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LABOR PRODUCTIVITY GROWTH AND CONVERGENCE IN THE KANSAS FARM SECTOR: A TRIPARTITE DECOMPOSITION USING THE DEA APPROACH

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Abstract

The objective of this paper is to analyze sources of labor productivity growth in the Kansas farm sector over the period 1993-2006 for a sample of 668 farms. The nonparametric production frontier method is used to decompose labor productivity growth into three components: (1) technological catch-up, (2) technological change, and (3) capital deepening. Kernel estimation methods are used to analyze the evolution of the entire distribution of labor productivity in the sample period. We find that labor productivity is primarily driven by capital deepening. On average, capital deepening is the main source of convergence in productivity and technical change is a source of divergence. We find little evidence of technological catch-up. The impact of the three components of labor productivity varies by farm size.

Key words: labor productivity, growth, technological catch-up, technological change, capital deepening

1. Introduction

Empirical research on economic growth has gained interest in recent years and points to total factor productivity (TFP) growth as the main source of economic growth. The economic growth research agenda has been dominated by two major strands: one strand uses cross-sectional type of regressions to determine whether there is tendency for world economies to converge over time while the other strand decomposes growth into components attributable to capital deepening and technological progress (Henderson and Zelenyuk, 2007; Salinas-Jimenez, 2003). Empirical work in this second strand of research identifies TFP growth with technological progress by assuming that all units of production are efficient. A relatively new third strand of research has emerged and is increasingly becoming popular. This strand has introduced efficiency as a third component into economic growth where efficiency is defined as the ability of a production unit to fully exploit its available resources in producing output. Thus, TFP is decomposed into two components: technological progress (shift in the production frontier) and efficiency change (movement towards or away from the frontier). This study is motivated and grounded on this new strand of research.

The growth rate of U.S. agricultural labor productivity has been on the increase in the past decades. Mundlak (2005:198) observed that on average, the annual growth rate increased from 0.20 to 4.08 percent in the periods 1900-1940 and 1940-90, respectively. The growth rate of capital productivity was practically zero in the ninetieth century but increased to 0.45 percent in 1900-1940 and then declined to -0.23 percent in 1940-90. This negative value is attributed to capital deepening triggered by capital-intensive technical change and possibly declining real prices of capital. The average growth rate of U.S. agricultural output was 1.00 and 1.94 percent in the periods 1900-1940 and 1940-90, respectively. This output

growth was triggered largely by new technology, which for the most part was labor-saving. Fuglie et al. (2007) decomposed the sources of labor productivity growth in U.S. agriculture in the time period 1981-2004 and found that labor productivity grew at a rate 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 was -2.1 percent. The main source of labor productivity identified was growth in total factor productivity (2.4 percent), increase in inputs per worker (1.2 percent), and improvements in quality of labor due to better education and more experience (0.1 percent).

One of the major impacts of the large increase in labor productivity over time has been the faster migration of labor out of agriculture due to a decline in the demand for labor and the rise for the demand for labor in the nonagricultural sector. The increased use of nonlabor inputs, such as new machinery and improved chemicals, helped to substitute for the loss of farm labor. This substitution was reflected in rising amounts of cropland, machinery and other inputs employed per farmworker. In general, U.S. farmers have been driven to adopt new technologies and farming methods that save on labor and use more nonlabor inputs instead because of the rising cost of labor relative to other inputs. The result has been increased productivity in agriculture. Currently, U.S. accounts for about 14 percent of world agricultural production that is produced by only about 2 percent of the labor force.

Empirical studies of growth often deal with decomposition of output growth into factor accumulation and technical change. For the case of U.S. agriculture, underlying this exercise rest the broader and more fundamental question of what has been the driving force behind the high growth rate in labor productivity in the farm sector. Previous empirical studies have tended to focus on the measurement of productivity or technological change (e.g., Ball et al., 1997), and convergence of total factor productivity across states (McCunn

and Huffman, 2000; Ball, Hallahan and Nehring, 2004). Others have focused on input biased technological change, which focuses on the relative measures of input bias, such as input using or saving with respect to each individual input (e.g. Managi and Karemara, 2004). Except for Fuglie et al. (2007), little empirical work has focused on labor productivity and the decomposition of labor productivity growth in components that isolate and identify the factors driving productivity growth.

The purpose of this study is to analyze labor productivity growth in the Kansas farm sector over the period 1993-2006. Specifically, we follow the Kumar and Russell (2002) approach that decomposes labor productivity growth into three components: efficiency change, technical progress, and capital accumulation per worker. The motivation for this decomposition is to identify the driving force behind high labor productivity growth rates. An accurate measure of labor productivity improvement for the farm sector is important because it provides useful information to indicate how economic welfare is being advanced through productivity gains in agriculture.

The structure of this paper article is as follows. Section 2 provides a brief overview of empirical studies related to labor productivity and its decomposition. Section 3 describes the approach followed to construct the production frontier and decompose labor productivity. Data is described in section 4 and Section 5 and 6 present the results and concluding remarks, respectively.

2. Previous Empirical Studies Related to Labor Productivity

Although very few empirical studies have analyzed the sources of labor productivity growth and productivity distribution in the U.S. farm sector (e.g., Fuglie et al., 2007), several

empirical studies have pursued this research agenda across nations, regions, or states. Färe et al. (1994) was the first to decompose total factor productivity growth (TFP) into two components, namely, technical change and efficiency change. The empirics were conducted using a panel of 17 OECD countries over the period 1979-1988. Efficiency change is a measure of technological catch up, or movement towards the best-practice frontier, while technical change is a measure of innovation, or shift of the best-practice frontier. Färe et al. (1994) found that productivity growth across nations was primarily driven by technical change.

Kumar and Russell (2002), hereafter KR, later decomposed labor productivity growth into components attributed to technological catch-up, technological change, and capital accumulation. A panel dataset of 57 countries over the period 1965-90 was used. Contrary to the Färe et al. (1994), this study found that labor productivity growth across countries was primarily driven by capital deepening.

Inspired by the KR methodology, Salinas-Jime´nez (2003) studied the labor productivity growth and convergence process undergone by Spanish regions between 1965 and 1995. Total factor productivity (TFP) gains were decomposed into technological progress and efficiency change using the Malmquist productivity index approach. Labor productivity growth was decomposed into components attributed to technical change, efficiency gains, and capital accumulation. Capital accumulation and technology progress were found to be the main sources of labor productivity growth.

Henderson and Russell (2005) extended the KR analysis by decomposing capital into physical capital and human capital. Using nonparametric production-frontier methods, labor productivity growth is decomposed into components attributed to technological change,

technology catch-up, 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). Results showed that efficiency change is a main source of polarization while human capital is a source of productivity growth.

