96}\times TECH\times KACC)$	0.082	0.368	0.578	2
$g(y_{96}\times EFF\times TECH\times KACC)$	0.098	0.178	0.698	2

Note: The values reported are p values of the uncalibrated Silverman test of multimodality. Results are generated with 1000 bootstrapped iterations. The test is conducted for an increasing number of modes until the null hypothesis cannot be rejected

For the 1996-05 period, visual inspection suggested bimodality in the 1996 distribution but the Silverman's test fails to reject the unimodality test. The effect of efficiency change and the combined effects of efficiency change and technical change results in three modes in those counterfactual distributions. However, the combined effects of efficiency change and capital deepening leads to two modes. The effect solely due to technical change and capital deepening results in single mode but their combined effect leads to two modes. Eventually, the 2005 distribution is bimodal. This indicates that bimodalism in the 2005 distribution cannot be attributed to the impact of a single component but the combined effects of all the components

The Silverman test has been found to be conservative because it is less likely to falsely reject the null hypothesis (Efron and Tibshirani, 1993; Pittau and Zelli, 2001). Henderson et al. (2008) have implemented a refinement of the Silverman test that corrects for its incorrect asymptotic level, the calibrated Silverman test suggested by Hall and York (2001). An alternative modality test is the Dip statistic proposed by Hartigan and Hartigan (1985) which has also been refined by Henderson et al. (2008) to correct for the incorrect asymptotic level of the Dip statistic using the calibration of Cheng and Hall (1998). Both of those tests are implemented here to verify the results from the uncalibrated Silverman test. The test results for the counterfactual distributions for the three periods are reported in Table 5.48.

Table 5-48 Modality Tests Results: Actual and Counterfactual Labor Productivity Distributions

Ho: One Mode **Ha: More than One Mode**	Uncalibrated Silverman p-value	Calibrated Silverman p-value	Unweighted Calibrated Dip p-value	Weighted Calibrated Dip p-value
1993-2007				
$g(y_{93})$	0.372	0.202	0.130	0.394
$g(y_{93}\times EFF)$	0.356	0.230	0.893	0.190
$g(y_{93}\times TECH)$	0.064	0.014	0.516	0.686
$g(y_{93}\times KACC)$	0.860	0.400	0.871	0.520
$g(y_{93}\times EFF\times TECH)$	0.772	0.710	0.202	0.107
$g(y_{93}\times EFF\times KACC)$	0.414	0.258	0.384	0.113
$g(y_{93}\times TECH\times KACC)$	0.420	0.254	0.389	0.281
$g(y_{93}\times EFF\times TECH\times KACC)$	0.512	0.332	0.729	0.015
1993-2002				
$g(y_{93})$	0.356	0.202	0.128	0.190
$g(y_{93}\times EFF)$	0.178	0.098	0.355	0.773
$g(y_{93}\times TECH)$	0.378	0.232	0.615	0.430
$g(y_{93}\times KACC)$	0.170	0.080	0.086	0.963
$g(y_{93}\times EFF\times TECH)$	0.177	0.074	0.960	0.307
$g(y_{93}\times EFF\times KACC)$	0.380	0.236	0.663	0.325
$g(y_{93}\times TECH\times KACC)$	0.340	0.206	0.668	0.164
$g(y_{93}\times EFF\times TECH\times KACC)$	0.189	0.090	0.312	0.628
1996-2005				
$g(y_{96})$	0.616	0.492	0.167	0.377
$g(y_{96}\times EFF)$	0.086	0.032	0.874	0.123
$g(y_{96}\times TECH)$	0.300	0.202	0.453	0.847
$g(y_{96}\times KACC)$	0.374	0.168	0.208	0.176
$g(y_{96}\times EFF\times TECH)$	0.034	0.020	0.516	0.030
$g(y_{96}\times EFF\times KACC)$	0.072	0.016	0.487	0.026
$g(y_{96}\times TECH\times KACC)$	0.082	0.030	0.492	0.007
$g(y_{96}\times EFF\times TECH\times KACC)$	0.098	0.024	0.231	0.205

Notes: The reported values are p values. The Silverman test was conducted with 1000 iterations while the Dip test conducted with 5000 iterations. The difference in the number of iterations is because the Silverman test is computationally time demanding. The p-values of the uncalibrated unweighted and the calibrated unweighted Silverman tests are presented in columns 1 and 2, and the p-values of the unweighted calibrated and weighted calibrated Dip tests are presented in columns 3 and 4.

At a significance level of 5-percent, the calibrated Silverman test results in the second column of Table 5.48 confirm the results from the uncalibrated Silverman test in the first column. Except for the counterfactual distribution due to technical change in the 1993-07 period, the null hypothesis of unimodality is not rejected for any of the distributions in the 1993-07 and 1993-02 periods. The calibrated Silverman test rejects unimodality for the counterfactual distribution due to technical change in the 1993-07 period at a 5-percent significance level compared to the uncalibrated Silverman test that rejected unimodality at the 10-percent significance level. However, in contrast to the Silverman tests, both the unweighted calibrated and weighted calibrated Dip tests fail to reject unimodality in the counterfactual distribution due to technical change for the 1993-07 period. On the other hand, the weighted calibrated Dip test rejects unimodality for the 2007 labor productivity distribution while the Silverman tests do not.

For the 1996-05 period, the calibrated Silverman test confirms the results obtained from the uncalibrated Silverman test. The unweighted calibrated Dip test fails to reject unimodality in all of the distributions. Compared to the Silverman tests, the weighted calibrated Dip test fails to reject unimodality for the counterfactual distributions due to efficiency change but provides results that are consistent to those of the Silverman tests for all of the other distributions. As noted by Henderson et al. (2008), conclusions concerning the presence of multimodality are sensitive to the test statistic employed and to the decision about weighting. Nonetheless, the tests provide evidence that the labor productivity distribution in the Kansas farm sector has generally remained unimodal.

5.3.4. *Equality of Distribution Test*

To complement the multimodality test and visual impression of the counterfactual distributions, the bootstrapped Kolmogorov-Smirnov (KS) test is used to test for the statistical differences between the actual labor productivity distribution in the current year and the counterfactual distributions for each of the three periods. Each test examines whether the effect of any of the tripartite decomposition components or the combined effects of any of those components caused the distribution of labor productivity in the base period to be different from that in the current period. For example, in the absence of capital deepening and technical change, the following identity examines whether efficiency change caused the labor productivity distribution in 1993 to be different from that found in 2007:

(5.38) $$f\left(y_{2007}\right) = g\left(y_{93} \times EFF\right).$$

The KS tests of the equality of the distributions are reported in Table 5.49. For the 1993-07 period, the results indicate that the distribution of labor productivity in 1993 and 2007 are significantly different at the 1 percent significance level (the KS test statistic is 0.527). The test result also indicates that all the counterfactual distributions are statistically different from the 2007 distribution at the 1 percent significance levels. Although the results indicate that all the counterfactual distributions are statistically different from the 2007 distribution, the small changes in the KS test statistics indicates that efficiency change (0.573) did little to shift the 1993 labor productivity distribution towards the 2007 distribution compared to technical change (0.266) and capital deepening (0.222). The combined effects of technical change and capital deepening had the greatest effect in shifting the 1993 distribution towards the 2007 distribution, although the two distributions are not equal. This confirms the findings above that technical change and capital deepening are the key factors driving productivity growth in this period.

For the 1993-02 period, the test statistics reject the null hypothesis that the 1993 and 2002 labor productivity distributions are equal (the KS test statistic is 0.154). Equality of all the other counterfactual distributions with the 2002 productivity distribution are rejected with the exception of the joint effects of efficiency change and capital deepening, and the joint effects of technical change and capital deepening. Both the p-values (0.870) and KS test statistic (0.036) indicate that the null hypothesis of equality between the counterfactual distributions of the combined effects of efficiency change and capital deepening and that of technical change and capital deepening with the 2002 productivity distribution cannot be rejected. A possible explanation is that capital deepening dominates both efficiency change and technical change in shifting the 1993 productivity distribution towards the 2002 distribution. These results are consistent with the visual impressions of the respective kernel densities graphs (Figure 5.12 to Figure 5.14).

The test results for the period 1996-05 indicate that capital deepening is the driving force in explaining the overall change in the distribution from 1996 to 2005. The null hypothesis cannot be rejected when the effect of capital deepening is solely considered but the null hypothesis is rejected when the combined effects of capital deepening and efficiency change or capital deepening and technical change are considered. The multimodality test indicated that the counterfactual distribution due to the impact of capital deepening is unimodal while that of the 2005 distribution is bimodal, hence the expectation would have been to reject the null. A possible explanation for this rejection is the fact that the second mode in the 2005 distribution appears to be in the far end of the upper fail.

Table 5-49 Testing for Changes in the Distribution of Labor Productivity due to Different Sources

Ho: Distributions are equal **Ha: Distributions are not equal**	Value of Statistic	Bootstrap p-value	Conclusion of testing Ho
1993-2007			
$f(y_{2007})$ vs. $g(y_{93})$	0.527	0.000	Reject
$f(y_{2007})$ vs. $g(y_{93}\times EFF)$	0.573	0.000	Reject
$f(y_{2007})$ vs. $g(y_{93}\times TECH)$	0.266	0.000	Reject
$f(y_{2007})$ vs. $g(y_{93}\times KACC)$	0.222	0.000	Reject
$f(y_{2007})$ vs. $g(y_{93}\times EFF\times TECH)$	0.314	0.000	Reject
$f(y_{2007})$ vs. $g(y_{93}\times EFF\times KACC)$	0.275	0.000	Reject
$f(y_{2007})$ vs. $g(y_{93}\times TECH\times KACC)$	0.275	0.000	Reject
1993-2002			
$f(y_{2002})$ vs. $g(y_{93})$	0.154	0.000	Reject
$f(y_{2002})$ vs. $g(y_{93}\times EFF)$	0.179	0.000	Reject
$f(y_{2002})$ vs. $g(y_{93}\times TECH)$	0.151	0.000	Reject
$f(y_{2002})$ vs. $g(y_{93}\times KACC)$	0.089	0.024	Reject
$f(y_{2002})$ vs. $g(y_{93}\times EFF\times TECH)$	0.165	0.000	Reject
$f(y_{2002})$ vs. $g(y_{93}\times EFF\times KACC)$	0.036	0.870	Fail to Reject
$f(y_{2002})$ vs. $g(y_{93}\times TECH\times KACC)$	0.036	0.870	Fail to Reject
1996-2005			
$f(y_{2005})$ vs. $g(y_{96})$	0.204	0.000	Reject
$f(y_{2005})$ vs. $g(y_{96}\times EFF)$	0.316	0.000	Reject
$f(y_{2005})$ vs. $g(y_{96}\times TECH)$	0.075	0.088	Fail to Reject
$f(y_{2005})$ vs. $g(y_{96}\times KACC)$	0.050	0.490	Fail to Reject
$f(y_{2005})$ vs. $g(y_{96}\times EFF\times TECH)$	0.204	0.000	Reject
$f(y_{2005})$ vs. $g(y_{96}\times EFF\times KACC)$	0.145	0.000	Reject
$f(y_{2005})$ vs. $g(y_{96}\times TECH\times KACC)$	0.145	0.000	Reject

Note: The values reported are the statistics and p values of the two-sample bootstrapped Kolmogorov-Smirnov test with 5000 bootstrap replications.

5.3.5. *Multimodality and Equality of Distribution tests for the Actual Distributions*

The equality of distributions tests were conducted for the actual labor productivity distribution in the entire sample, from 1993 to 2007. The results of the uncalibrated Silverman test of multimodality are reported in Table 5.50. As revealed in the table, unimodality is the norm in the entire sample except for the years 1997 and 2005 when unimodality was rejected for bimodality (null of m =1 is rejected but the null of m =2 is not at 10 significance level). The calibrated Silverman test in Table 5.51 tells the same story except that unimodality is rejected at 10-precent significance level for the years 1997, 2000, 2002, 2004 and 2005. The unweighted calibrated Dip statistic rejects unimodality at 10-percent significance level in the year 1998 while the weighted calibrated Dip statistic rejects unimodality at 10-percent significance level for the years 1997 and 2004.

