Labor Productivity Growth in the Kansas Farm Sector: A Tripartite Decomposition Using a Non-Parametric Approach

Amin W. Mugera, Michael R. Langemeier, and Allen M. Featherstone

We use nonparametric production function methods to decompose farm-level labor productivity growth into components attributable to efficiency change, technical change, and factor intensity. The estimation is accomplished using balanced panel data drawn from the Kansas Farm Management Association for the period 1993 to 2007. We find that labor productivity growth is primarily driven by factor intensity and technical change. Efficiency change is declining with increasing productivity growth, and technical change is not Hicks-neutral and occurs at high levels of factor intensity, suggesting that innovation is embodied in factor intensity.

Key Words: labor productivity growth, efficiency change, technical change, factor intensity

The rise in agricultural productivity has been chronicled as the single most important source of economic growth in the U.S. farm sector (Acs, Morck, and Yeung 1999, Ball and Norton 2002). The remarkable growth in productivity has been attributed to research and development (Huffman and Evenson 1993, Alston, Craig, and Pardey 1998, McCunn and Huffman 2000), development of human capital (Huffman and Evenson 1992, McCunn and Huffman 2000, Yee et al. 2002), production contracts (Key and McBride 2003), and increasing farm size (Weersink and Tauer 1991, Thirtle, Schimmelpfennig, and Townsend 2002). Several empirical studies have focused on understanding the sources of productivity growth by decomposing total factor productivity (TFP) into technical change and efficiency change, while others have focused on understanding factors that contribute to convergence or divergence of TFP (Ball et al. 2001, Ball, Hallhan, and Nehring 2004, Managi and Karemera 2004, Liu et al. 2011).

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This paper contributes to the literature by focusing on labor productivity as one of the main drivers of total factor productivity growth in production agriculture. Specifically, we contribute to the literature in three ways: (i) by decomposing labor productivity growth into efficiency change, technical change, and factor intensity, (ii) by focusing our analyses at the farm rather than state or national level, and (iii) by relating labor productivity change to important farm policy developments. The motivation for this decomposition is to identify the main sources of labor productivity growth. From a policy perspective, accurate measures of the sources of productivity growth are important because they provide policymakers with information about which areas could be targeted for appropriate policy intervention to improve labor productivity.

The passage of the 1996 Federal Agricultural Improvement and Reform (FAIR) Act introduced substantial changes to the overall U.S. farm policy environment. Price support measures and deficiency payments were reduced in favor of income support direct payments. As observed by Serra, Goodwin, and Featherstone (2005), the introduction of the fixed decoupled payments may have reduced the likelihood of off-farm labor participation in Kansas because of an increase in the income support system. However, the effects of the new policy environment on farm income variability were attenuated by changes in crop insurance programs and by the increase in emergency assistance payments by the end of the 1990s. This motivated a higher participation in non-farm labor markets, thus reducing the net effects of the policy on off-farm labor participation. Serra et al. (2006) showed that use of inputs that are risk-increasing will have an impact on output variability. Serra, Zilberman, and Gil (2008) observed that an increase in the decoupling of government payments would likely decrease technical efficiency (technological diffusion) because higher production yields would not receive any premium because payments are not linked to yield. Mugera and Langemeier (2011) confirm this by finding that Kansas farms experienced declining technical efficiencies over the 1993 to 2007 period. However, their study was inconclusive on whether the decline in efficiency is solely because the frontier is shifting over time or that producers are falling further behind a static frontier or a combination of both factors. Technical efficiency was found to be positively related to farm size but differences in farm specializations (crop, mixed, and livestock) were insignificant.