Enflo and Hjertstrand (2007) 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 by means of data envelopment analysis (DEA). Unlike previous studies on productivity, this study followed the Simar and Wilson (1998, 2000) approach in using bootstrapping methods that provide means of incorporating stochastic elements in DEA. Capital accumulation was found to have divergent effects on labor productivity distribution

Henderson, Tochkov, and Badunenko (2007) followed the nonparametric production technology frontier method illustrated by Henderson and Russell (2005) and decomposed labor productivity into four components: technological change, technological catch-up, and physical and human capital accumulation. The study estimated the contribution of growth of each of the four components for 28 Chinese provinces over the period 1978-2000. The objective of the paper was to determine the sources of growth at the provincial level in China and to examine their impact on regional inequality. The paper differs from previous work in that it examines inter-provincial convergence by analyzing the entire distribution of provincial output per worker and its dynamics over the sample period. The study found that convergence was driven by capital accumulation but regional disparities were driven by technological progress and human capital accumulation.

3. Methodological Framework

The nonparametric approach is used to construct a best-practice production frontier that enables us to identify inefficient behavior for the Kansas farm sector (i.e. distance of each farm household from the best frontier). The computed technical efficiency scores are used to decompose labor productivity into components attributable to technological catch-up, technical change, and capital deepening.

3.1 Production Technology

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 $x_i^t = \left(K_i^t, L_i^t, I_i^t\right)$ where K_i^t is physical capital, L_i^t is labor, and I_i^t is intermediate inputs. 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:

$$T_i^t \equiv \left\{\left(x_i^t, y_i^t\right) | \, can \text{ produce } y_i^t\right\}. \tag{1}$$

The same technology can be characterized by the output sets

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

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

$$D_i^t\left(x_i^t, y_i^t \mid P_i^t\left(x_i^t\right)\right) = \inf\left\{\theta \mid y_i^t/\theta \in P_i^t\left(x_i^t\right)\right\}. \tag{3}$$

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

$$D_i^t\left(x_i^t, y_i^t \mid P_i^t\left(x_i^t\right)\right) \le 1 \Leftrightarrow y_i^t \in P_i^t\left(x_i^t\right). \tag{4}$$

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:

$$TE_i^t \equiv TE_i^t\left(x_i^t, y_i^t \mid P_i^t\left(x_i^t\right)\right) = \sup\left\{\theta \mid y_i^t/\theta \in P_i^t\left(x_i^t\right)\right\} = 1\Big/D_i^t\left(x_i^t, y_i^t \mid P_i^t\left(x_i^t\right)\right). \tag{5}$$

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.

3.2 Empirical DEA Model

Given the production technology in equation (1), 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:

$$e\left(Y_i^t, K_i^t, L_i^t, I_i^t\right) = \min\left\{\lambda \mid \left\langle Y_i^t/\lambda, K_i^t, L_i^t, I_i^t\right\rangle \in T^t\right\}. \tag{6}$$

In the above equation Y is output, K is capital, L is labor and I represent intermediate inputs. The subscript *i* refers 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 program:

$$\min_{\lambda, z^1, \ldots, z^j} \lambda$$

$$subject\ to \begin{cases} Y_i / \lambda \leq \sum_k z_k Y_k^t \\ K_i \geq \sum_k z_k K_k^t \\ L_i \geq \sum_k z_k L_k^t \\ I_i \geq \sum_k z_k I_k^t \\ z_k \geq 0 \forall k. \end{cases} \tag{7}$$

The solution value λ is the efficiency index for farm *i* at time *t*.

3.3 Tripartite Decomposition of Labor Productivity

After computing the technical efficiency scores, we follow Kumar and Russell (2002) to decompose labor productivity growth into components attributed to changes in efficiency, technological change, and capital accumulation. We use the assumption of constant returns to scale to decompose labor productivity growth.

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 base period and the current period respectively, and e_a and e_b represent the current and base technical efficiency for farm *i*. The potential base year output per worker is:

$$\bar{y}_b(k_b) = y_b / e_b, \tag{8}$$

and the potential current year output per worker is:

$$\bar{y}_c\left(k_c\right) = {y_c}/{e_c}\,. \tag{9}$$

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

$$\frac{y_c}{y_b} = \frac{e_c \times \bar{y}_c\left(k_c\right)}{e_b \times \bar{y}_b\left(k_b\right)}\,. \tag{10}$$

If we multiply the numerator and the denominator of the above equation by the potential output per worker during base period, we obtain the following:

$$\frac{y_c}{y_b} = \frac{e_c}{e_b} \times \frac{\bar{y}_c\left(k_c\right)}{\bar{y}_b\left(k_b\right)} \times \frac{\bar{y}_b\left(k_c\right)}{\bar{y}_b\left(k_b\right)}\,. \tag{11}$$

The above equation decomposes the relative change in output-labor ratio in the two periods into change in efficiency, $\left(\frac{e_c}{e_b}\right)$, technology change, $\left(\frac{\bar{y}_c\left(k_c\right)}{\bar{y}_b\left(k_b\right)}\right)$, and movement along the frontier, $\left(\frac{\bar{y}_b\left(k_c\right)}{\bar{y}_b\left(k_b\right)}\right)$.

Technological change can alternatively be measured at the base period capital-labor ratio by multiplying the numerator and denominator of equation (11) by the potential output per worker during the current period to obtain:

$$\frac{y_c}{y_b} = \frac{e_c}{e_b} \times \frac{\bar{y}_c\left(k_b\right)}{\bar{y}_b\left(k_b\right)} \times \frac{\bar{y}_c\left(k_c\right)}{\bar{y}_c\left(k_b\right)}\,. \tag{12}$$

Finally, we follow 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 technological change and capital

accumulation by multiplying the numerator and denominator of equation (11) by $\left(\bar{y}_b\left(k_c\right)\bar{y}_c\left(k_b\right)\right)^{1/2}$ to obtain the measure of labor productivity change:

$$\frac{y_c}{y_b} = \frac{e_c}{e_b} \times \left(\frac{\bar{y}_c\left(k_c\right)}{\bar{y}_b\left(k_c\right)} \times \frac{\bar{y}_c\left(k_b\right)}{\bar{y}_b\left(k_b\right)}\right)^{1/2} \times \left(\frac{\bar{y}_b\left(k_c\right)}{\bar{y}_b\left(k_b\right)} \times \frac{\bar{y}_c\left(k_c\right)}{\bar{y}_c\left(k_b\right)}\right)^{1/2} \tag{13}$$

$$= EFF \times TECH \times KACC$$

In the above equation, *EFF* is the measure of efficiency change, *TECH* is the measure of technological change, and *KACC* is the measure of capital accumulation between the base period *b* and current period *c*. For this study, the base year is 1993 and the current year is 2006.

The above piecewise linear technology and the decomposition of labor productivity change is illustrated in Figure 1. We have labor productivity and capital-labor ratio for time period *b* and *c*.