The Kolmogorov-Smirnov test is used to test the equality of the productivity distribution for each pair of years, starting with 1993-94 to 2006-07. The results reported in Table 5.52 indicate that the transition of the 1993 productivity distribution towards that of 2007 took place between the years 1995 to 1999, 2001 to 2004 and in 2007. No significant changes are detected in the shapes of the productivity distributions for the years 1993 to 1995, 2000 to 2002, and 2004 to 2006.

Table 5-50 Bootstrap Silverman Test for *m*-number of Modes

	Ho: *m* = 1 **Ha: *m* > 1**	**Ho: *m* = 2** **Ha: *m* > 2**	**Ho: *m* = 3** **Ha: *m* > 3**	
	p-value	p-value	p-value	Mode
1993	0.372	0.350	0.656	1
1994	0.684	0.812	0.624	1
1995	0.610	0.680	0.252	1
1996	0.604	0.056	0.016	1
1997	0.026	0.334	0.302	2
1998	0.508	0.334	0.572	1
1999	0.790	0.724	0.384	1
2000	0.164	0.558	0.286	1
2001	0.354	0.440	0.352	1
2002	0.116	0.042	0.108	1
2003	0.226	0.638	0.216	1
2004	0.116	0.644	0.306	1
2005	0.098	0.122	0.734	2
2006	0.552	0.086	0.036	1
2007	0.504	0.164	0.042	1

Notes: the reported results are p-values of the Silverman's test of multimodality. The null hypothesis is that there is m number of modes and the alternative is that there are more than *m* modes. The test is conducted for an increasing number of modes until the null hypothesis cannot be rejected

Table 5-51 Bootstrap Test for Modality, 1993 to 2007

Year	Uncalibrated Silverman p-value	Calibrated Silverman p-value	Unweighted Calibrated Dip p-value	Weighted Calibrated Dip p-value
1993	0.372	0.202	0.128	0.890
1994	0.684	0.504	0.782	0.847
1995	0.610	0.414	0.377	0.232
1996	0.604	0.478	0.178	0.523
1997	0.026	0.010	0.824	0.091
1998	0.508	0.356	0.068	0.374
1999	0.790	0.604	0.824	0.396
2000	0.164	0.082	0.719	0.315
2001	0.354	0.214	0.784	0.167
2002	0.116	0.080	0.312	0.413
2003	0.226	0.128	0.907	0.279
2004	0.116	0.044	0.984	0.026
2005	0.098	0.028	0.221	0.365
2006	0.552	0.374	0.808	0.275
2007	0.504	0.342	0.725	0.301

Notes: The reported values are p values. The Silverman test was conducted with 1000 iterations while the Dip test conducted with 5000 iterations. The difference in the number of iterations is because the Silverman test is computationally time demanding. The p-values of the uncalibrated unweighted and the calibrated unweighted Silverman tests are presented in columns 1 and 2, and the p-values of the unweighted calibrated and weighted calibrated Dip tests are presented in columns 3 and 4.

Table 5-52 Testing for Changes in the Distribution of Labor Productivity over Sample Period

Ho: Distributions are equal Ha: Distributions are not equal	Value of Statistic	Bootstrap p-value	Conclusion of testing Ho
$g(y_{1993})$ vs. $f(y_{1994})$	0.041	0.736	Fail to Reject
$g(y_{1994})$ vs. $f(y_{1995})$	0.061	0.250	Fail to Reject
$g(y_{1995})$ vs. $f(y_{1996})$	0.247	0.000	Reject
$g(y_{1996})$ vs. $f(y_{1997})$	0.108	0.038	Reject
$g(y_{1997})$ vs. $f(y_{1998})$	0.247	0.000	Reject
$g(y_{1998})$ vs. $f(y_{1999})$	0.131	0.000	Reject
$g(y_{1999})$ vs. $f(y_{2000})$	0.050	0.487	Fail to Reject
$g(y_{2000})$ vs. $f(y_{2001})$	0.044	0.637	Fail to Reject
$g(y_{2001})$ vs. $f(y_{2002})$	0.098	0.011	Reject
$g(y_{2002})$ vs. $f(y_{2003})$	0.140	0.000	Reject
$g(y_{2003})$ vs. $f(y_{2004})$	0.099	0.009	Reject
$g(y_{2004})$ vs. $f(y_{2005})$	0.037	0.829	Fail to Reject
$g(y_{2005})$ vs. $f(y_{2006})$	0.067	0.171	Fail to Reject
$g(y_{2007})$ vs. $f(y_{2007})$	0.199	0.000	Reject

Notes: The values reported are the statistics and p value of the two-sample Kolmogorov-Smirnov test bootstrapped at 5000 iterations. The null hypothesis is that the two distributions are equal.

5.3.6. *Concluding Remarks*

This section used nonparametric density estimation methods to investigate changes in the labor productivity distribution of a sample of Kansas farms over three periods: 1993-07, 1993-02, and 1996-05. The effects of each of the tripartite components - efficiency change, technical change, and capital deepening - on the evolution of the entire labor productivity distribution and the presence of modes were tested using two nonparametric tests: the Silverman tests and the Dip tests. Finally, the Kolmogorov-Smirnov test was used to investigate whether observed changes in the distributions are statistically significant. The following conclusions can be drawn from the above analyses:

(1) The evolution of the labor productivity distribution from 1993 to 2007 cannot be accounted for solely by efficiency change, technical change, or capital deepening but by the combined effect of all three components.

(2) Capital deepening is the main driving force behind the increase in output per worker in the entire sample period, 1993-07, and within the sub-periods 1993-02 and 1996-05.

(3) Technical change plays a significant role in the increase in output per worker in the years when output per worker is high. Increases in capital per worker are very important in sustaining productivity growth in both low and high productivity years.

(4) Productivity growth is hampered by the inability of the farms to utilize the available technology, and hence efficiency change has a negative impact on productivity improvement. Rather than trying to increase productivity using the same level of inputs, farmers strive to increase productivity by increasing capital per worker and adopting new technologies.

(5) The distribution of labor productivity has remained unimodal in the sample period, although there are some periods within the sample when the distribution is bimodal. Out of the 15 years, bimodality was detected in two years only, 1997 and 2005. However, these results need to be interpreted with caution because unimodality does not exclude the presence of two or more groups in the data. The implication of this is that there are no persistent patterns of clustering in the farm sector. Unimodality implies convergence in the growth of output per worker to a common steady state over the cross-section of Kansas farms.

(6) For the 1993-07 period, the effect of technical change introduced bimodality in the labor productivity distribution. This may indicate that technical change leads to two different points of convergence where technological leaders converge at one point while the followers converge at a different point.

5.4. Convergence Tests

The last objective of this study was to test for convergence/divergence of labor productivity across the Kansas farms by investigating whether there is any systematic relationship between the initial level of productivity and the annual growth rates of four variables, namely labor productivity, efficiency change, technical change, and capital deepening. Several empirical studies have examined convergence in the U.S. agricultural sector (e.g., Ball et al., 2001; Ball et al., 2004). However, no study has investigated the convergence of labor productivity at the farm level and the factors that are driving the convergence.

Following Ball et al. (2001) two hypotheses that are not mutually exclusive are tested. The first is the "catching-up" hypothesis which states that those farms that lagged behind the leading farms in terms of labor productivity levels at the beginning of the period would exhibit the most rapid rates of growth. This would be indicated by an inverse relationship between initial levels of labor productivity and each of the four rates of growth. The second hypothesis is that technological innovation is embodied in capital deepening. In this case, there will be a positive relationship between the growth rate of labor productivity and capital deepening.

To investigate cross-sectional convergence, previous literature have regressed the average annual growth rate of any of those four variables (growth rates in labor productivity, efficiency change, technical change, and capital deepening) on initial labor productivity, along with other variables. For instance, Kumar and Russell (2002) and Henderson et al. (2007) considered the initial level of labor productivity only as a regressor. Unel and Zebregs (2007) considered other factors that have possible effects on the growth rates of the tripartite components such as foreign direct investment, domestic investment, and geography. Salinas-Jime´nez (2003) used nonparametric regression to investigate whether a process of technological catch-up and convergence has taken place in Spain by regressing annual growth rate in efficiency against initial levels of efficiency. Ball et al. (2001) used both cross-sectional and time series approaches to investigate convergence in total factor productivity (TFP) across 48 U.S. states and found that the range of TFP has narrowed over time.

This study follows the Kumar and Russell (2002) approach where only the initial level of labor productivity is considered as a regressor. However, the approach used in this study extends previous literature by proposing the use of semi-parametric regression methods to investigate convergence in growth rates. The study is different from previous literature because we control for farm size using three different types of regression models: ordinary least square (OLS), the partial linear model (PLM), and the smooth coefficient model (SCM). The first model is a parametric model and the latter two are semi-parametric models. Taking each farm as an observation, convergence is implied if any of the four growth rates is inversely correlated with the initial levels of labor productivity. A direct relationship would imply divergence.

The growth of the U.S. economy is tied to the growth of industries, which comes from the growth of firms, including farms in the agricultural sector. Therefore, the productivity growth of the agricultural sector is attributable to the growth of productivity at the farm level. From a policy perspective, it is important to investigate the role of technological diffusion, technological innovation, and capital deepening to the convergence of labor productivity across the Kansas farm sector. It is important to mention that the purpose of this section is to test for convergence and not to explain the factors that influence the growth rate of labor productivity or any of the components.

5.4.1. *Data and Methods*

The data used in this section are the computed annual growth rates of labor productivity, efficiency change, technical change, capital deepening, and logarithm of initial level of labor productivity for the period 1993-07 and two sub-periods: 1993-02 and 1996-05. A descriptive summary of the growth rates was reported in Table 5.46 of the previous section. Three dummy variables for very small farms, small farms, and medium sized farms are used to control for farm sizes in the parametric model. Large farms are left out and therefore represent the reference farms. The methods used to estimate the regression models were outlined in sections 3.12 and 3.13.

5.4.2. *Empirical Results*

This section used three empirical models (OLS, PLM, and SCM) to explore the relationship between initial levels of labor productivity and the annual growth rates of labor productivity, efficiency change, technical change, and capital deepening. Tables 5.53 present the estimated results for the period 1993-07. The columns marked (1) show the results when the dependent variable is the average annual growth rate of labor productivity for the OLS model, PLM and SCM, respectively. The coefficient on initial labor productivity is negative and comparable across the three models (-5.230, -5.224, and -5.067). This suggests that,

Table 5-53 Regression results of growth rates in output per worker and the three decomposition indices on growth rate in output per worker in base (1993) period

	Ordinary Least Square Model				Partial Linear Model				Smooth Coefficient Model			
	(1) g_Y	(2) g_{EFF}	(3) g_{TECH}	(4) g_{KACC}	(1) g_Y	(2) g_{EFF}	(3) g_{TECH}	(4) g_{KACC}	(1) g_Y	(2) g_{EFF}	(3) g_{TECH}	(4) g_{KACC}
Intercept	69.270***	32.237***	-7.739***	44.772***					63.530	30.062	-9.098	41.549
	(3.452)	(2.186)	(0.971)	(2.892)								
Slope	-5.230***	-2.715***	0.933***	-3.448***	-5.224	-2.712	0.933	-3.440	-5.067	-2.670	0.999	-3.300
	(0.299)	(0.183)	(0.081)	(0.242)	(0.298)	(0.183)	(0.081)	(0.242)				
D-VSF	-9.294***	-4.553***	-0.651***	-4.090***								
	(0.455)	(0.279)	(0.124)	(0.369)								
D-SF	-5.254***	-2.091***	-0.795***	-2.369***								
	(0.360)	(0.220)	(0.098)	(0.292)								
D-MF	-2.334***	-0.753***	-0.566***	-1.015***								
	(0.351)	(0.215)	(0.096)	(0.285)								
Sd(Resid)	8.847	3.321	0.655	5.815	8.781	3.295	0.649	5.787	8.712	3.239	0.631	5.727
Adj. R^2	0.494	0.400	0.358	0.298	0.497	0.339	0.362	0.300	0.501	0.409	0.380	0.308
Jn Test	-0.741	-0.712	2.451**	-0.686								

Note: 564 observations are used in the regressions. Figures in parenthesis represent the robust standard errors. The asterisks *, **, and *** means the corresponding coefficient is significant at the 10 percent, 5 percent, and 1 percent level. The Jn test is the Hsiao et al. (2007) test statistic for the null of correct parametric model specification. D stands for dummy, VSF for very small farms, SF for small farms, and MF medium sized farms.

average, farms that had lower initial labor productivity levels achieved higher annual growth rates in labor productivity relative to those that had higher initial labor productivity levels. The slope and dummy variable coefficients for the OLS model are all statistically significant at the 1-percent significance level. The large farms are the reference farms so the coefficients on the dummy variables provide estimates of the difference in the speed of convergence relative to the large farms. Values of the dummy coefficients indicate that the speed of convergence is inversely correlated with farm size. The speed of convergence for very small farms (-9.294), small farms (-5.294), and medium sized farms (-2.334) are much faster relative to large farms.