Previous farm productivity literature has focused on total factor productivity growth at the state level. A brief review of the questions addressed by this literature can be found below. A central question in productivity decomposition analyses has been the relative importance of technology adoption (technical change) versus technology diffusion (efficiency change) in productivity growth. Another question is whether the growth rates of those two components across states or farms tend to converge over time. Ball et al. (2001) investigated the levels of farm sector productivity for the United States and nine European countries for the period 1973 to 1993. Their study found convergence of TFP over the sample period and 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.[1] The rate of beta convergence was found to be variable and depended on R&D state spillover, private R&D, and farmers' education. Ball, Hallhan, and Nehring (2004) investigated whether there was a tendency for TFP levels to converge across states and whether convergence could be explained by differences in the rates of growth of factor intensities or by productivity catch-up. They found the existence of technological catch-up. The range of TFP had narrowed over time, suggesting that states with lower initial levels of productivity grew more rapidly than those with higher initial levels of productivity. Managi and Karemera (2004) used a 48-state–level data set to measure the TFP in U.S. agriculture over the period 1960 to 1996. Total factor productivity was decomposed into input- and output-biased technical change, efficiency change, and scale change, under constant returns to scale (CRS) and variable returns to scale (VRS). Technical change was found to be the principal factor responsible for productivity increase since efficiency scores remained relatively constant. Liu et al. (2011) tested three convergence hypotheses about TFP in U.S. agriculture and examined the role of key dynamic drivers. Cross-sectional tests were conducted for σ-convergence and absolute β-convergence. A pooled cross-section and time-series test was conducted for conditional β-convergence. Strong evidence was found in favor of both absolute and conditional β-convergence, but no support for σ-convergence was found. The evidence supported the notion that states with lower initial TFP levels tended to grow more rapidly than those with higher initial TFP levels. The study by Liu et al. (2011) also provided evidence that public investments and incentives for private investment in rural health care supply and privately funded research spillovers can substantially strengthen agricultural productivity growth.

An emerging consensus from both theoretical and empirical work is that public agricultural research, public extension, and education have significant positive impacts on productivity growth. However, it has also been noted that

> most of us know less about the timing and magnitude of the important changes in agricultural output and productivity, and the direction and magnitude of changes in aggregate input use, and few know anything much about the changing composition of agricultural outputs and inputs—apart from knowing that agriculture uses much less labor and more purchased inputs than it once did [Acquaye, Alston, and Pardey 2003, p. 59].

Firm-level studies have received less attention in the productivity literature. Also, additional

[1] Beta convergence occurs when the partial correlation between growth in total factor productivity over time and its initial level is negative. Sigma convergence occurs when the dispersion of total factor productivity growth across a group of firms, states, or economies falls over time.

research pertaining to labor productivity and policy developments is merited. Empirical evidence suggests that the high growth rate in agricultural productivity is due to the growth of labor productivity (Fuglie, MacDonald, and Ball 2007, Mundlak 2005). However, with the exception of Fuglie, MacDonald, and Ball (2007), very few empirical studies have analyzed the sources of labor productivity growth in the U.S. farm sector. Therefore, the purpose of this study is to analyze labor productivity growth in the Kansas farm sector over the 1993 to 2007 period. Specifically, we follow the Kumar and Russell (2002) approach that decomposes labor productivity growth into efficiency change, technical change, and capital accumulation per worker, with the exceptions being that we compute factor intensity instead of capital accumulation and that we use firm-level data.

Methodology

This study follows the approach by Henderson and Zelenyuk (2007) to define the underlying production technology. For each farm i (i = 1, 2… n), the period-t input vector is $x_i^t = (K_i^t, L_i^t)$, 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

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

The same technology can be characterized by the following input sets:

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

We assume that the technology follows standard regularity assumptions under which the Farrell input-oriented distance function can be represented as

$$(3) \quad D_i^t \left(x_i^t, y_i^t \mid C_i^t \left(y_i^t \right) \right) = \text{ infinum} \left\{ \theta \mid x_i^t / \theta \in C_i^t \left(y_i^t \right) \right\}.$$

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

$$(4) \quad D_i^t \left(x_i^t, y_i^t \mid C_i^t \left(y_i^t \right) \right) \leq 1 \Leftrightarrow x_i^t \in C_i^t \left(y_i^t \right).$$

This function is simply the ratio of minimum (or potential) input to actual input that can produce the same amount of output. The Farrell input-oriented technical efficiency measure can thus be defined as

$$(5) \quad TE_i^t \equiv TE_i^t \left(x_i^t, y_i^t \mid C_i^t \left(y_i^t \right) \right) = \text{infinum} \left\{ \theta > 0 \mid x_i^t / \theta \in C_i^t \left(y_i^t \right) \right\} \forall y_i^t \in \Re_+^2.$$

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

Given the production technology in equation (5), we use linear programming to estimate the input distance function. The Farrell input-based efficiency index for farm i at time t is defined as

$$(6) \qquad e\left(x_i^t, y_i^t \right) = \min \left\{ \theta \mid \left\langle x_i^t / \theta, y_i^t \right\rangle \in T^t \right\}.$$