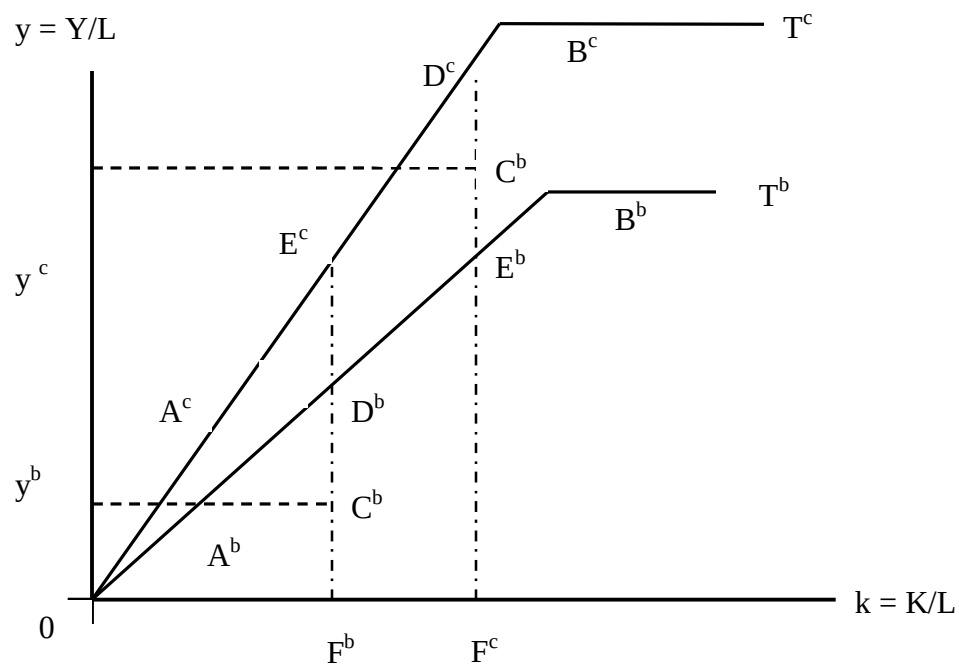


Figure 1. Labor productivity change

In the above figure, the frontier technology in the current period is represented by $0T^c$ while the frontier technology in the base period is represented by $0T^b$. Therefore, for the farm at C^b, its technical efficiency equals $e^c = F^c C^c / F^c D^c$. Labor productivity change can be represented as follows:

$$y^c / y^b = \left(\frac{F^c C^c / F^c D^c}{F^b C^b / F^b D^b} \right) \times \left(\frac{F^c D^c}{F^c E^b} \times \frac{F^b E^c}{F^b D^b} \right)^{0.5} \times \left(\frac{F^c D^c}{F^b E^c} \times \frac{F^c E^b}{F^b D^b} \right)^{0.5} \tag{14}$$

Using Färe et al. (1994) and Kumar and Russell (2002), we take the logarithms of both sides of equation (13) or (14) and divide by the number of years between the two periods to get:

$$g_Y = g_{EFF} + g_{TECH} + g_{KACC} \tag{15}$$

where g_Y represent 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 (13) because in this way we present 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.

3.4 Kernel Density Estimation

Each distribution used in this paper is a kernel based estimate of a density function. Let $X_{1,\ldots,} X_n$ be a sample from X, where X has the probability density function $f(x)$. The density of X can be estimated as:

$$\hat{f}(x) = \frac{1}{nh}\sum_{t=i}^{n} k\left(\frac{x_i - X}{h}\right), \tag{16}$$

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

$$\int_{-\infty}^{\infty} k\left[z\right]dz = 1; k \geq 0;\ k(x) = k(\text{-}x)\ . \tag{17}$$

X is the observations that the kernel is centered on, n is the number of observations, and h is the optimal bandwidth (smoothing parameter). Based on simulation studies, 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:

$$h = 0.9An^{-1/5}, \tag{18}$$

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

Therefore, Gaussian density functions are used and the Silverman rule of thumb is used to choose the optimal bandwidth.

4. Data

Data for this study comes from the Kansas Farm Management Association database (Langemeier, 2003). We use a panel of 668 farm households for the period 1993-2006. The data includes one output and three inputs – capital, labor and intermediate inputs. Output is measured in dollars as the total value of farm production (VFP). The nominal VFP is deflated by the Consumer Price Index, with 2003 as the base year. Labor is measured as the number of farm workers per farm per year. To obtain this value, we first deflate the total annual cost

of labor (includes hired and unpaid labor) by the price index with 2003 as the base year. This value is then divided by the average annual salary of a farm worker assuming a 40 hour work week, 48 work weeks in a year, and average hourly wages. Capital is measured as a flow variable. It includes repairs, cash interest, opportunity interest, depreciation, rent, property taxes, and insurance. Intermediate inputs are measured as total expenditures on purchased inputs. This variable includes fuel, utilities, seed, fertilizer, herbicides, insecticide, veterinarian expenses and miscellaneous expense. The information on price indexes used is obtained from the Unites States Department of Agriculture (U.S.D.A) website. For this study we focus on the first and last years only. The descriptive statistics of the data is presented in Table 1.

Table 1: Efficiency Indexes by Farm Size for 668 Farms in Kansas, 1993 and 2006

	Output	Capital	Labor	Intermediate Inputs
Mean, 2006	255350.40	128665.60	2.91	89189.46
Max, 2006	1570067.00	787141.70	14.97	757172.60
Min, 2006	14253.13	6037.45	0.23	2819.77
SD, 2006	220050.10	93578.00	1.72	83761.78
Mean, 1993	219792.30	120094.20	4.73	54952.81
Max,1993	1145446.00	605394.20	24.69	391138.70
Min,1993	21712.72	9244.38	1.05	3596.04
SD,1993	161823.50	78876.22	2.70	43219.93

5. Empirical Results and Discussion

This study involves 668 farms. Instead of presenting the disaggregated results for each farm and year, we turn to a summary description of the average performance based on farm size categories. We disaggregate the data into four groups: very small farms (VSF)

involve farms with less than $100,000 in value of farm production; small farms (SF) include farms with a value of farm production between $100,000 and $250,000; medium farms (MF) include with a value of farm production between $250,000 and $500,000; and large farms (LF) are farms with a value of farm production above $500,000. Note that we use the year 2006 rather than 1993 to define the farm size categories. Performance here is also measured relative to the best practice in the sample, where best practice represents the production frontier.

5.1 Production Frontiers

The Kansas farm sector production frontiers in 1993 and 2006 along with the scatter plots of output per worker vs. capital per worker are presented in Figure 2 and Figure 3. Note that there is an upward shift in the production frontier from 1993 to 2006. It is evident from the graphs that for all the farms output per worker and capital per worker almost doubled between the two periods. However, the shift is disproportionate and primarily driven by only a few farms.