Comparing the in-sample fit across the three models, the SCM performed better (R^2 = 0.501) compared to the PLM (R^2 = 0.497) and the OLS model (R^2 = 0.494). The SCM also has narrower residual standard errors (8.712) compared to the PLM (8.781) and the OLS model (8.847). Therefore, the additional flexibility offered by allowing the initial productivity parameter to vary with respect to farm size improves the fit of the model.

The columns marked (2) show the results when the dependent variable is the average annual growth rate of the efficiency indices. The coefficient on initial labor productivity is negative across the three models: OLS Model, PLM, and SCM (-2.715, -2.712, and -2.670). All the coefficients for the OLS model are statistically significant at the 1-percent level. This suggests that, on average, the improvement in efficiency was higher on the farms with lower initial productivity levels. This implies that improvement in efficiency supports convergence in productivity growth across the Kansas farms. The speed of convergence varies inversely by farm size with very small farms achieving high speed (-4.553) compared to small farms (-2.091) and medium farms (-0.753). Again, in terms of the in-sample fit, the SCM (R^2 = 0.409) performs better than the PLM (R^2 = 0.339) and the OLS model (R^2 = 0.400).

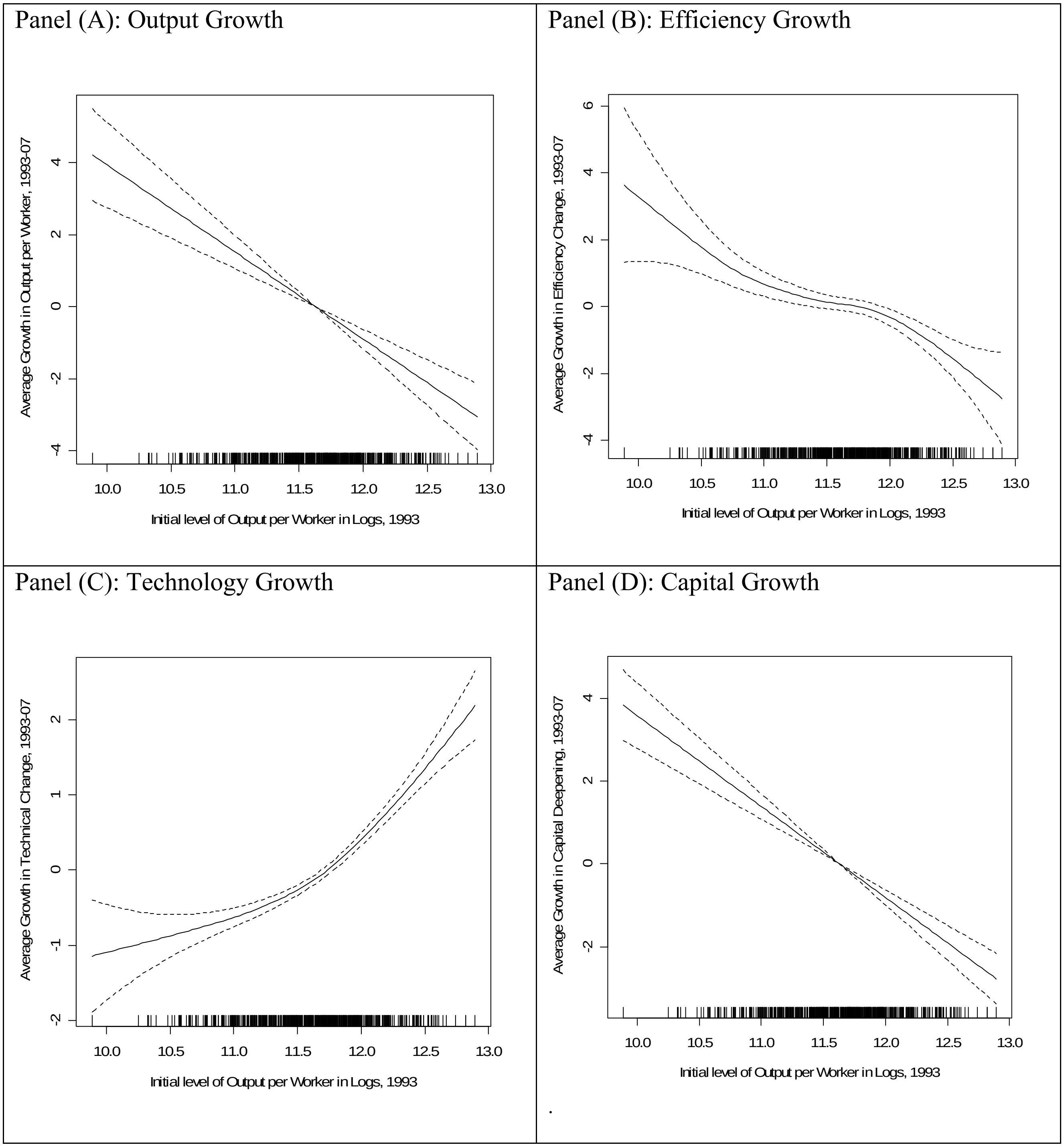
The regression results when the dependent variable is the annual growth rate in technical change are reported in the columns marked (3). All three models (OLS, PLM, and SCM) indicate a positive relationship between the growth rate of technical change and initial labor productivity (0.993, 0.993, and 0.999). This suggests that technological change contributed to productivity disparity rather than convergence during the 1993-07 period. Farms with a high level of productivity at the beginning of the period benefited more from technological innovation relative to those that started with lower levels of productivity. All estimated parameters in the OLS model are statistically significant at the 1-percent level and the speed of divergence varies inversely with farm size. The SCM produces a better in-sample fit (R^2 = 0.380) compared to the PLM (R^2 = 0.362) and OLS models (R^2 = 0.358).

The columns marked (4) present the estimated results when the dependent variable is the annual growth rate of capital deepening. All the three models (OLS, PLM, and SCM) show an inverse relationship between the annual growth rate of capital deepening and the initial labor productivity levels (-3.448, -3.440, and -3.300). This indicates that, on average, farms with lower initial labor productivity levels acquired capital at a higher rate than farms that started with high productivity levels. The SCM had better in-sample fit (R^2 = 0.308) compared to the PLM (R^2 = 0.300) and the OLS model (R^2 = 0.298). The speed of convergence varied inversely with farm size with smaller farms converging at a faster rate than small, medium and large farms.

Although the estimated results are comparable across the three models, the parametric linear model is adequate in explaining the relationship between the initial levels of labor productivity and the annual growth rates in output per worker, efficiency change, and capital deepening. This is indicated by the Hsiao et al. (2007) tests where the null hypothesis of correct parametric model specification is not rejected (test results are reported on the last row of Table

5.53). However, the parametric linear model is rejected for the relationship between initial labor productivity and the annual growth rate in technical change (p-value for the null of correct specification is < 0.05). This result implies that the semi-parametric models are more appropriate specification for this latter relationship.

Figure 5.19 summarizes the above results by plotting the partial regression functions for the four growth rates (labor productivity and its three components) on the logarithm of initial labor productivity levels. The broken lines in each panel give point-wise 95-percent confidence envelopes around the fit. Panels A, B, C, and D show the relationship between the initial productivity levels and the growth rates of labor productivity, efficiency change, technical change, and capital deepening, respectively. The slope of the regression lines in panels A, B, and D are negative while that of panel C is positive. This indicates that, on average, there has been convergence in the growth rate of labor productivity, efficiency change and capital deepening. Panels A and D are remarkably identical suggesting that the pattern of productivity growth attributable to capital deepening is similar to the pattern of growth in labor productivity. This lends support to the previous conclusions that capital deepening has been the major driving factor of labor productivity growth in the 1993-07 period. Farms with higher output-per worker (in the base period, 1993) benefited more from technical change than those that started with a low level of productivity. Therefore, technological change contributed to further divergence in output per worker across the Kansas farms.



Note: Dotted lines show a 95-percent confidence envelope around the fit

Figure 5-19 Growth Rates in Output per Worker and the Three Decomposition Components plotted against the 1993 Output per Worker for the period 1993-07

5.4.2.1 *Sub-period 1993-02*

The estimated parametric and semi-parametric results for the period 1993-02 are reported in Table 5.54. All three models indicate an inverse relation between the initial levels of labor productivity and the four growth rates. This is in contrast to the 1993-07 period where a positive relationship between the average annual growth of technical change and initial labor productivity was found. Comparisons across the three models (OLS model, PLM and SCM) indicate convergence in the annual growth rates of labor productivity (-7.001, -7.001, and -6.916), efficiency change (-2.616, -2.613, and -2.485), technical change (-0.179, -0.179, and -0.195), and capital deepening (-4.213, -4.208, and -4.198). The farm size dummies in the OLS model indicate that the speed of convergence is inversely correlated with farm size for the growth rates in labor productivity, efficiency change, and capital deepening. However, the speed of convergence in the annual growth rates of technical change is higher for small farms (-0.348) compared to very small farms (-0.197) and medium sized farms (-0.196).

Overall, all three models produce parameter estimates that are comparable in magnitude, although the estimates for the SCM are slightly higher than those from the other two models when the dependent variable are growth rates in labor productivity, efficiency change and capital deepening. The SCM produced a slightly lower estimate when the dependent variable was the growth rate in technical change. The SCM also performed slightly better in terms of the in-sample fit for all the four growth rates compared to the other two models. For instance, the in-sample fit when the dependent variable is the growth rate in capital deepening is higher in the SCM (R^2 = 0.336)