The efficiency index value for each farm is found by solving the following linear program using the data envelopment analysis (DEA) approach:

$$(7) \qquad \underset{\theta, z^1, \ldots, z^J}{\text{Minimize}} \, \theta_i$$
$$\text{subject to} \begin{Bmatrix} Y_i \leq \sum_k z_k Y_k^t \\ \theta K_i \geq \sum_k z_k K_k^t \\ \theta L_i \geq \sum_k z_k L_k^t \\ z_k \geq 0 \forall k \end{Bmatrix},$$

where θ_i is the efficiency measure to be calculated for each farm$_i$ at time t, and z_k is the intensity variable for farm k.

The above model assumes constant returns to scale (CRS). Constant returns to scale suggest that all firms operate at the optimal scale. However, imperfect competition and financial constraints may cause farms to operate below optimal scale (Coelli et al. 2005). Thus, adding equation (8) to the constraints in the above model allows for variable returns to scale (VRS).

$$\sum_{k=1}^{k} Z_k = 1 . \tag{8}$$

One of the most common critiques of the DEA approach is that it assumes no measurement error and so could potentially suffer from outliers that might be highly influential if they distort the enveloping estimator of the frontier. A smooth homogenous bootstrap DEA approach introduced by Simar and Wilson (1998, 2000) is used to allow for consistent estimation of the production frontier, corresponding efficiency scores, bias, and bias-corrected efficiency scores, as well as standard errors and confidence intervals. Bootstrapping tests the reliability of data by creating a pseudo-replicate data set. Bootstrapping also allows the assessment of whether the distribution has been influenced by stochastic effects and can be used to build confidence intervals for point estimates that cannot be derived analytically. Random samples are obtained by sampling with replacement from the original data set, which provides an estimator of the parameter of interest. With DEA bootstrapping, the data-generation process (DGP) is repeatedly simulated by resampling the sample data and applying the original estimator to each simulated sample. It is expected that the bootstrap distribution will mimic the original unknown sampling distribution of the estimators of interest (using a nonparametric estimate of their densities). Hence, a bootstrap procedure can simulate the DGP by using Monte Carlo approximation and may provide a reasonable estimator of the true unknown DGP. Further details of the DEA bootstrapping process are documented in Simar and Wilson (1998, 2000).

After computing technical efficiency scores, we follow Kumar and Russell (2002) to compute and decompose labor productivity growth into components attributed to changes in efficiency, technology change, and factor intensity. Unlike Kumar and Russell (2002), the tripartite decomposition is computed under the assumption of variable returns to scale (VRS) rather than constant returns to scale (CRS) because not all farms necessarily operate at the optimal scale. To be consistent with the 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 (6) and (7).

Assume the production function is represented by $Y = F(K,L)$, factor use 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 period, 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

$$\bar{y}_b(k_b) = y_b / e_b , \tag{9}$$

and the potential current year output per worker is

$$\bar{y}_c(k_c) = y_c / e_c . \tag{10}$$

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

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

Multiplying the numerator and the denominator of (11) by the potential output per worker during the base period $[\bar{y}_b(k_c)]$, we obtain the following:

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

Equation (12) decomposes the relative change in output-labor ratio in the two periods into change in efficiency (i.e., movement towards the best-practice frontier),

$$\left(\frac{e_c}{e_b}\right),$$

technical 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),

$$\left(\frac{\bar{y}_b(k_c)}{\bar{y}_b(k_b)}\right).$$

In this case, technical change is measured at the current period's 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 (11) by the potential output per worker during the current period $[\bar{y}_c(k_b)]$ to obtain

$$(13) \qquad \frac{y_c}{y_b} = \frac{e_c}{e_b} \times \frac{\bar{y}_c(k_b)}{\bar{y}_b(k_b)} \times \frac{\bar{y}_c(k_c)}{\bar{y}_c(k_b)}.$$