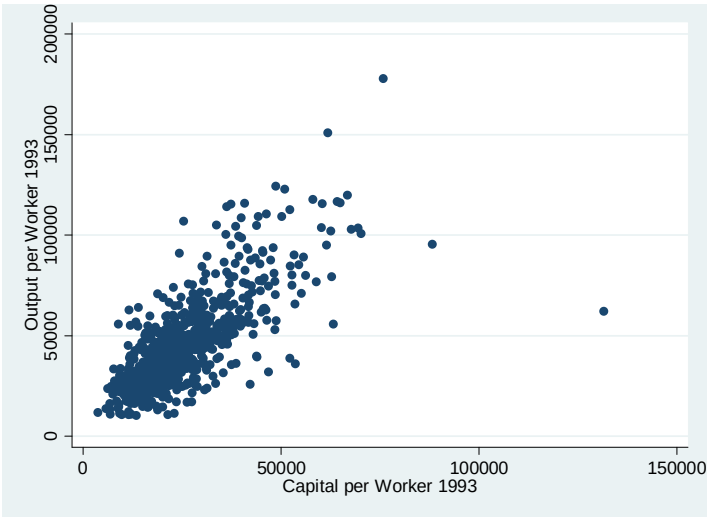


Figure 2. Production Frontier for 1993

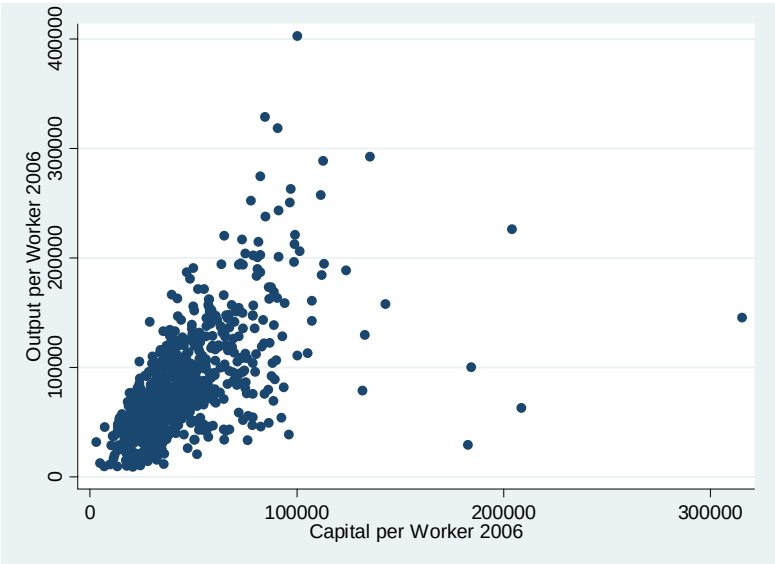


Figure 3. Production Frontier for 2006

The kernel distribution of labor productivity in 1993 and 2006 is presented in Figure 4 where the solid line is 1993 and dashed line is 2006. The figure indicates that the

distribution of labor productivity in both years appears to be non-normal and skewed to the left. However, a profound change in the shape of the distribution occurred over the sample period, shifting the distribution to the right. This suggests a general increase in productivity across the farms.

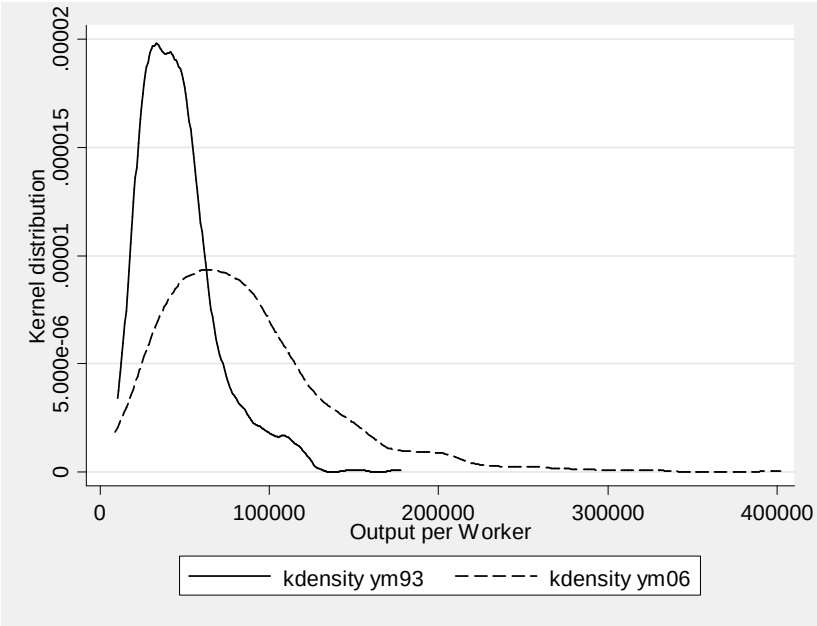


Figure 4: Distributions of Output per Worker, 1993 and 2006

5.1 DEA Efficiency Measurement

We examine the efficiency of each farm relative to the frontier. The efficiency index for each farm size category is reported in Table 2. The second and forth columns are the bias-corrected technical efficiency indices after bootstrapping with 1000 iterations (see Simar and Wilson, 1998; 2000 for details pertaining DEA bootstrapping). On average, there are inefficiencies in the sample with no improvement in efficiency (catching-up) between the two periods, 1993 and 2006. The average efficiency index between the two periods was

0.593 and 0.547 respectively, a clear indication of a decline in efficiency. Average technical efficiency varies with farm size category with large farms being more efficient than medium farms, medium farms more efficient that small farms, and small farms more efficient than very small farms. The general impression is a movement away from the frontier rather than towards the frontier over time. It is important to note that there are farms that operate on the best-practice frontier for each farm size category. This artifact should not be misinterpreted; it simply means that farms operating on the frontier have exploited their resources relatively better than other farms in the sample with similar levels of inputs.

Table 2: Efficiency Indexes by Farm Size for 668 Farms in Kansas, 1993 and 2006

Farm Size		Technical Efficiency 1993	Bias - corrected TE 1993	Technical Efficiency 2006	Bias - corrected TE 2006
V.S.F (151)	Mean	0.5077	0.4752	0.3729	0.3360
	Max	1.0000	0.8224	1.0000	0.7629
	Min	0.1807	0.1687	0.0847	0.0733
S.F (264)	Mean	0.5741	0.5469	0.5192	0.4919
	Max	1.0000	0.9764	0.8974	0.8655
	Min	0.2063	0.2014	0.0365	0.0337
M.F (183)	Mean	0.6487	0.6072	0.6501	0.6114
	Max	1.0000	0.9300	1.0000	0.9519
	Min	0.2546	0.2313	0.3201	0.3130
L.F (70)	Mean	0.7023	0.6415	0.7532	0.6855
	Max	1.0000	0.9101	1.0000	0.8768
	Min	0.4315	0.4196	0.5008	0.4825
Total (668)	Mean	0.5930	0.5571	0.5465	0.5097
	Max	1.0000	0.9764	1.0000	0.9519
	Min	0.1807	0.1687	0.0365	0.0337

The bootstrapped bias corrected efficiency scores reinforce our observation, the efficiency of the Kansas farms, on average, dropped between the period 1993 and 2006, and that large farms are relatively more efficient than smaller farms. Given that we used the input orientated DEA approach, this implies that, on average, large farms are able to produce more

output per unit of input used relative to smaller farms. The kernel distribution of efficiency indices across the farms for the years 1993 and 2006 are presented in Figure 5. There is a general shift of the probability mass to the left between 1993 and 2006, an indication of the general drop in efficiency for farms that initially had a low efficiency.