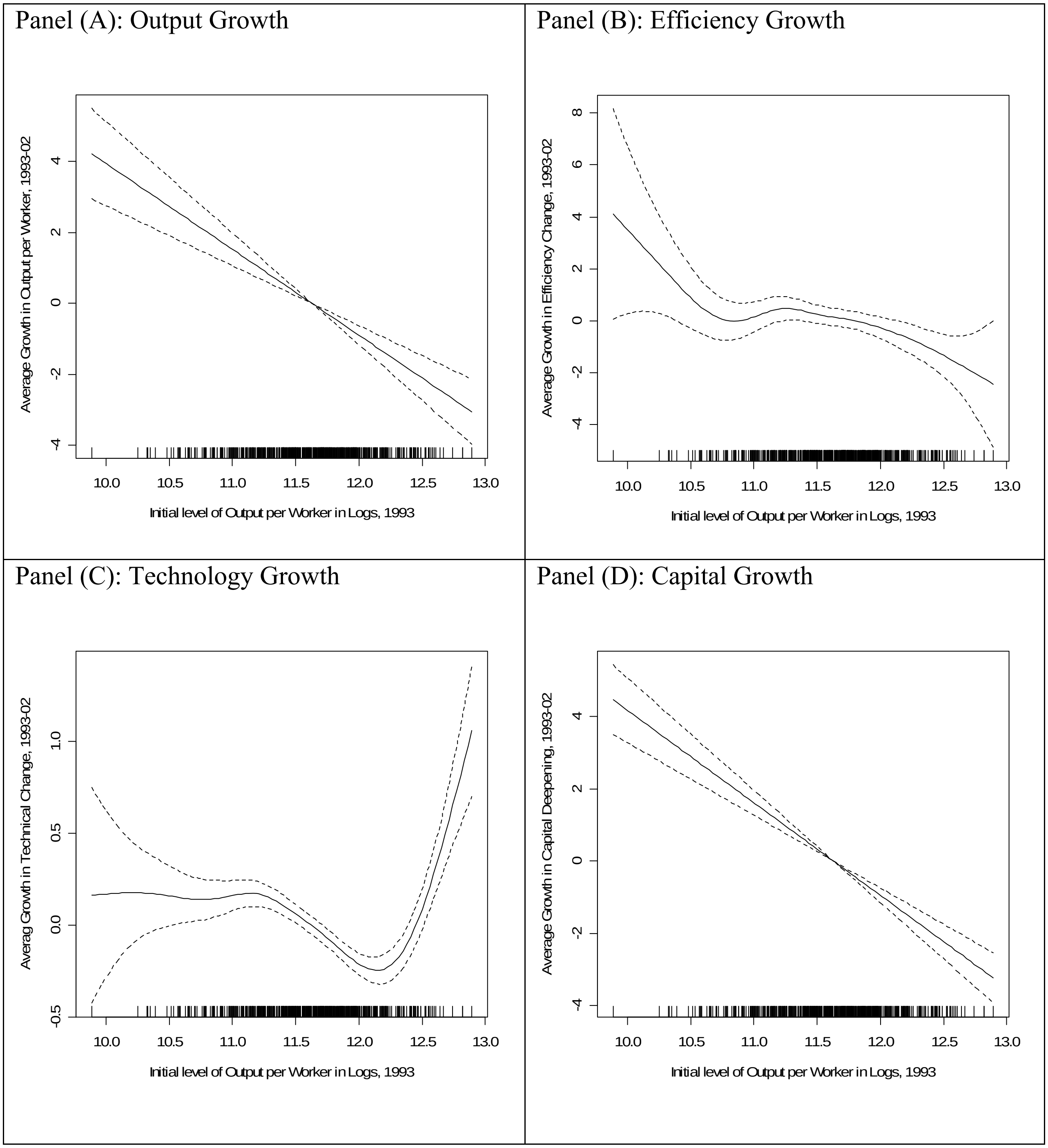
Table 5-54 Regression results of growth rates in output per worker and the three decomposition indices on growth rate in output per worker in base (1993) period

	Ordinary Least Square Model				Partial Linear Model				Smooth Coefficient Model			
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
	g_{Y}	g_{EFF}	g_{TECH}	g_{KACC}	g_{Y}	g_{EFF}	g_{TECH}	g_{KACC}	g_{Y}	g_{EFF}	g_{TECH}	g_{KACC}
Intercept	88.125**	32.567**	2.572**	52.987**					81.741	28.039	2.462	50.796
	(4.505)	(3.243)	(0.494)	(3.401)								
Slope	-7.001**	-2.616**	-0.179**	-4.213**	-7.001	-2.613	-0.179	-4.208	-6.916	-2.485	-0.195	-4.198
	(0.369)	(0.265)	(0.040)	(0.278)	(0.368)	(0.265)	(0.040)	(0.278)				
D-VSF	-10.122**	-5.351**	-0.197**	-4.574**								
	(0.932)	(0.671)	(0.102)	(0.703)								
D-SF	-5.020**	-2.799**	-0.348**	-1.872**								
	(0.882)	(0.635)	(0.097)	(0.666)								
D-MF	-1.534**	-1.128**	-0.196**	-0.210**								
	(0.896)	(0.645)	(0.098)	(0.676)								
Sd(Resid)	12.788	6.626	0.154	7.290	12.702	6.575	0.153	7.238	12.488	6.530	0.146	7.081
Adj. R^2	0.460	0.245	0.078	0.317	0.463	0.250	0.083	0.321	0.472	0.255	0.124	0.336
Jn Test	-0.490	0.105	6.952***	0.367*								

Note: 564 observations are used in the regressions. Figures in parenthesis represent the robust standard errors. The asterisks *, **, and *** means the corresponding coefficient is significant at the 10 percent, 5 percent, and 1 percent level. The Jn test is the Hsiao et al. (2007) test statistic for the null of correct parametric model specification. D stands for dummy, VSF for very small farms, SF for small farms, and MF medium sized farms.

compared to the PLM ($R^2 = 0.321$) and the OLS model ($R^2 = 0.317$). Using the Hsiao et al. (2007) test, the null hypothesis of correct parametric specification is rejected for the relationship between the initial labor productivity and the growth rates of technical change and capital deepening (p-values are <0.01 and <0.1, respectively). Hence, the semi-parametric models are appropriate in making inferences for those two relationships.

Figure 5.20 summarizes the above results by plotting the partial regression functions for the four growth rates (labor productivity and its three components) on the logarithm of initial labor productivity levels. Panels A and D suggest that farms that had lower initial labor productivity achieved higher growth rates in labor productivity and capital deepening than those that started with higher labor productivity. The plots indicate that the farms that started with the highest levels of productivity experienced declining growth rates. Panel B shows that the decrease in the growth rate of efficiency has been disproportionate. Farms that started with lower initial productivity levels experienced a rapid decline in efficiency while others experience gradual decline in efficiency. A few farms experienced gains in efficiency. Panel C suggests that growth in technical change was positive for many farms, although some farms that started with lower productivity levels experienced almost negligible growth in technical change. Other farms that started with moderate productivity levels experienced rapid decline in technical change while those that started with high productivity levels had a very rapid growth in technical change. This observation lends support to the notion that technological innovation and adoption was correlated with very high initial level of labor productivity.



Note: Dotted lines show a 95-percent confidence envelope around the fit

Figure 5-20 Growth Rates of Output per Worker and the Three Decomposition Components plotted against 1993 Output per Worker for the period 1993-02

5.4.2.2 *Sub-period 1996-05*

Finally, Table 5.55 provides the regression results for the sub-period 1996-05. All three models (OLS, PLM, and SCM) indicate an inverse relation between the four growth rates (labor productivity, efficiency change, technical change, and capital deepening) and the initial level of labor productivity. The estimated parameters are comparable across the three models. The models show convergence in the growth rates of labor productivity (-7.010, -7.003, and -6.879) efficiency change (-3.849, -3.846, and -3.597), technical change (-0.337, -0.337, and -0.394), and capital deepening (-2.823, -2.818, and -2.756). All estimated parameters in the OLS model are statistically significant at the 1-percent significance level. The SCM model outperforms the other two models in terms of the in-sample fit. The parameter estimates of the dummy variables indicate that the speed of convergence varies inversely with farm size for the growth rates in labor productivity, efficiency change, and capital deepening. However, the dummy parameter estimates for very small farms and small farms when the dependent variable is annual growth rate in technical change are positive and close to zero. This indicates that although there is convergence in growth of technical change, the convergence is primarily driven by medium and large farms. The Hsiao et al. (2007) test rejects the null hypothesis of correct parametric specification of the relationship between initial labor productivity and the growth rates of efficiency change and technical change (p-values are <0.001). Hence, the semiparametric models are appropriate in making inferences for those two relationships.

Table 5-55 Regression results of growth rates in output per worker and the three decomposition indices on growth rate in output per worker in base (1993) period

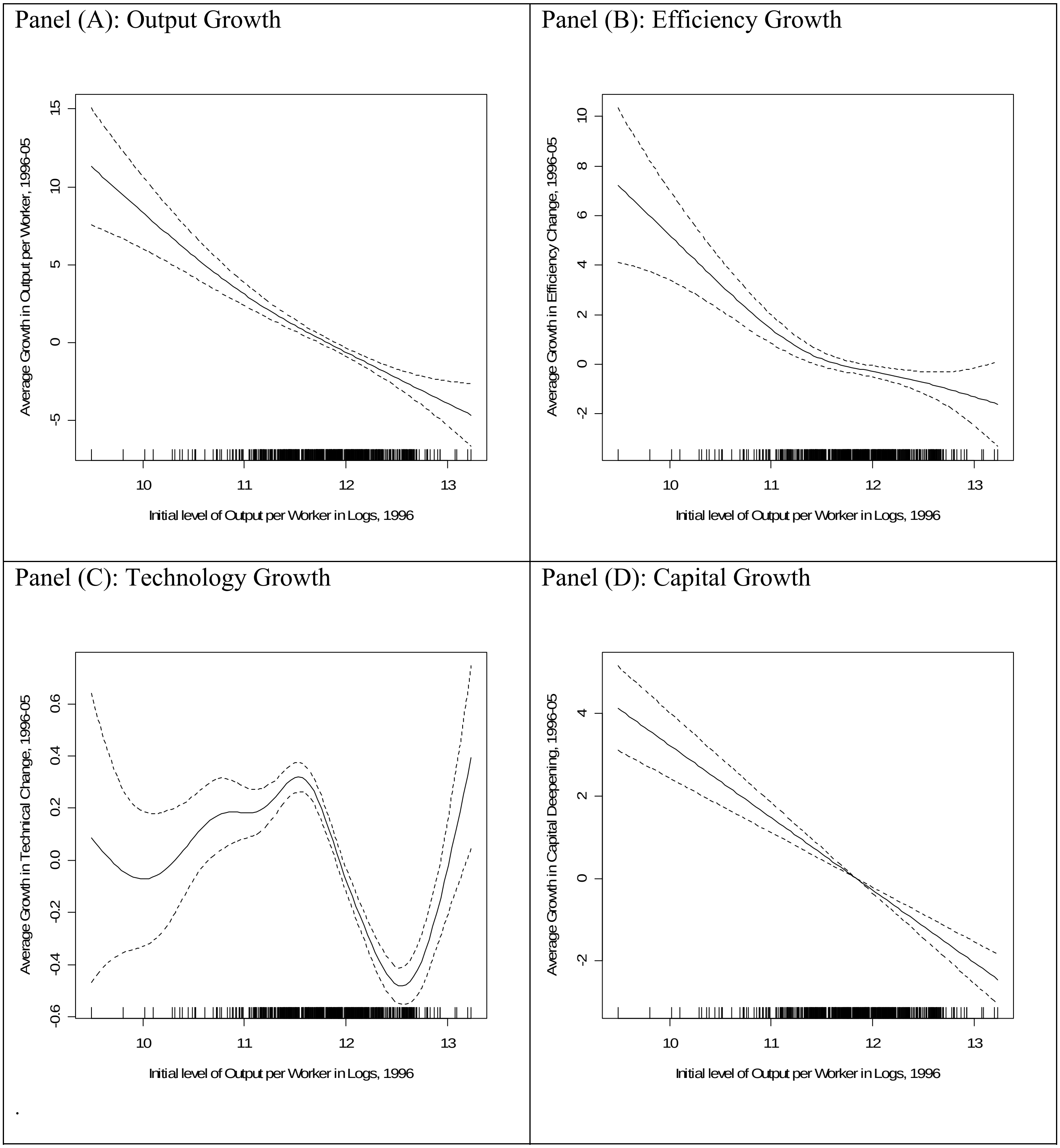
	Ordinary Least Square Model				Partial Linear Model				Smooth Coefficient Model			
	(1) g_{Y}	**(2)** g_{EFF}	**(3)** g_{TECH}	**(4)** g_{KACC}	**(1)** g_{Y}	**(2)** g_{EFF}	**(3)** g_{TECH}	**(4)** g_{KACC}	**(1)** g_{Y}	**(2)** g_{EFF}	**(3)** g_{TECH}	**(4)** g_{KACC}
Intercept	90.101**	46.964**	5.747**	37.391**					83.401	40.495	6.472	34.882
	(4.196)	(2.985)	(0.444)	(2.982)								
Slope	-7.010**	-3.849**	-0.337**	-2.823**	-7.003	-3.846	-0.337	-2.818	-6.879	-3.597	-0.394	-2.756
	(0.340)	(0.242)	(0.036)	(0.242)	(0.340)	(0.242)	(0.036)	(0.242)				
D-VSF	-10.551**	-7.172**	0.057**	-3.436**								
	(0.626)	(0.445)	(0.066)	(0.445)								
D-SF	-5.847**	-3.775**	0.075**	-2.147**								
	(0.508)	(0.361)	(0.054)	(0.361)								
D-MF	-2.655**	-1.561**	-0.045**	-1.049**								
	(0.509)	(0.362)	(0.054)	(0.362)								
Sd(Resid)	12.624	6.386	0.141	6.376	12.548	6.340	0.140	6.342	12.452	6.176	0.132	6.251
Adj. R^2	0.470	0.398	0.215	0.198	0.472	0.402	0.221	0.201	0.476	0.417	0.270	0.213
Jn Test	-1.101	1.579*	27.798*	-0.968								

Note: 564 observations are used in the regressions. Figures in parenthesis represent the robust standard errors. The asterisks *, **, and *** means the corresponding coefficient is significant at the 10 percent, 5 percent, and 1 percent level. The Jn test is the Hsiao et al. (2007) test statistic for the null of correct parametric model specification. D stands for dummy, VSF for very small farms, SF for small farms, and MF medium sized farms.