Finally, since the decomposition of productivity changes (i.e., technical change and factor intensity) is path-dependent and the choice between equations (12) and (13) is arbitrary, we follow the approach of Caves, Christensen, and Diewert (1982) and Färe et al. (1994) by computing the geometric average of the two measures of the effects of technical change and factor intensity by multiplying the numerator and denominator of equation (11) by

$$\left(\bar{y}_b(k_c)\bar{y}_c(k_b)\right)^{1/2}$$

to obtain the measure of labor productivity change:

$$(14) \qquad \frac{y_c}{y_b} = \frac{e_c}{e_b} \times \left(\frac{\bar{y}_c(k_c)}{\bar{y}_b(k_c)} \times \frac{\bar{y}_c(k_b)}{\bar{y}_b(k_b)}\right)^{1/2} \times \left(\frac{\bar{y}_b(k_c)}{\bar{y}_b(k_b)} \times \frac{\bar{y}_c(k_c)}{\bar{y}_c(k_b)}\right)^{1/2} = EFF \times TECH \times KACC.$$

In the above equation, *EFF* is the measure of efficiency change, *TECH* is the measure of technical change, and *KACC* is the measure of factor intensity between the base period *b* and current period *c*.

The technological frontier and the decomposition of labor productivity change are illustrated in Figure 1. Labor productivity is measured on the vertical axis and the 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 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 factor intensity 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. The movement along the current period frontier from point E^c to point D^c measures factor intensity. 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:

$$(15) \qquad \frac{y^c}{y^b} = \left(\frac{F^cC^c/F^cD^c}{F^bC^b/F^bD^b}\right) \times \left(\frac{F^cD^c}{F^cE^b} \times \frac{F^bE^c}{F^bD^b}\right)^{0.5} \times \left(\frac{F^cD^c}{F^bE^c} \times \frac{F^cE^b}{F^bD^b}\right)^{0.5}.$$

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

$$(16) \qquad g_Y = g_{EFF} + g_{TECH} + g_{FI},$$

where g_Y represents the average annual growth rate of output per worker, and g_{EFF}, g_{TECH}, and g_{FI} are the average annual growth rate of the efficiency index, the average annual growth rate of technical change, and the average annual growth rate of the potential outputs due to change in factor intensity, respectively. This approach is more appealing than that represented by equation (14) because the average annual growth rate of output per worker is the sum of the average annual growth rates of the efficiency index, technical change, and the factor intensity between the two periods.

Data and Descriptive Evidence

The data for this study come from the Kansas Farm Management Association (Langemeier 2010).