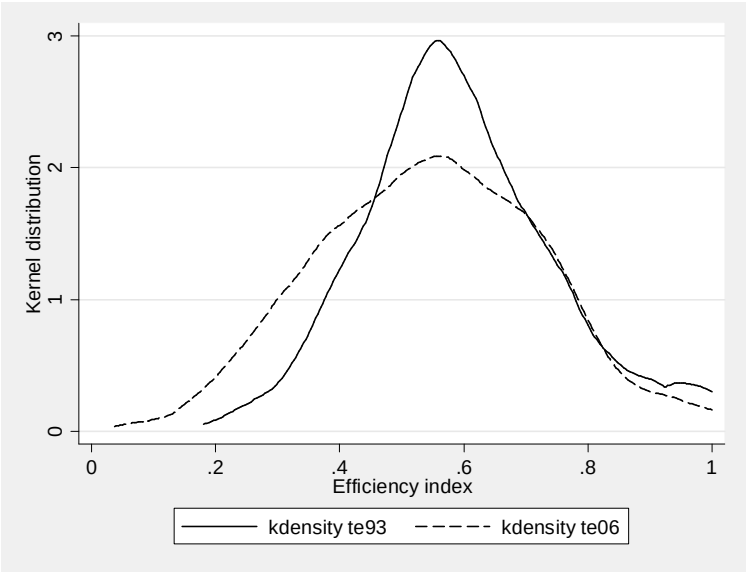


Figure 5: Distributions of Efficiency Index, 1993 and 2006

5.2 Tripartite Decomposition of Labor Productivity

We now turn to the analysis of the sources of labor productivity using equations (13) and (15). A summary of the decomposition of changes in output per worker by the four farm size categories is presented in Table 3. The last three columns report the contribution to percentage change in output per worker for each of the tripartite component. The overall average percentage change in labor productivity for the 668 farms is 98.76. This high productivity increase was primarily driven by capital accumulation (103.77%). Technical

change made a very small contribution (0.89%) while efficiency change had a negative contribution (-2.06%).

Table 3: Percentage Change of Tripartite Decomposition Indexes, 1993-2006

Farm size category		Output per worker, 1993	Output per worker, 2006	Percentage change in output per worker	Contribution to percentage change in output per worker of:		
					Efficiency change	Change in technology	Capital deepening
V.S.F	Mean	30816.48	39696.60	46.21	-9.87	-9.23	83.29
(151)	Max	74934.66	157706.70	351.37	141.50	24.27	448.99
	Min	10172.54	8859.22	-77.85	-73.53	-29.42	-58.48
S.F	Mean	41479.39	72526.56	95.38	0.80	-1.00	103.95
(264)	Max	101890.00	201974.60	625.48	201.05	28.48	814.73
	Min	10742.11	29359.49	-43.47	-64.98	-27.48	-47.75
M.F	Mean	57205.70	110987.40	118.29	-0.69	6.49	108.92
(183)	Max	124326.00	274442.10	410.77	187.54	40.82	460.34
	Min	19371.97	38581.84	-34.44	-56.40	-18.89	-14.35
L.F	Mean	68616.47	165675.20	173.84	0.47	15.25	133.80
(70)	Max	177690.50	402276.80	702.11	88.48	42.44	417.75
	Min	20439.02	53622.87	-26.01	-46.51	-19.57	1.91
Total	Mean	46221.02	85402.93	98.76	-2.06	0.89	103.77
(668)	Max	177690.50	402276.80	702.11	201.05	42.44	814.73
	Min	10172.54	8859.22	-77.85	-73.53	-29.42	-58.48

V.S.F = Very small farms; S.F = Small farms; M.F = Medium sized farms; L.F = Large farms.

Looking at the farm size categories, it is evident that large farms and medium sized farms achieved high improvement in labor productivity, 173% and 118% respectively, compared to the small and very small farms, 95.38% and 46.21%, respectively. Capital deepening, the primary factor driving productivity, was most pronounced for the large farms (133.80%), followed by medium farms (108.91%). Small and very small farms each had a capital deepening contribution of 103.94% and 83.30%, respectively. The contribution of change in technology was more pronounced for the large farms (15.24%) compared to the

medium farms (6.50%). The contribution of technological change was negative for the small farms (-1.00%) and very small farms (-9.23%), a possible indication of technological regress rather than progress. On average, the small farms and large farms moved slightly towards the frontier (catching-up) while the very small farms and medium farms moved away from the frontier between the time period 1993 and 2006.

To gain more insight into the growth rate of productivity per worker, we also compute annual growth rates. Table 4 reports the annual growth rate of output per worker and the relative contribution of each of the tripartite components. The overall annual growth rate is 3.97% and is primarily driven by a high annual growth rate in capital deepening. These results are consistent with Fugile et al. (2007) who reported an average growth rate of 3.70% for the U.S. farms between the period 1980 and 2004. Technology change has a negative contribution (-14.70%) and efficiency change has a positive contribution (26.44%) to labor productivity growth. Looking at the growth rates by farm size categories, large farms experienced a high annual growth rate (6.34%) compared to medium farms (4.97%), small farms (4.12%), and very small farms (1.42%). However, the growth rate in capital deepening is relatively more pronounced on very small farms and small farms, an indication that these farms are catching-up in capital accumulation compared to the other farm size categories. However, it is important to note that very small farms and small farms experienced technological regress.

Table 4: Decomposition of Annual Labor Productivity Growth, 1993-2006

Farm size category		Annual Growth Rate of Change in:				Relative (Percentage) Contribution to Growth of :		
		Output per worker	EFF	TECH	KACC	EFF	TECH	KACC
V.S.F (151)	Mean	1.42	-1.33	-0.72	3.47	32.53	2.63	64.85
S.F (264)	Mean	4.12	-0.34	-0.10	4.56	-18.54	-6.81	125.34
M.F (183)	Mean	4.97	-0.34	0.42	4.89	103.64	-53.67	50.03
L.F (70)	Mean	6.34	-0.24	0.97	5.61	-18.85	19.99	98.86
Total (668)	Mean	3.97	-0.55	0.01	4.51	26.44	-14.70	88.26

V.S.F = Very small farms; S.F = Small farms; M.F = Medium sized farms; L.F = Large farms.