Figure 5.21 provides a summary of the results for the sub-period 1996-05. Panels A and D indicate that convergence in the growth rates of output per worker and capital deepening follow the same pattern. Farms that started with low levels of output per worker experienced a rapid growth in labor productivity and capital deepening relative to those that started with high levels of output per worker. This suggests that farms with low initial levels of output per worker increased their capital per worker intensity rapidly in order to improve productivity. Panel B indicates that convergence in the growth rate of efficiency change was proportionate across all the farms. Panel C presents a mixed picture on the relationship between the growth rate in technical change and initial levels of output per worker. A majority of the farms experienced convergence in the growth rates of technical change while some farms experienced divergence. Hence, technical change is both a source of convergence and divergence in the growth rates of labor productivity.

5.4.3. *Comparison across Periods*

A comparison of the results obtained for each period (1993-07, 1993-02, and 1996-05) shows variation in the role played by each component. The rate of convergence of productivity growth was rapid in the two sub-periods (1993-02 and 1996-05) compared to the entire sample. With regard to the existence of a process of technological catch up, all periods show a trend towards convergence although the speed of convergence is not uniform for two periods (1993-07 and 1993-02).



Note: Dotted lines show a 95-percent confidence envelope around the fit

Figure 5-21 Growth Rates of Output per Worker and the Three Decomposition Components plotted against 1993 Output per Worker for the period 1996-05

The 1993-02 period show some tendency towards divergence. The tendency towards convergence in labor productivity and capital deepening followed an identical pattern across the three periods. The results with respect to the effect of technical change are mixed. Technical change has been a significant source of divergence for the 15-year period (1993-07). However, analyses of the 10-year sub-periods show both tendencies of convergence and divergence, with convergence playing a dominant role. The process of convergence is rapid for farms that had initial output per worker levels between $59,900 and $162,800. Farms with initial output per worker above $162,800 exhibit tendencies towards divergence[16]. The implication of this is that technological innovation hinges strongly on high labor productivity.

5.4.4. *Technology and Capital Deepening*

Finally, the analysis focused on testing whether technology is embodied in the factors of production, hereby represented by capital. If this is the case, there should be a positive relationship between the average annual growth in technical change and the initial level of capital-to-labor ratio. Again, using the generated cross-sectional data for the tripartite decomposition for the three periods, each farm is treated as an observation to test this relationship using the local regression (LOESS) method. The local regression method is used because a suitable parametric form of the relationship between the two variables is not known. Results are shown in Figure 5.22 to Figure 5.24 for the periods 1993-07, 1993-02, and 1996-05, respectively. The vertical axis represents the annual growth of technical change while the horizontal axis is the initial level of capital-labor ratio. The dashed lines represent the 95 percent

[16] Those figures are computed by taking the antilog of initial labor productivity as depicted on the graphs

confidence band. The results for the test of whether technology is embodied in capital inputs are mixed. For the period 1993-07, there is a positive relationship between the growth rate in technical change and capital-labor ratio, indicating that technology is embodied in capital deepening. This implies that farms that started the period with high capital-labor ratios also achieved higher annul growth rates in technical change compared to those that started with low capital-labor ratios. However, for the periods 1993-02 and 1996-05, the relationships are both positive and negative at different levels of capital-labor ratios with a positive relationship occurring at high levels of capitalization. This may suggest that embodiment of technology in capital occurs in the long-run rather than in the short-run.

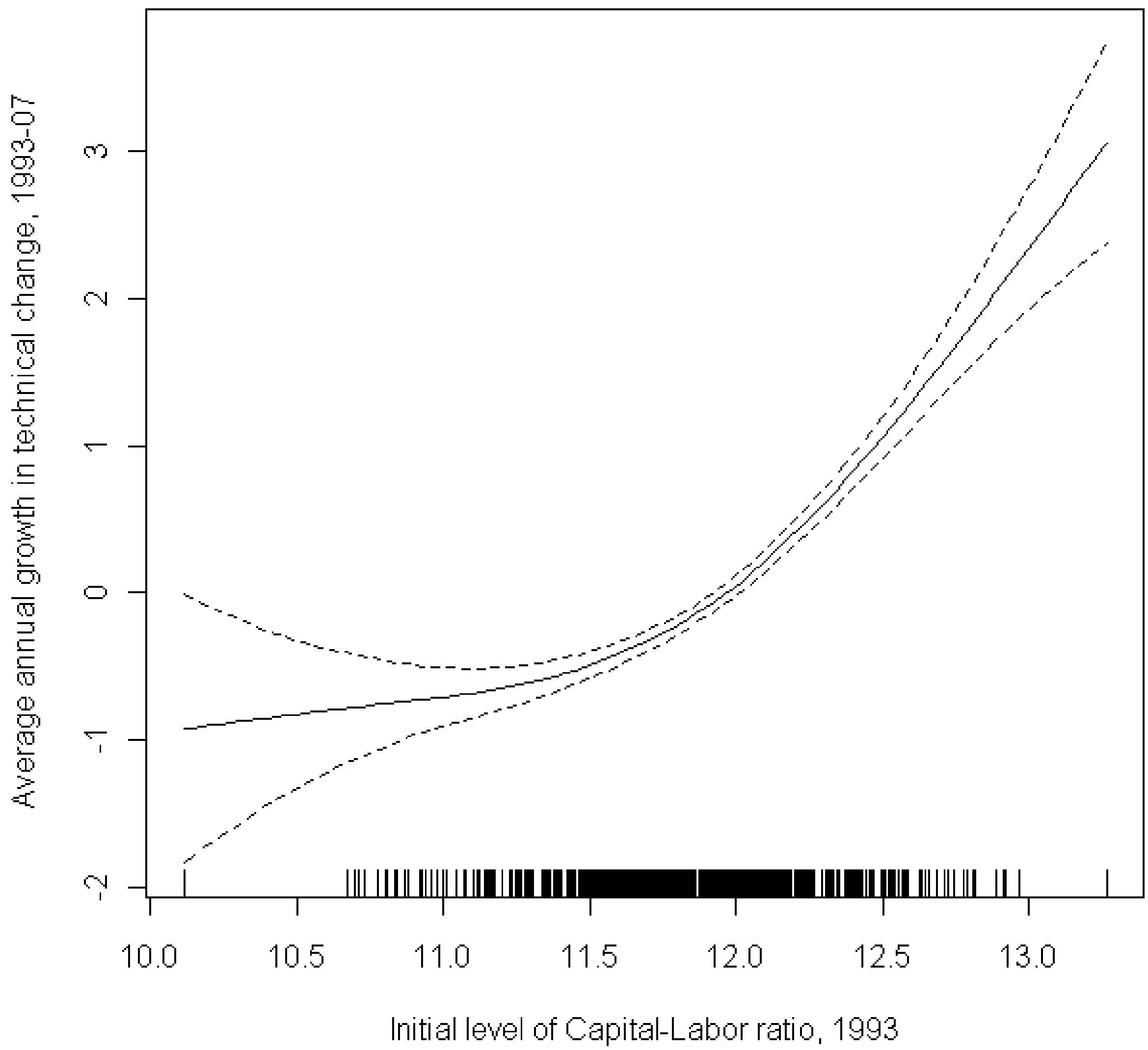


Figure 5-22 Local regression plot for annual rate of growth in technical change against initial level of capital-labor ratio, 1993-2007

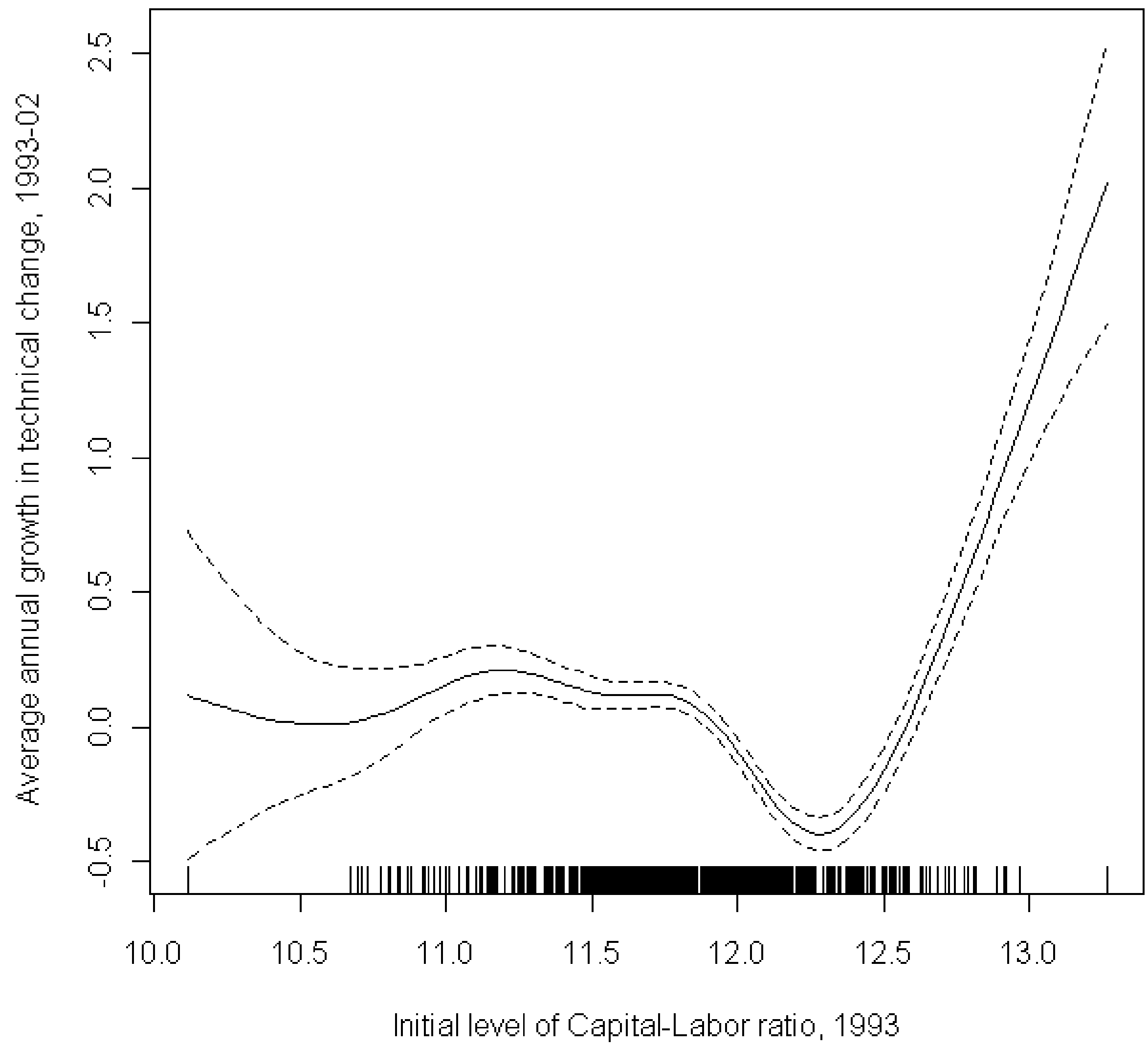


Figure 5-23 Local regression plot for annual rate of growth in technical change against initial level of capital-labor ratio, 1993-2002