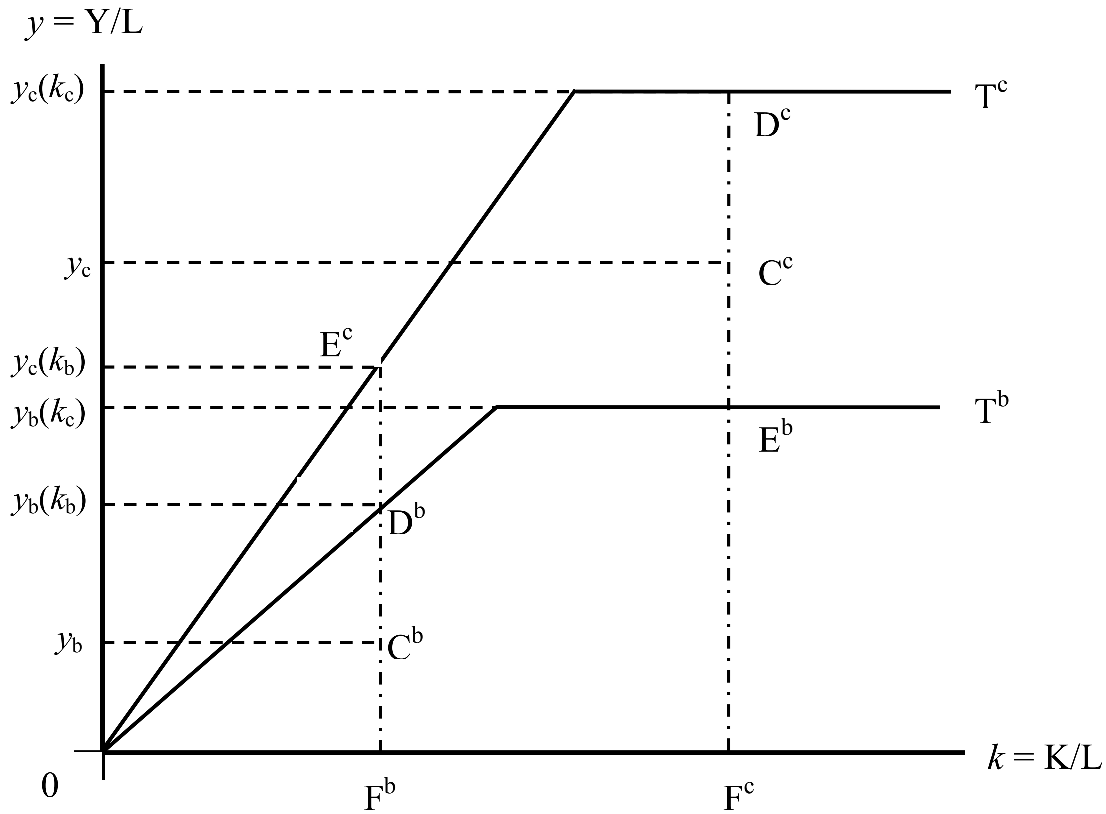

Figure 1. Illustration of Labor Productivity Decomposition

We use a balanced panel of 564 farm households for the period 1993 to 2007. The original data include two outputs—livestock and crop income—and three inputs—labor, asset charges, and purchased inputs. Labor is measured as the number of farm workers per farm per year. To obtain this value, we deflate the total annual cost of labor (which includes hired and unpaid labor) by a labor price index, with 2007 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. Asset charges are measured as a flow variable and include repairs, machine hire, auto expenses, conservation expense, cash interest, cash farm rent, real estate tax, property tax, general farm insurance, depreciation, and opportunity interest charged on owned equity. Purchased inputs are measured in dollar terms and include 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.

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 (GFI) and asset charges and purchased inputs into one input, factor use.[2]

[2] The database we used does not provide information on the allocation of variable inputs across crops and livestock enterprises. Hence, we define a single output category that aggregates crop and livestock income. The asset charges and purchased input variables are aggregated into one variable, factor use. Due to the high correlation between asset charges and purchased inputs, the magnitude of the efficiency scores would not change very much if the inputs were disaggregated.

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), U.S. Department of Commerce, and is considered to be more comprehensive and theoretically a more compelling measure of consumer prices than the Consumer Price Index (Hakkio 2008). Real factor use is calculated in the following manner. First, total factor is calculated as the sum of asset charges and purchased inputs. Second, a deflator is constructed using the price indices for purchased inputs (*Purinp*) and asset charges (*Capp*) by farm and year, with 2007 as the base year, and weighted with the total capital:

$$\text{(17)}\quad \text{deflator} = \left(\frac{\text{purchased inputs}}{\text{total capital}}\right) \times Purinp + \left(\frac{\text{asset charges}}{\text{total capital}}\right) \times Capp.$$

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

$$\text{(18)}\quad \text{real factor use} = \frac{\text{assets charges} + \text{purchased inputs}}{\text{deflator}} = \frac{\text{nominal factor}}{\text{deflator}}.$$

As with other productivity decomposition studies, no attempt is made to account for quality differences in inputs due to lack of such information in the database. However, the data is cleaned for outliers using visual inspection approaches to identify and eliminate extreme values for each pair of output and input combination (i.e., gross farm income versus factor use and gross farm income versus labor) for each year over the entire sample period, 1993 to 2007. Seaver and Triantis (1989) cautioned that it is wise to use more than one outlier detection. Therefore, scatter plots were used in conjunction with box plots to identify extreme values. After the above detection and deletion of extreme values, the remaining data had usable values for 564 farms from the original 583 farms for each year for the entire sample period.[3] The descriptive statistics of the data are presented in Table 1. In general, the series indicates an upward trend for real GFI and real capital, although real GFI exhibits more variability than real capital, possibly due to weather pattern fluctuations. Average GFI increased from $196,099 in 1993 to $384,593 by 2007. Real capital increased from $237,324 to $368,311. However, the labor input decreased from 1.56 workers to 1.38 workers during the same time period.

The observations in the sample are grouped according to farm size to provide additional insights about labor productivity growth across the farm sector. Farms are disaggregated into four groups: (i) very small farms (VSF) involve farms with less than $100,000 in GFI; (ii) small farms (SF) include farms with GFI between $100,000 and $250,000; (iii) medium farms (MF) include farms with GFI between $250,000 and $500,000; and (iv) large farms (LF) are farms with GFI above $500,000. The sample sizes within each group are not constant over time; some farms moved from one class to another as farms grew or shrank.