5.3 Analysis of Labor Productivity Distributions

The analysis in the foregoing sections is based on average growth rates and percentage changes and therefore appropriate in explaining the behavior of the farms at the mean level. However, it provides little information about the cross-sectional distribution of labor productivity and its evolution. Quah (1996b) has argued compellingly that analyses based on standard regression methods focusing on the first moments of the distribution cannot adequately address the convergence issue. He suggested that the issues of convergence should be related to the evolution of the whole income distribution (i.e., we want to know what happens to the entire cross-sectional distribution of economies). Thus, in the spirit of Quah (1993, 1996a, 1996b, 1997), we analyze the entire distribution of labor productivity in the Kansas farm sector in the period 1993 and 2006. This analysis helps us

answer the following question: what would the labor productivity distribution in 2006 be if the initial labor productivity in 1993 had changed due to only one of its components (i.e., efficiency change, technical change, or capital deepening)?

It is important to note here that the labor productivity in the current period (2006) can be constructed by successively multiplying labor productivity in the base period (1993) by each of the three factors. This process allows us to construct the counterfactual distributions by sequentially introducing each of these factors as:

$$y_{2006} = \left(EFF \times TECH \times KACC\right) \times y_{1993} \tag{19}$$

The actual and counterfactual distributions are estimated by employing the nonparametric kernel methods. We use the Epanechnikov kernel to estimate the distribution and the Silverman rule of thumb method for choice of the optimal bandwidth (Silverman, 1986).

Figure 6 shows the distribution of output per worker due to the effect of each of the tripartite components. The dashed curve is the distribution of labor productivity in 2006 while the solid curve in panel (A) to (D) is the counterfactual distribution. Panel (A) plots the actual labor productivity distributions in 1993 and 2006, indicating a shift to the right of the probability mass. As stated earlier, this indicates a general increase in productivity across the farms. Panel (B) plots the effect of efficiency change. The plot indicates that efficiency change did have a very slight impact on the base year distribution. However, the direction of this change was not towards the 2006 distributions. This confirms the results in Table 2 and 3, that efficiency changes, on average, actually caused regress in productivity growth.

Panel (C) plots the effect of technical change. The "eye-ball" analysis of this counterfactual distribution indicates more than one local maximum, suggesting that the distribution may have more than one mode.

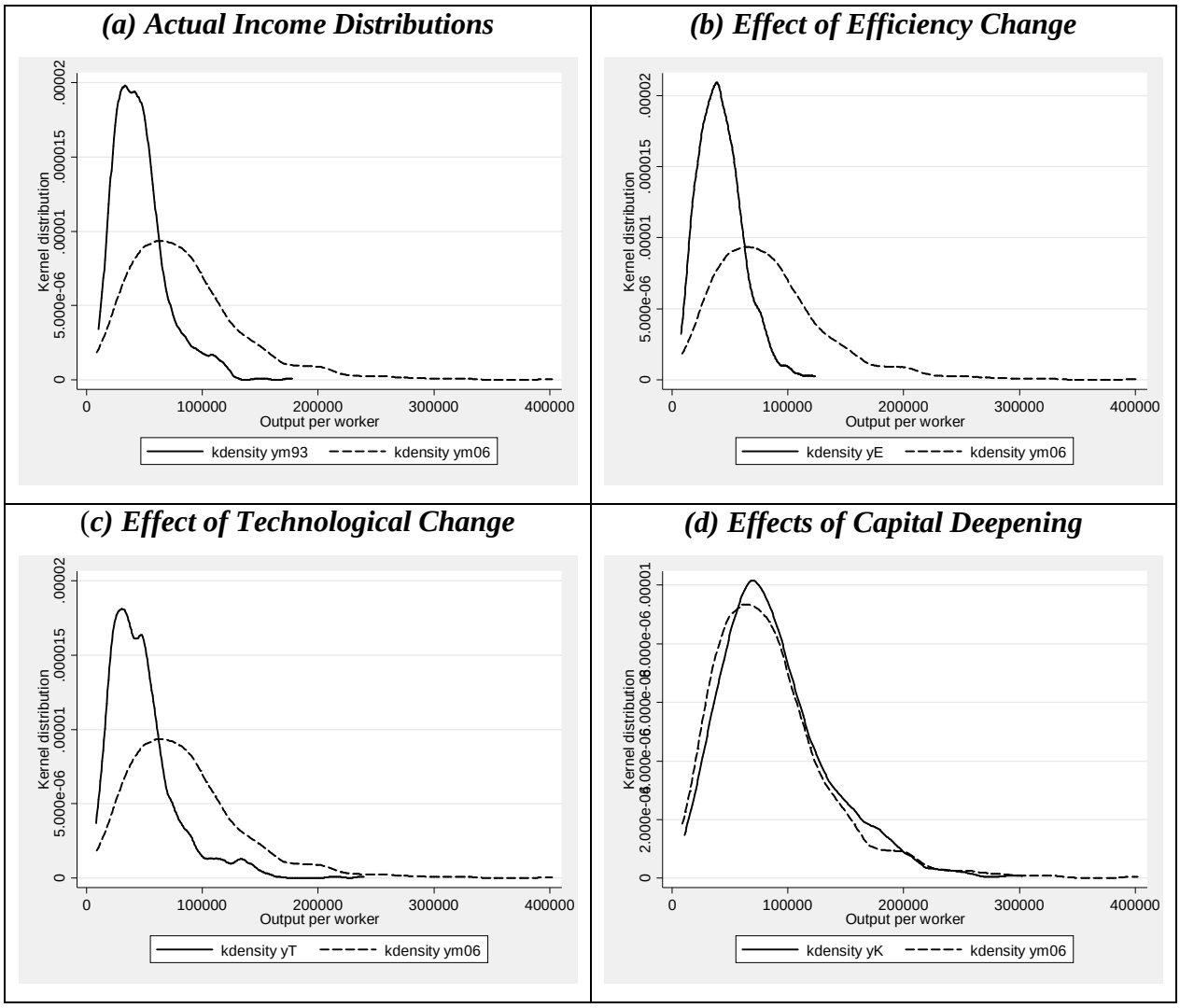


Figure 6: Counterfactual Distributions of Output per Worker, 1993-2006

There is a slight shift of the probability mass towards the 2006 distribution in the upper tail of the distribution. Again, this is consistent with previous results that technical change had a positive but marginal contribution to growth in productivity.

Panel (D) plots the effect of capital deepening. It is clear that capital deepening is the primary factor that has contributed to convergence and increase in labor productivity in the entire sample period. There is an almost one to one mapping of the counterfactual distribution and the 2006 labor productivity distribution.

Overall, we find that all the three labor productivity components had an impact on the evolution of the base year distribution (1993) towards or away from the current year distribution (2006). On average, efficiency change and technical change alone cannot explain the distribution shift from 1993 to 2006. Neither can the combined effect of the two explain the shift. In fact, efficiency change introduced regress rather than progress. Only capital deepening brought about a significant shift of the entire base year distribution towards the current year distribution. Technology change appears to introduce modes in the evolution of the distribution.