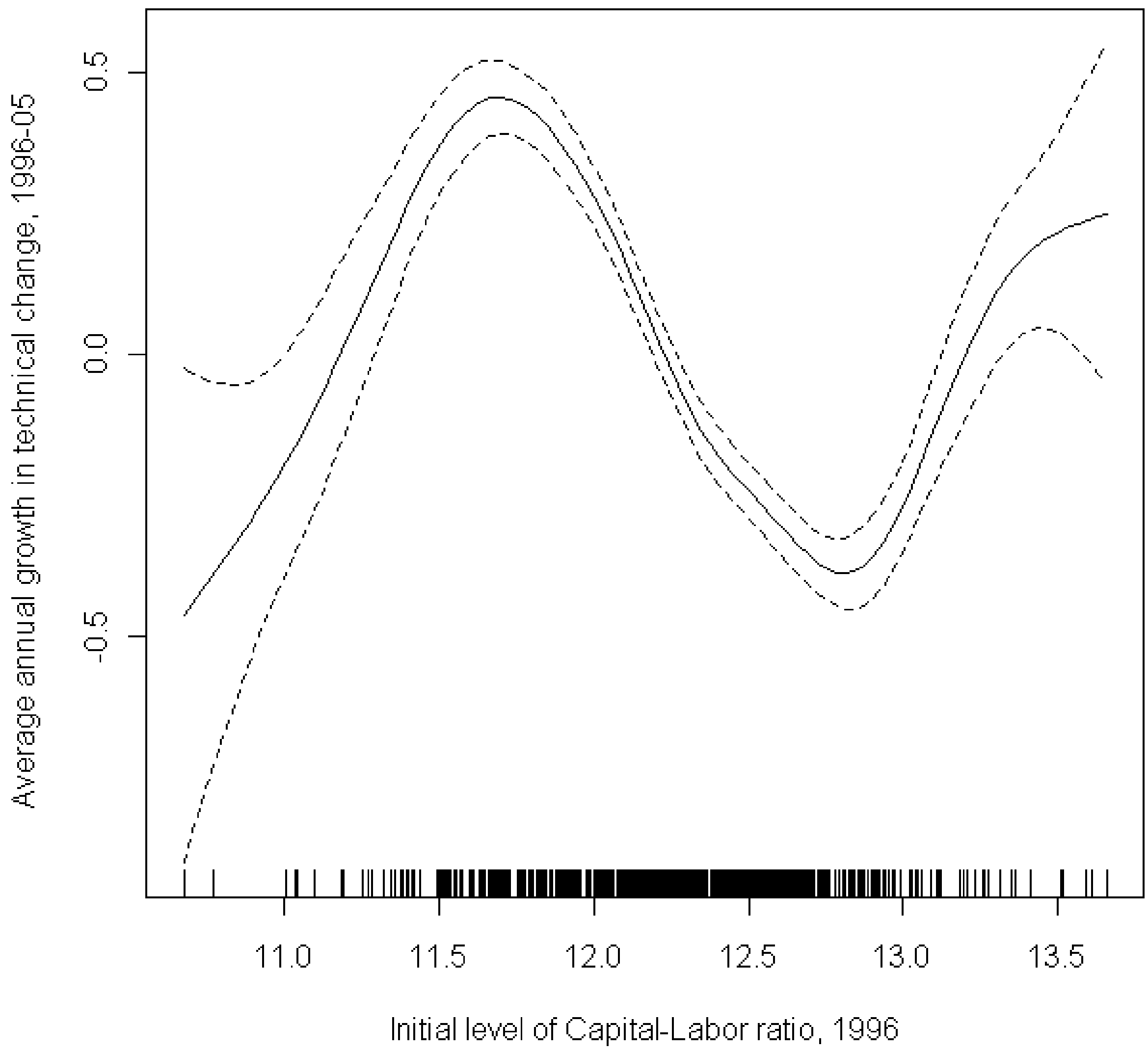


Figure 5-24 Local regression plot for annual rate of growth in technical change against initial level of capital-labor ratio, 1996-2005

5.4.5. *Concluding Remarks*

This section tested the "catching-up" hypotheses by looking at the relationship between the initial labor productivity for three periods (1993-07, 1993-02, and 1996-05) and growth rates in labor productivity, efficiency change, technical change, and capital deepening. Taking a departure from previous literature on convergence, the speed of convergence was allowed to vary by farm size. This contribution was modeled by a general function that was estimated via semi-parametric techniques. The results from the semi-parametric models are contrasted to those from a parametric model that assumes the speed of convergence to be invariant to farm size.

The analysis for the 1993-07 period finds an inverse relationship between labor productivity at the beginning of the period (1993) and annual growth rates in labor productivity, efficiency change, and capital deepening. This lends support to the "catching-up" hypotheses that farms that lagged behind the productivity leaders in 1993 exhibited rapid rates of growth in output per worker, efficiency change and capital deepening. However, the hypothesis is rejected for the growth rate of technical change. Farms that were productivity leaders at the beginning of the period benefited more from technological innovation relative to those farms that where followers.

It is noteworthy to clarify that although capital deepening is the main source of convergence in productivity, it also contributes to the growth in efficiency improvement and technological progress. There is a positive correlation between the rates of growth in capital deepening and labor productivity (0.823), technical change (0.321) and efficiency change (0.100). The positive relationship between the rates of growth in capital deepening and technical change lend support to the hypothesis that technological innovation is embodied in capital deepening. The positive relationship between growth rates in capital deepening and efficiency change may also support the notion that improvement in efficiency is also embodied in capital deepening.

For the sub-periods 1993-02 and 1996-05, the main conclusions are similar to the above with one exception. There is an inverse relationship between growth rates of technical change and labor productivity at the beginning of the periods (1993 and 1996). This indicates that technical change was a source of both convergence and divergence in the sub-periods, although convergence dominated divergence.

The policy implications for the convergence test results are several. Given that capital deepening is found to be a major driving force of convergence in labor productivity, agricultural sector policies that encourage farms to invest in capital goods and use of purchased inputs would help to mitigate wide disparities in labor productivity across the farm sector.[17] Although prior results indicate that farms have lagged behind rather than caught-up in the sample period, convergence tests indicate that efficiency deterioration was a source of labor productivity convergence. Therefore, policies that promote the diffusion of new production ideas and techniques would improve the productivity of many farms in the farm sector. A key policy question is whether the best available technology is also implementable. Policies that focus on making the available technology to be implemented by the majority of farms would promote the convergence of labor productivity.

Overall, from a policy perspective, the results obtained are positive because they imply reduction in the inequality in labor productivity across Kansas farms. However, further research is needed to investigate what led to convergence in labor productivity. Could it be that convergence took place due to the slowdown of the most productive farms to match the growth

[17] Capital is defined as the sum of assets and purchased inputs

performance of the less productive farms rather than the latter group of farms catching-up? Why did convergence take place due to deterioration in efficiency? Why did technical change contribute to divergence rather than convergence?

CHAPTER 6 - SUMMARY AND CONCLUSIONS

The rise in agricultural productivity has been chronicled as the single most important source of economic growth in the U.S. farm sector and the importance of productivity change in economic growth in agriculture has stimulated interest in trying to explain productivity change (Ball and Norton, 2007). For U.S. agriculture, few studies have examined labor productivity growth rates to gain an understanding of sources of growth. The goal of this study was to provide insight into the sources and distributional dynamics of labor productivity growth in the Kansas farm sector. Drawing on the latest theories and methods in nonparametric production function approach, a panel of 564 farms over a 15-year period, 1993 to 2007, was used to estimate labor productivity growth and its sources following the Kumar and Russell (2002) approach. The data comprised of one output (real gross farm income) and two inputs (real capital and labor).

The main contribution of this work to the existing body of literature on U.S. agricultural productivity was to decompose farm level labor productivity into three components - efficiency change, technical change, and capital deepening - and to determine the relative contributions of each of those components to the evolution of labor productivity distribution and convergence over selected sample periods. The study also introduced the use of semiparametric models to test for convergence in labor productivity growth where the speed of convergence/divergence is allowed to vary by farm size. To the best of the author’s knowledge, no study has applied this approach to analyze U.S. agricultural productivity at either the state or national level.

The first objective of this study was to estimate the technical and scale efficiency scores for a sample of 564 farms in Kansas and to investigate how those efficiency indices vary by farm size and farm specialization categories. The nonparametric production method (i.e., data envelopment analysis) using one output (gross farm income) and two inputs (capital and labor) and the smoothed homogenous bootstrapped procedure were used to estimate the production frontier under three technological sets: constant returns to scale (CRTS), variable returns to scale (VRTS) and nonincreasing returns to scale (NIRTS). The input oriented approach was used to compute the technical efficiency scores, the bias corrected efficiency scores, and the 95 percent confidence interval.

In general, the mean technical efficiency scores, assuming NIRTS technology, for all farms for the entire sample period was 57 percent, with a maximum of 62 percent (in 2002) and a minimum of 50 percent (in 2005). The bias corrected mean was 54 percent with a 95 percent confidence interval range of 52 to 57 percent. The empirical results suggest that Kansas farms are moderately technically efficient, although relative to the best-practice frontier, efficiency has not improved over time. On average, the technical efficiency score under the three technological sets have been declining over the sample period thus providing evidence of technological lagging-behind rather than technological catching-up. This observation lends support to the view that most Kansas farms have not been able to keep pace with technological leaders in the sector. The technical efficiency indices were found to vary directly by farm size, with large farms being more technically efficient compared to very small farms, but not by farm specialization categories. This suggests that farm size does matter in influencing farm technical efficiency compared to farm specialization. Scale efficiency analyses reveals that farms are more scale efficient than technically efficient. Smaller farms are getting both technically and scale inefficient while larger farms are becoming technically and scale efficient.

The second objective focused on decomposing labor productivity growth into components attributable to efficiency change (*movement towards or away from the best practice frontier*), technical change (*shift in the best practice frontier*), and capital deepening (*movement along the frontier*). Changes in productivity were computed sequentially for two subsequent years (i.e., from 1993/1994 to 2006/2007) and cumulatively by holding 1993 as the reference base year (i.e., from 1993/1994 to 1993/2007) using the Kumar and Russell (2002) nonparametric production frontier approach.

The main findings are that the Kansas farm sector experienced growth in labor productivity over the sample period, although the growth varied widely by year and farm typologies. Capital deepening and technical change are the main sources of labor productivity growth. On average, output per worker grew at an annual rate of about 5 percent, with capital deepening and technical change accounting for about 3.2 percent and 2.8 percent of the growth, respectively. Efficiency change, on average, accounted for an annual decline of about 1.0 percent in the growth of output per worker. This implies that, on average, most farms were further away from the best-practice frontier in 2007 than in 1993. These results are consistent with the results obtained from the U.S. manufacturing sector by Weber and Domazlicky (2006) and Grosskopf et al. (2007) who found that capital deepening, and not technical change, is the main source of growth in output per worker. Grosskopf et al. (2007) also reported technological lagging behind rather than catching up in the U.S. manufacturing sector. Technical change was not Hicks neutral and occurred at high levels of output per worker, an indication that technological innovators tend to be farms with high levels of labor productivity. Technical change also occurred at high levels of capital intensity, suggesting that innovation is embodied in capital deepening. The annual growth rate in output per worker was found to vary directly with farm size, an indication that farm size is an important component of productivity growth and any policy to improve productivity should take this into account. From a specialization viewpoint, diversified farms achieved higher growth rates in productivity and technical change compared to crop or livestock enterprises.