Empirical Results

The tripartite decomposition analysis of output per worker was estimated for the entire sample, starting from 1993/94 to 2006/2007, using 1993 as the base year. For productivity changes by farm size, the analysis concentrated on changes for three periods: 1993 to 2007, 1993 to 2002, and 1996 to 2005. The 1993 to 2002 period represents a 10-year window when real output was low, relative to the entire sample, while the 1996 to 2005 period represents a window when real output was high. The second sub-period also reflects a ten-year period after the passage of the 1996 Federal Agricultural Improvement and Reform (FAIR) Act. This farm policy legislation introduced substantial changes in the overall farm policy environment in that price support measures and deficiency payments were reduced in favor of

[3] A comparison of the average farm from the Kansas Farm Management Association (KFMA) database and the 2007 Census of Agriculture data from the U.S. Department of Agriculture (USDA) made by the authors revealed that KFMA farms accounted for approximately 6.5 percent of all farmland in Kansas in 2007. The average KFMA farm, based on total acres and average market value of sales, is approximately 2.7 times larger than the average Census farm in Kansas. The average Census farm is approximately 14 percent smaller than the average KFMA farm in 2007.

Table 1. Mean and Standard Deviation of Output, Capital, and Labor for 564 Kansas Farms

Year	Real Gross Farm Income (in $10,000)	Real Factor Use (in $10,000)	Labor Inputs (in persons/farm)
1993	19.610 (15.057)	23.732 (17.365)	1.560 (1.010)
1994	19.566 (14.842)	25.162 (18.841)	1.560 (0.970)
1995	19.764 (16.513)	25.416 (19.324)	1.570 (1.040)
1996	25.351 (21.216)	26.245 (20.161)	1.560 (1.000)
1997	27.171 (21.106)	28.244 (20.847)	1.590 (1.100)
1998	20.885 (16.521)	28.395 (20.919)	1.590 (1.080)
1999	23.325 (18.936)	29.115 (22.245)	1.550 (1.020)
2000	23.926 (19.419)	29.476 (22.473)	1.490 (0.920)
2001	24.274 (20.576)	30.458 (23.803)	1.500 (1.050)
2002	22.487 (19.300)	29.878 (23.118)	1.480 (1.000)
2003	26.508 (22.600)	30.590 (23.745)	1.470 (0.980)
2004	29.337 (26.572)	31.682 (25.137)	1.460 (0.960)
2005	29.730 (26.705)	33.557 (26.294)	1.440 (0.950)
2006	30.532 (26.273)	34.265 (26.831)	1.420 (0.920)
2007	38.459 (34.821)	36.831 (29.188)	1.380 (0.970)
Average	25.395 (22.527)	29.536 (23.149)	1.510 (1.000)

Note: Figures in parenthesis are standard deviations. Mean measured in constant 2007 dollars.

production flexibility contract payments. As noted by Serra, Zilberman, and Gil (2008), the Act had significant effect, not only on farm output price and subsidy levels, but also on farm income variability and household wealth. This could have altered the off-farm work decisions that in turn impacted labor productivity. Therefore, the 1996 to 2005 period depicts productivity changes post 1996 FAIR Act, while the 1993 to 2002 period depicts the pre- and transition period. A 10-year window is chosen to capture any effects of technological innovation. This window reflects the fact that productivity response to new technology unfolds over time. The 1997 to 2006 period was not chosen because both 1997 and 2006 represent unusual years; 1997 was followed by a slump in output and 2006 was followed by a remarkable increase in real output.

Production Frontier and Efficiency

The Kansas farm sector best-practice production frontiers for the beginning and end of the sample period, 1993 and 2007, along with the scatter plots for the output per worker versus factor use per worker, are presented in Figure 2. The estimated best-practice frontier for 2007, indicated by long dash lines, is superimposed on the best-practice frontier for 1993, indicated by the solid lines. The upward shift of the frontier between the two periods indicates technical change and the kinks on each frontier represent technically efficient farms for the specified year. It is evident from these frontiers that technology change is non-neutral. The best-practice frontiers shifted upwards between the two periods, but not by the same proportion for every value of the factor-labor ratio. This result is consistent with the observations by Managi and Karemera (2004) that rejected Hicks-neutral technical change in U.S. agriculture.