5.4 Bootstrap Test of Multimodality

The presence of more than a single mode in the distribution of labor productivity can suggest a number of separate underlying productivity distributions, each of which may refer to certain economically important population subgroups. Silverman (1981) introduced a formal statistical test for investigating the number of modes in a sample distribution where a mode is defined as a point at which the density has a local maximum.

Silverman (1981) developed a method to test the null hypothesis that a density function $f(.)$ has k modes against the alternative that $f(.)$ has more than k modes, where k is a non-negative integer. The test statistics in this case is the critical window width, defined by:

$$h_{crit(k)} = \inf\left\{h \mid \hat{f} \text{ has at most } k \text{ modes}\right\}. \tag{20}$$

For $h < h_{crit(k)}$, the estimated density has at least k+1 modes. The value of $h_{crit(k)}$ is computed through a binary search algorithm, and its significance level can be assessed by the smoothed bootstrap procedure (Efron, 1979).

We use the Silverman test for multimodality to determine the number of modes in the counterfactual distributions presented in the previous section. The results are reported in Table 5. We find that the distribution of labor productivity in 1993 contained a single mode (reject the null of more than one mode). We then focus on the mean preserving shift of changes in productivity by sequentially introducing and testing for modality on the effect of each of the three components. We later test the combined effects of efficiency change and technical change, efficiency change, and capital accumulation and the effects of all the three components combined.

Table 5. Modality Test using the Silverman Test[1]

Distribution	Ho: One Mode Ha: More than One Mode	Ho: Two Modes Ha: More than Two Mode
$g(y_{93})$	0.217 (Ho not rejected)	0.677 (Ho not rejected)
$g(y_{93}\times EFF)$	0.475 (Ho not rejected)	0.432 (Ho not rejected)
$g(y_{93}\times TECH)$	0.00 (Ho rejected)	0.054 (Ho rejected)
$g(y_{93}\times KACC)$	0.300 (Ho not rejected)	0.314 (Ho not rejected)
$g(y_{93}\times EFF\times TECH)$	0.060 (Ho not rejected)	0.539 (Ho not rejected)
$g(y_{93}\times EFF\times KACC)$	0.474 (Ho not rejected)	0.310 (Ho not rejected)
$g(y_{93}\times EFF\times TECH\times KACC)$	0.192 (Ho not rejected)	0.717 (Ho not rejected)

* Reported results are P-values

Except for the counterfactual effects of technical change on initial productivity, all the tests for multimodality for the other counterfactual distributions are not rejected and conclusion is drawn that the distribution of labor productivity over the sample period remained unimodal. The Silverman test for more than one and two modes is rejected for the technical change counterfactual distribution, suggesting that the distribution has more than two modes. A possible explanation for this observation is that there are different groups of farms with different capacity to absorb and utilize the available technology. New knowledge or "technology" is only appropriate for the farms that produce according to technologies similar to the innovator's technology (Los and Timmer, 2005). Thus, there are a group of farms that can readily adopt the available technology, others take time to adopt the technology while others are unable to adopt or keep pace with available and changing technology. Thus, technical change is a cause of divergence rather than convergence of productivity across farms. Going by the evidence from the growth analysis, the rate of growth of technical change varies widely across the four farm size categories.

[1] The authors would like to 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. The Silverman test was run using 1000 iterations. Given our sample size, this analysis is computationally demanding and took more than six hours.

However, the effect of technical change is overshadowed once the effect of capital deepening combined with efficiency are included in the initial productivity level. This lends support to the view that technical change is not the primarily driving factor in labor productivity growth.

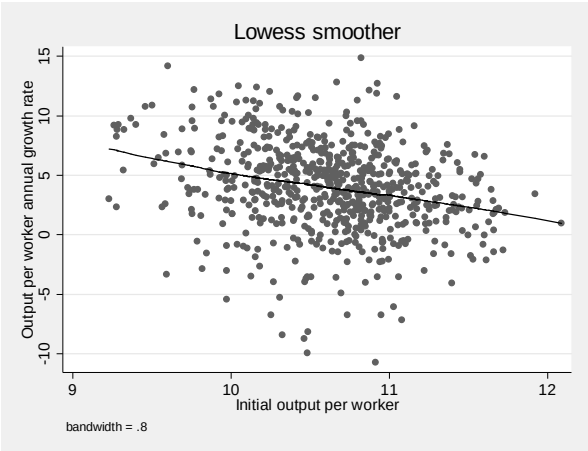
5.5 Sources of Labor Productivity Convergence

The subject of this section is to analyze the influence of each of the three components (catching-up, technical change, and capital accumulation) on convergence of labor productivity. Of interest here is to know whether the growth rate of labor productivity due to each of these factors has been greater for farms with lower initial labor productivity, hence an indication of convergence. Thus, we estimate by means of ordinary least squares (OLS) the regression of the average growth of labor productivity and each of those components on the logarithm of the initial labor productivity. We also include three dummy variables to capture the performance of the very small farms, small farms, and medium sized farms relative to the large farms. A negative sign for any of these coefficients indicates convergence and a positive sign indicates divergence.

Figure 7 plots the logarithm of the initial labor productivity in the base year 1993 (on the horizontal axis) against the annual growth rate in labor productivity (panel A), the efficiency index (panel B), technical change (panel C), and capital deepening (panel D), along with fitted regression lines. Panel (A) reveals a clear relationship between the growth rate of labor productivity and its initial level. The downward sloping regression line suggests

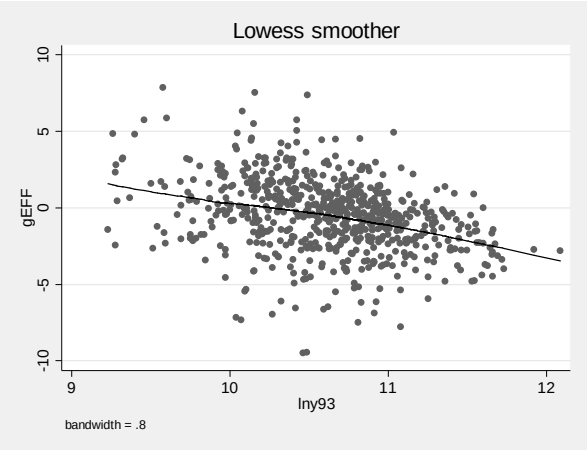
that farms with initial low productivity have, on average, had a higher growth rate in productivity relative to farms that had initial high productivity.