The third objective used nonparametric kernel density methods to examine the evolution of the labor productivity distribution over the sample period, 1993-07, and two sub-periods, 1993-02, and 1996-05. Counterfactual distributions were used to investigate the relative contribution of each of the tripartite decomposition components to the evolution of labor productivity in each of those three periods. The visual inspections from the kernel densities were augmented with statistical methods to test for the number of modes in the distributions and the equality of the distributions. Results obtained from these analyses indicate that capital deepening was the main factor contributing to the evolution of the entire labor productivity distribution. Efficiency change contributed negatively to the shift of the probability mass of labor productivity distributions from the base to current year in each of the three periods. However, in analyzing the dynamics of the overall distribution of output per worker and the relative contribution of each of its components, none of the tripartite decomposition components was able to explain the entire evolution of labor productivity distribution alone.

The hypotheses of multimodality in the counterfactual and actual labor productivity distributions were consistently rejected using the both Silverman test and the Dip test, with the exception of the effect of technical change on the 2007 labor productivity distribution when the entire sample period is considered, 1993-07. Therefore, the main conclusion is that the labor productivity distribution has remained unimodal and has primarily been driven by capital deepening and technical change. This implies that labor productivity across the farm sector is converging to a common growth rate. The Kolmogorov-Smirnov test of equality of distributions provided confirmation to the visual inspection from the kernel densities that, indeed, there were differences in the shape of the counterfactual distributions. However, considering the sub-period 1993-02, the combined effects of efficiency change and capital deepening and technical change and capital deepening were not significantly different from the actual productivity distribution in 2002.

Both the multimodality test and the equality of two distributions tests were applied to the actual distributions of labor productivity for the 15-year period, 1993-07. Except for two years, 1997 and 2005, the empirical results from the multimodality tests lend support to the conclusion that labor productivity distribution in the Kansas farm sector has remained unimodal. The equality of distribution tests suggest that labor productivity distribution significantly changed from 1993 to 2007, indicating that economic and social changes affected the farm sector in a relevant way. The fact that the shape of labor productivity distribution has remained unimodal suggests that although there were variations within the farm size categories, ranging from very small to large farms, the objective measure of size in those categories tend to overlap.

The final objective of this study was to test for the evidence of labor productivity convergence and the contribution of each of the tripartite decomposition components to this process, i.e., to determine whether there is a narrowing of productivity dispersion or catching-up in farm level labor productivity. Cross-section tests of convergence, where productivity growth rates were regressed against initial productivity levels, were conducted for the three sample periods: 1993-07, 1993-02, and 1996-05. A parametric regression and two semi-parametric regression models, the partial linear model (PLM) and the smooth coefficient model (SCM), were used to estimate convergence. The SCM is a generalization of the PLM wherein coefficients in linear explanatory variables are treated as unknown functions of observable covariates. The main difference between the two models is that while the PLM assumes the slope coefficient to be invariant to the farm size, the SCM allows the coefficient to vary with farm size. The semi-parametric model is justified where a parametric model is not the correct specification thus leading to inconsistent results. The Hsiao et al. (2007) test was used to determine whether the parametric model is an adequate description of the data.

Estimated results indicate that there is evidence of convergence in labor productivity growth across the farm sector. This is a positive finding from a policy perspective because it implies a possible reduction in productivity inequality in the Kansas farm sector in the long-run. Capital deepening is found to be the main factor affecting convergence in labor productivity growth. Efficiency change is also a source of convergence in all the three periods. However, earlier evidence indicated technological lagging behind rather than catching-up. This raises the question whether convergence due to efficiency change took place as a result of most farms slipping farther behind technological leaders instead of catching-up to the frontier. Results for technical change were mixed: technical change was found to be a source of divergence for the 15-year period, an indication that farms that started with high productivity level benefitted more from technological progress than those that started with low productivity level. However, technical change displayed both tendencies of convergence and divergence in the two sub-periods, with divergence occurring at high levels of output per worker. From a methodological perspective, the semiparametric model fit the data better than the parametric model, with the SCM outperforming the PLM model.

Following the above results, several policy implications can be drawn from this study: *First*, there is room for eliminating technical inefficiencies but any policy intervention should also take into consideration the relationship between technical efficiency and farm size. The policy instrument should also have an exit strategy for the small farms that cannot make improvements on the technical and scale efficiencies fronts. Efficiency is found to affect the growth of labor productivity negatively and policy measures that address methods to improve efficiency would also improve labor productivity. *Second*, policies that focus on improving investment in capital goods are likely to improve labor productivity and narrow productivity differences across farms in the long run. Increases in capital deepening appear to be a pre-condition for technical change (innovation). *Third*, policies that focus on making the available production technology to be both accessible and implementable by the majority of farms would improve productivity across the farm sector. This would include policies that promote agricultural extension. Research and extension focused on meeting the needs of the farming community can result in technical change which reduces the demand for factors per unit of output and increases total output, and hence output per worker.

Possible extensions of this research include the following: *First*, the factors that explain the presence of technical inefficiency should be investigated, especially how the input-output configuration and different managerial practices affects efficiency. *Second*, studies that investigate how various policy-related variables have affected the growth in labor productivity, efficiency change, technical change, and capital deepening would be useful. For example, it would be interesting to find out what factors have contributed to capital deepening being the key factor that is driving growth in labor productivity and what are the prospects for their continued influence. *Third*, following Henderson and Russell (2005), an extended decomposition of labor productivity growth to include human capital as a component of productivity change would add to the literature. This would shed light on the effects of agricultural producer's investment in schooling on productivity change.

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Appendix A - Summary of Reviewed Literature

Table 6-1 Summary of Empirical Studies that focus on Labor Productivity Decomposition, 2002-2007

Authors	Method	Data	Labor Prod Decomposition	Empirical Results
Kumar & Russell (2002)	DEA deterministic	57 countries 1965-1990 Labor, capital & Real GDP	Efficiency change Technical change Capital deepening	Evidence of technical catch-up Capital deepening drive polarization Technical change nonneutral
Salinas -Jime´nez (2003)	DEA deterministic	Spanish regions 1965-1995 Private labor, capital, & value added to factor cost	Efficiency change & Technical progress for TFP Efficiency change Technical change Capital deepening	Capital accumulation and technology progress main source of labor productivity growth Technological catch-up and convergence in efficiency levels
Moutinho et al. (2003)	Stochastic production frontier finite mixture model	45 countries in different development stages, 1967-1992	Efficiency change Technological change, Factor accumulation & Stochastic shock Productivity change in agriculture and economy as a whole	labor productivity distribution in agriculture driven by total factor productivity change, not factor accumulation Reduction in capital per worker, stronger catch-up and technological change relative to the economy Capital accumulation is the main factor for international divergence
Henderson & Russell (2005)	DEA deterministic	52 countries in 3 segments, 1965-1990 Labor, physical capita, years of schooling & Real GDP	Efficiency change Technical change Physical capital accumulation Human capital accumulation	Efficiency change main source of polarization Human capital source of productivity growth Technological change nonneutral

Authors	Method	Data	Labor Prod Decomposition	Empirical Results
Nissan & Niroomand (2006)	DEA deterministic	Same as Kumar and Russell (2002) Break data into 4 groups based on income levels; low, low-medium, high-medium & high incomes	Efficiency change Technical change Capital deepening	Widening gap between efficiency index and output per worker between the groups Labor productivity growth differs between groups
Enflo & Hjertsrand (2006)	DEA bootstrap	69 regions in Western Europe, 1980-2002	Efficiency change Technical change Capital deepening	Relative efficiency ranking remain stable after bias correction Capital accumulation has divergent effects on labor productivity distribution Efficiency improvement and catch-up experienced in only 8 regions Convergence of unproductive regions driven by capital accumulation
Weber & Domazlicky (2006)	DEA deterministic	Manufacturing sector in the U.S., 50 states, 1977-1996 Labor, capital & real manufacturers output	Efficiency change Technical change Capital deepening	Capital deepening and technological progress have contributed to beta convergence in labor productivity Technical change cause of divergence in labor productivity No sigma convergence

Authors	Method	Data	Labor Prod Decomposition	Empirical Results
Grosskopf et al. (2007)	DEA deterministic Productivity changes and its components are modeled as functions of some policy related variables using a fixed effect model	Manufacturing sector in the U.S., 47 States, 1991-1999 Gross state product, employment, and manufacturing capital stock Change in industrial mix, increase in labor quality, increase in public capital stock or decrease in size of public sector	Efficiency change Technical change Capital deepening	Labor productivity accelerated during the 1990s. Capital deepening and technical change were the primary determinants of labor productivity growth. Most states ended the decade further from the production frontier than they started. Growing technological sector strong contributor to productivity growth while a growing public sector was a drag. Capital deepening significantly greater in states with a more highly educated population Improvement in labor quality has little impact on the pace of technical change or diffusion of technology.
Henderson & Zelenyuk (2007)	DEA bootstrap	Same as Henderson and Russell (2005) Break data into 2 groups, developed and developing countries.	Efficiency change Technical change Physical capital accumulation Human capital accumulation Investigate 3 types of catching up: entire group, within group and between groups, i.e. club convergence	Efficiency scores of some countries misjudged when standard DEA is applied Significant difference between groups No significant change of efficiency distribution within groups Efficiency lag behind in developing countries and catching up in developed countries Efficiency convergence within each group

Authors	Method	Data	Labor Prod Decomposition	Empirical Results
Margaritis et al. (2007)	DEA deterministic Panel unit root	OCED countries, 1979-2002	Input biased Net technical change Efficiency change Capital accumulation	Gaps in labor productivity narrowing down (i.e., convergence) Twin distribution of labor productivity Technical change primarily drive labor productivity growth Technical change source of divergence
Henderson et al. (2007)	DEA deterministic	28 provinces in China, 1978-2000 Labor, physical capital, human capital & output	Efficiency change Technical change Physical capital accumulation Human capital accumulation Sample divided into 2 sub-periods to find evidence of turning point after Chinas reform	Labor productivity distribution multimodal Poor provinces catching up Convergence driven by capital accumulation Labor productivity growth primarily driven by physical capital accumulation Technology change nonneutral Regional disparities driven by technological progress and human capital accumulation

Appendix B - Outlier Detection in Data

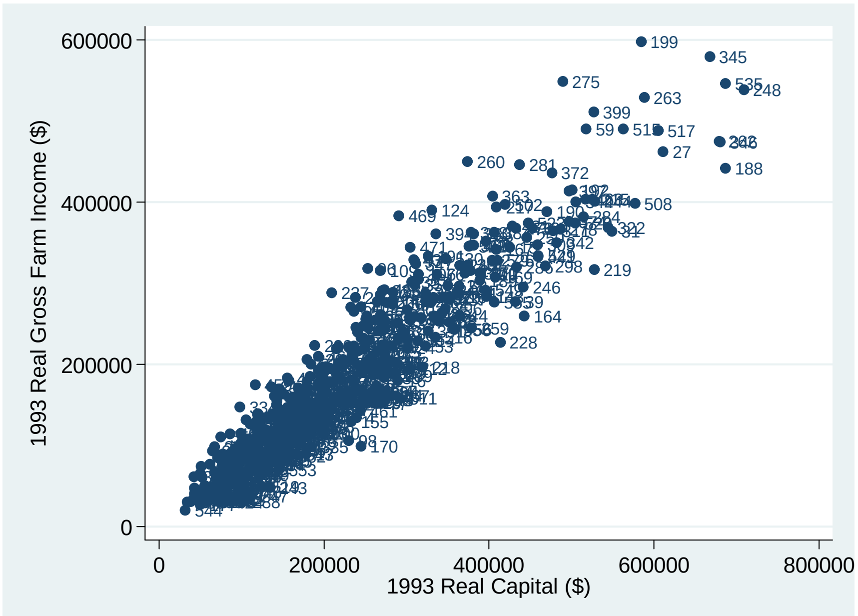

Figure 6-1 Scatter plot of gross farm income against capital in real values for 564 farms, 1993