The annual average technical efficiency scores for the 564 farms under a VRS technology are presented in Table 2. The 15-year average technical efficiency score for 1993 to 2007 is 59.3 per-

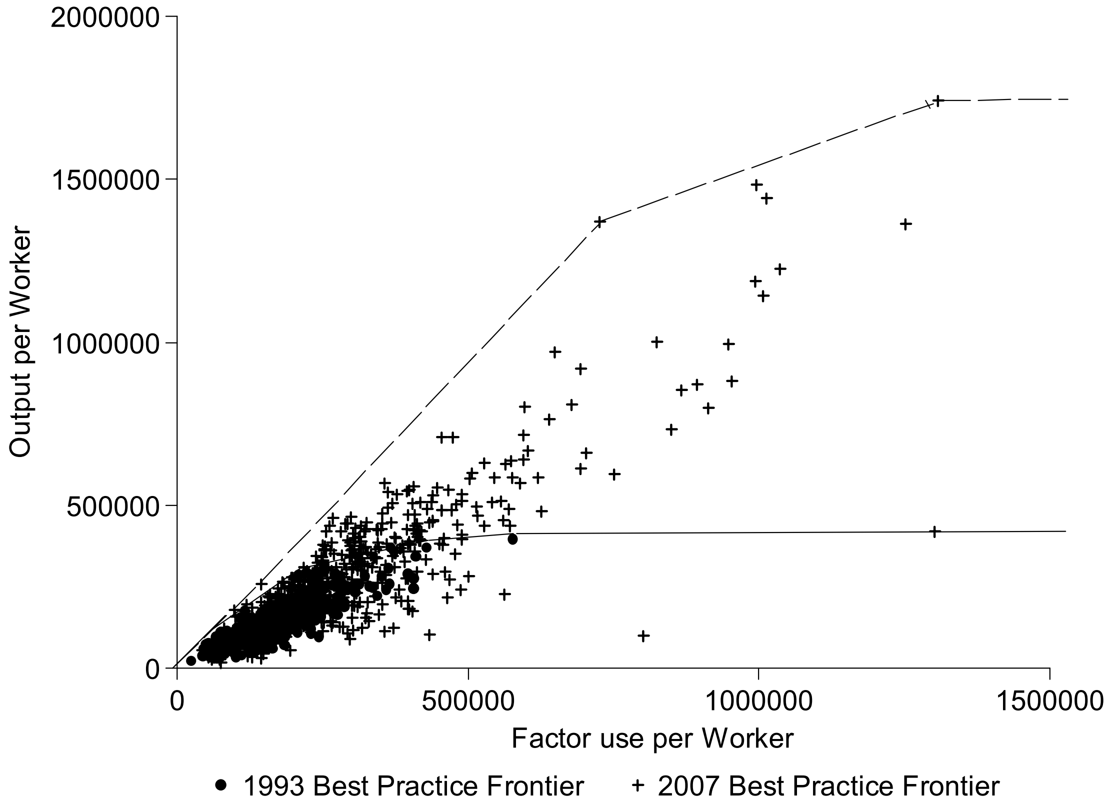

Figure 2. 1993 and 2007 Kansas Farm Sector Production Frontiers

cent and the bias-corrected score[4] is 55.0 percent. The average efficiency score by year varied from a minimum of 51.6 percent in 2005 to a maximum of 64.5 percent in 2001. For the bias-corrected technical efficiency score, the minimum by year was 45.8 percent (2005) and the maximum was 60.5 percent (2001). The lower bound ranged from 44.1 percent (2005) to 58.7 percent (2001), while the upper bound ranged from 50.6 percent (2005) to 63.9 percent (2001). 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). This range reflects the uncertainty about the real value of the efficiency score. The empirical results suggest that Kansas farms are technically inefficient and have been facing efficiency deterioration over time. In general, the reported results are consistent with those reported in the 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.

Tripartite Decomposition of Labor Productivity

Table 3 reports the annual growth rates of output per worker and the decomposition of the contribution of efficiency change, technical change,

[4] The deterministic DEA can be treated as an estimate of the frontier based on a single sample drawn from some unknown population. Estimates of efficiency scores from the deterministic DEA model are biased because the estimated points on the observed production frontier may be inefficient in the presence of the "true" production frontier. Bootstrap DEA is based on the idea that the known bootstrap distribution will mimic the unknown sampling distribution of the estimator of interest. The empirical bootstrap distribution is used to estimate the bias defined as the difference between the empirical mean of the bootstrap distribution and the original efficiency point estimates. The bias-corrected estimator is obtained by subtracting the bias from the original efficiency estimates.