Panel (A)



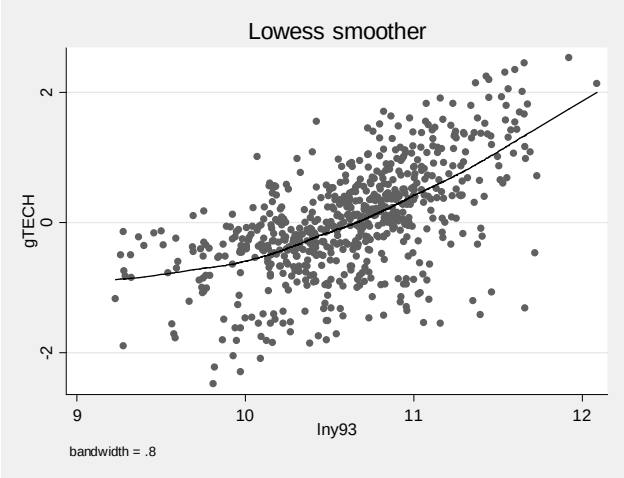
Note: In the panel, the horizontal axis is the log of initial labor productivity and the vertical axis is the annual growth rate of labor productivity

Panel (B)



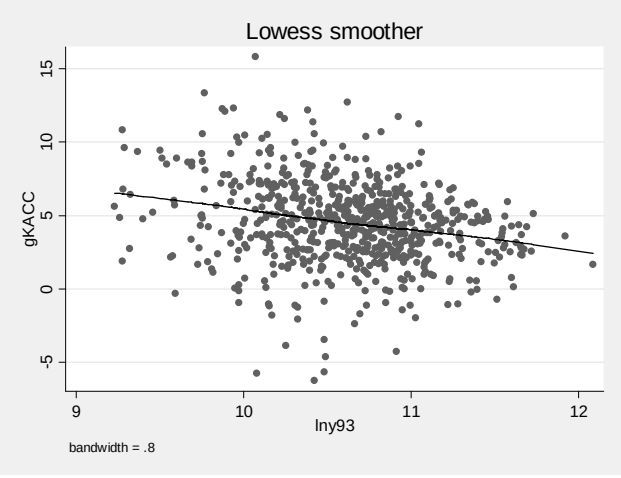
Note: In the panel, the horizontal axis is the log of initial labor productivity and the vertical axis is the annual growth rate of efficiency.

Panel (C)



Note: In the panel, the horizontal axis is the log of initial labor productivity and the vertical axis is the annual growth rate of technical change.

Panel (C)



Note: In the panel, the horizontal axis is the log of initial labor productivity and the vertical axis is the annual growth rate of capital deepening.

Figure 7: Growth Rate between 1993 and 2006 in Output per Worker and the Three Decomposition Components, Plotted against 1993 Output per Worker

The regression results are reported in Table 6. In column 1, the negative and significant coefficient on initial labor productivity supports the conditional convergence hypothesis. All the dummies are negative and statistically significant and indicate that the speed of convergence was correlated with farm size category with very small farms achieving a higher growth rate relative to other farm size categories.

Panel (B) indicates that that there has been a disproportionate growth in efficiency in the sample. Few farms that had initial low productivity experienced high growth rate in efficiency while some farms with initial high productivity experienced a negative growth rate in efficiency. For many farms, the annual growth rate of efficiency clusters around zero. The plot indicates that efficiency growth contributed negatively to productivity growth with farms moving away from the frontier rather than towards the frontier. Column 2 in Table 4 reports the regression results when the dependent variable is the average growth rate of the efficiency index. The coefficient on initial labor productivity is negative and statistically significant. This suggests that overall convergence in efficiency occurred and is higher for farms with initial low productivity than for farms with initial high productivity. All the dummies are negative and statistically significant.

Panel (C) suggests that technical change contributed to positive productivity growth for large farms. Farms with initial high productivity benefited more from technological change than those with initial low productivity. In column 3 of Table 4, the regression coefficient for initial labor productivity against average growth rate in technical change is positive and significant. This indicates that technological growth contributed to the divergence in productivity rather than convergence.

Panel (D) indicates that the growth rates of capital deepening was positive for most farms and has a significant relationship with the base output per worker. Capital deepening contributed to convergence of farms and was the major source of labor productivity growth from 1993-2006. In fact, Panel (D) replicates almost perfectly the pattern observed in panel (A) suggesting that convergence in capital deepening is the main source of labor productivity growth.

Table 6. Cross-Sectional Regression Results

	Dependent Variable			
	(1)	(2)	(3)	(4)
	g_Y	g_{EFF}	g_{TECH}	g_{KACC}
Initial Productivity -Ln(y_{93})	-5.071*	-2.805*	0.634*	-2.900*
	(0.300)	(0.202)	(0.648)	(0.232)
Dummy - Very Small Farms	-9.054*	-3.374*	-1.182*	-4.498*
	(0.518)	(0.341)	(0.106)	(0.417)
Dummy - Small Farms	-4.701*	-1.473*	-0.760*	-2.468*
	(0.377)	(0.241)	(0.872)	(0.310)
Dummy - Medium Farms	-2.314*	-0.619*	-0.442*	-1.253*
	(0.370)	(0.222)	(0.900)	(0.288)
Constant	62.384*	30.762*	-6.031*	37.653*
	(2.900)	(2.255)	(0.713)	(2.588)
Adj. R^2	0.481	0.264	0.479	0.227

Note: 668 observations are used in the regressions. Figures in parenthesis represent the robust standard errors. *(**) means the corresponding coefficient is significant at the 1 %(5%) level.

6. Conclusion

This paper examined the labor productivity growth and convergence process undergone by the Kansas farm sector between 1993 and 2006. Labor productivity growth was decomposed into three components: technological catch-up, technological change, and

capital deepening. The dynamics of the overall distribution of labor productivity and the relative contribution of each of these components to convergence were analyzed. We draw the following conclusions from this analysis:

(a) Capital deepening is the primary factor driving labor productivity growth and convergence. Small farms have been playing ‘catch-up” in accumulation of capital inputs over time.

(b) The effect of efficiency change contributed to regress rather than progress. Between the two sample periods, efficiency deteriorated with the largest regress exhibited by very small farms.

(c) Technological change had very little contribution to the growth in labor productivity and was a source of divergence rather than convergence. Farms with initial high labor productivity benefitted more from technological progress relative to those with initial low productivity. The small growth rate in technological change suggests that new innovations take time before they are assimilated.

This study has policy implications. A natural question to address is why the rate of technological spillover is very slow in being absorbed and why the counterfactual distribution of technical change is multimodal. Is technological transfer specific to particular combinations of inputs?

A natural extension of this work would be to break the farm size categories into two groups, large and small, and investigate the dynamics and labor productivity and convergence within each group and between groups. Another extension, along the lines of Henderson and Russell (2005), is to split capital input into two inputs, physical and human

capital. Finally, it is important to note that the approach used in this study was to decompose labor productivity into three components. We provide no rationale behind the behavior of each of these components. Therefore, further study can investigate why some farms are improving while others are stagnating in both technological catch up and technological change.

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