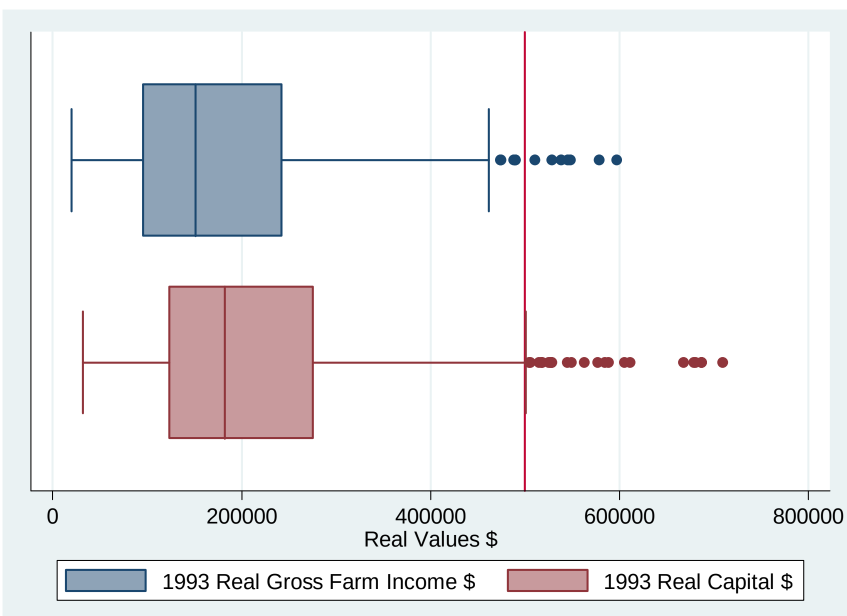

Figure 6-2 Boxplot of gross farm income and capital in real values, 1993

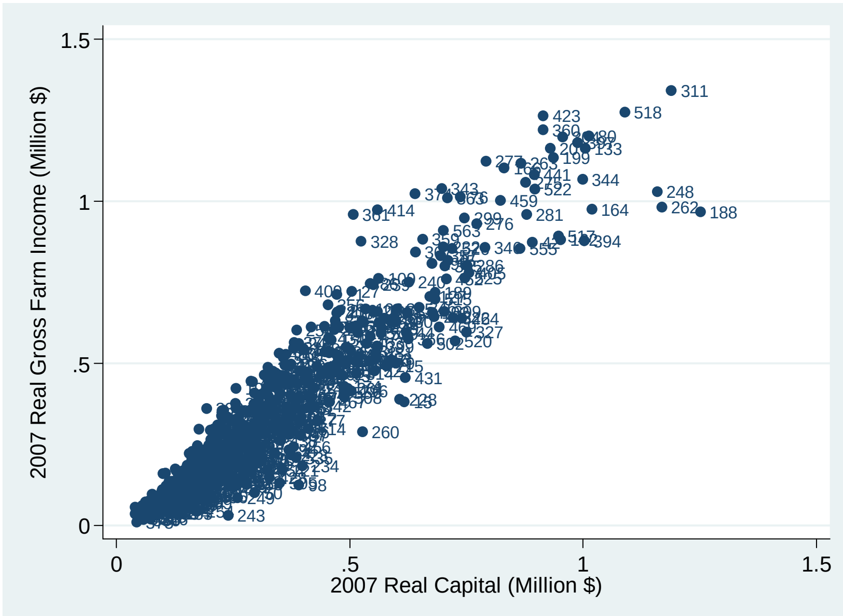

Figure 6-3 Scatter plot of gross farm income against capital in real values for 564 farms, 2007

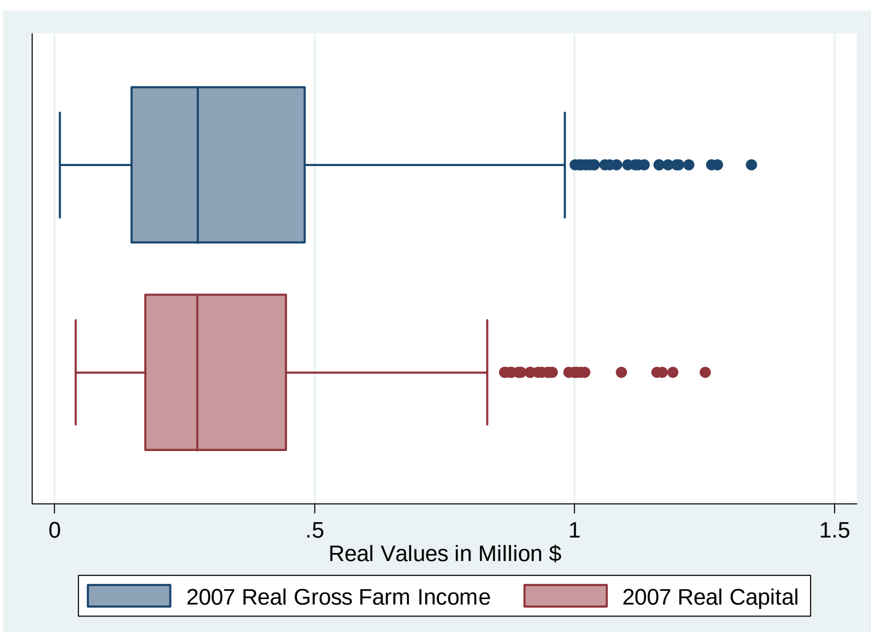

Figure 6-4 Boxplots of gross farm income and capital in real values, 1993

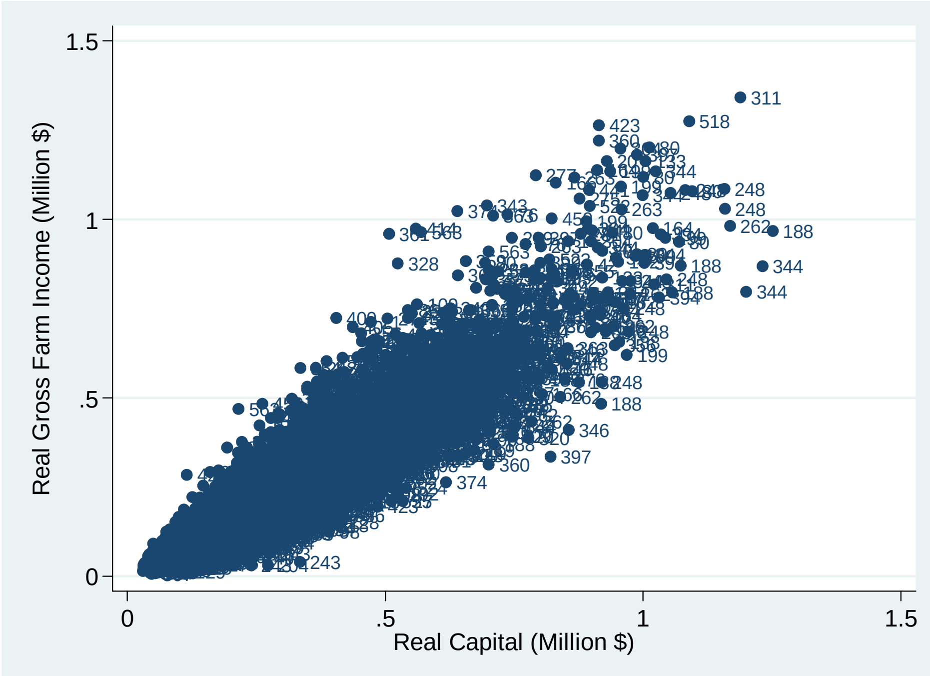

Figure 6-5 Scatter plot of gross farm income against capital in real values for 564 farms, 1993-2007

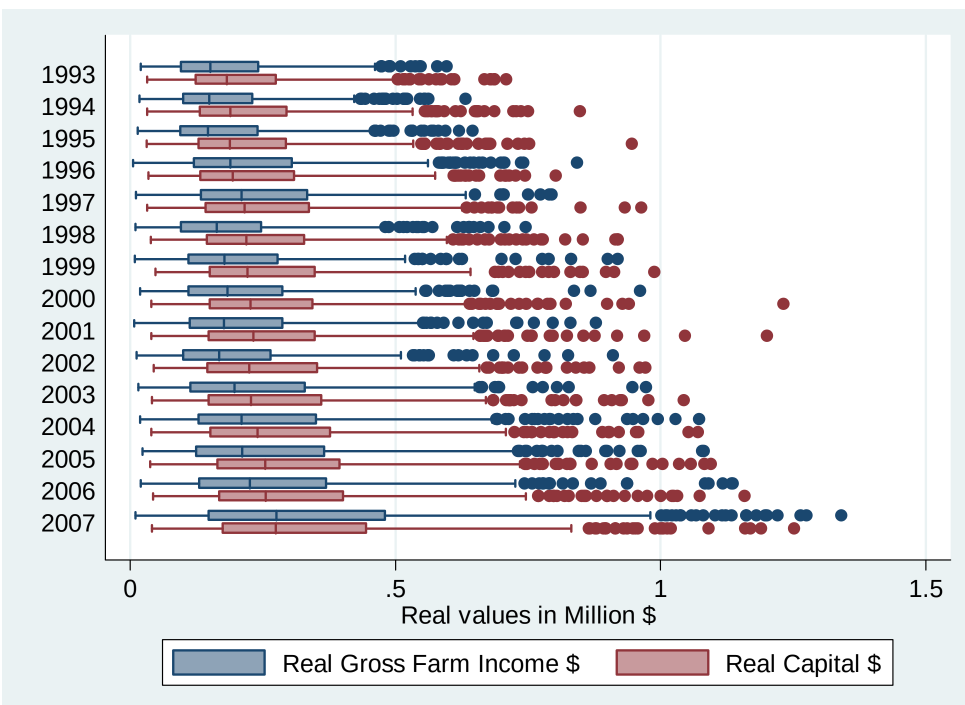

Figure 6-6 Boxplot of gross farm income and capital in real values, 1993-2007

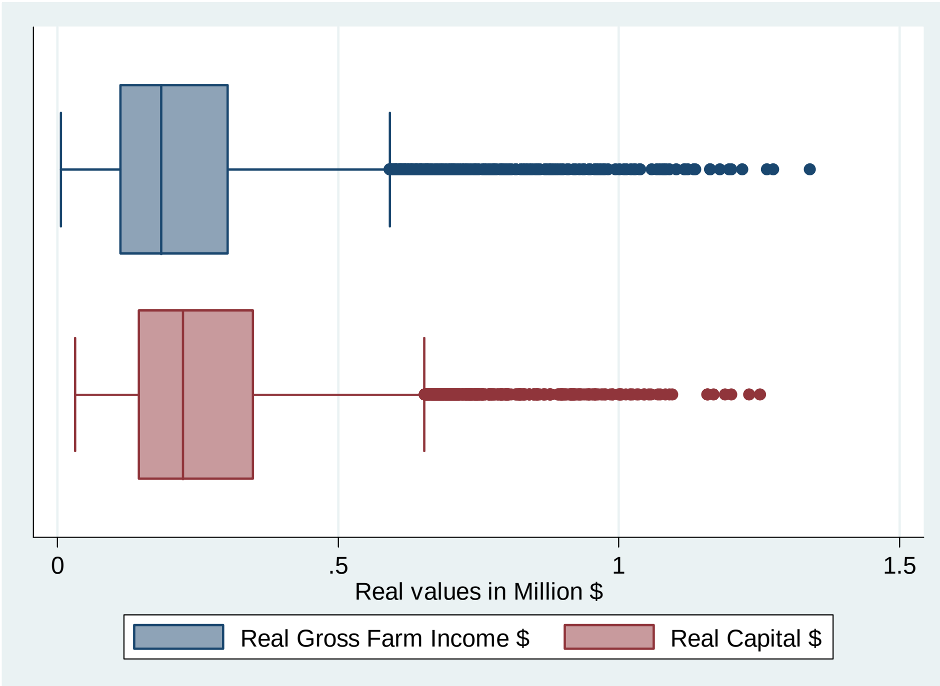

Figure 6-7 Boxplot of gross farm income and capital in real values, 2007