Table 2. Input-Oriented Technical Efficiency Scores with Variable Returns to Scale Model for Kansas Farms

Year	Efficiency Score	Bias Corrected Efficiency Score	Bias	Standard 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
Average	0.5925	0.5499	0.0426	1.9033	0.5321	0.5858

Note: Mean technical efficiency scores were bootstrapped with 2,000 iterations. Total number of farms for each year is 564.

and factor intensity to labor productivity growth.[5] The growth rate of labor productivity between two consecutive years is the sum of the growth rates of efficiency change, technical change, and the contribution of the increase in factor intensity. On average, productivity grew at an annual average rate of 5 percent, of which 3.18 percent is accounted for by factor intensity and 2.81 percent by technical change. Efficiency change declined by an average of 0.98 percent, suggesting that most farms did not experience efficiency catch-up in the sample period. Labor productivity growth was lowest between 1997 and 1998 and highest between 1995 and 1996, possibly due to weather fluctuations. The period 1997 to 1998 was El Niño years. El Niño winters are expected to be wet in the Great Plains, but this period was very dry. The November–January period was one of the driest on record in Kansas and winter wheat deteriorated badly with the worsening drought (Martell 2003).

The reported results indicate that high rates of technical progress can coexist with deteriorating technical efficiency performance. Likewise, relatively low rates of technical progress can also coexist with an improving technical efficiency performance. The technical change component of productivity growth captures shifts in the frontier and can be interpreted as a measure of innovation or adoption of new technology by “best practice” farms, while efficiency change is a measure of diffusion of technology. Full technical efficiency is achieved by following the best practice techniques, given the available technology. Thus, technical efficiency is determined by the method of application of inputs, regardless of the level of inputs, and different methods of applying various inputs will influence the output differently. Coexistence of high rates of technical change and

[5] We have also replicated our analysis using a stochastic frontier approach to confirm that our results are robust to different frontier estimated methods. Those results are available from the authors upon request.

Table 3. Tripartite Decomposition of Labor Productivity Growth, 1993–2007

Period	Annual Growth Rate of Change in ... Output per Worker (g_Y)	Efficiency (g_{EFF})	Technology (g_{TECH})	Factor Intensity (g_{FI})
1993–1994	-0.52	0.37	-4.79	3.89
1994–1995	-4.44	-11.23	7.56	-0.76
1995–1996	25.67	4.67	18.49	2.51
1996–1997	9.63	7.89	-4.41	6.15
1997–1998	-28.00	-1.94	-26.95	0.89
1998–1999	12.81	-17.40	27.14	3.06
1999–2000	4.41	20.32	-18.40	2.49
2000–2001	1.64	0.12	-1.77	3.30
2001–2002	-7.75	-10.74	3.74	-0.75
2002–2003	16.96	-12.86	27.74	2.08
2003–2004	9.82	18.91	-12.72	3.62
2004–2005	1.42	-23.02	18.91	5.54
2005–2006	4.41	8.55	-6.50	2.36
2006–2007	24.00	2.59	11.30	10.11
Average	5.00	-0.98	2.81	3.18

Note: The reported estimates are growth rates and the following equality holds: $g_Y = g_{EFF} + g_{TECH} + g_{FI}$.

low rates of efficiency change, and vice versa, may reflect the failures in achieving technological mastery or diffusion.

To gain deeper insight on the changes in productivity, each subsequent year can be compared with the base year (i.e., 1993) 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 a pair of two adjacent years over the sample period. The findings in Table 4 confirm the results of the previous analysis: namely, that labor productivity change is primarily driven by changes in factor intensity and technical change. Specifically, between 1993 and 2007, productivity across the whole farm sector grew at an average of 5 percent, which comprised of growth in factor intensity and technical change of 3.21 percent and 2.77 percent, respectively, and a decline in efficiency of 0.98 percent. Relative to the base year, 1993, productivity growth was lowest in 1994 and 1995 and highest in 1996 and 1997.

Tripartite Decomposition by Farm Categories

Table 5 shows the mean growth rates of labor productivity and its three components—efficiency change, technical change, and factor intensity—for three periods (1993 to 2007, 1993 to 2002, and 1996 to 2005) disaggregated by farm size.[6] The sample is decomposed into two sub-periods to reflect fluctuations in output due to weather and other factors such as policy changes. The 1993 to 2007 period captures labor productivity dynamics over the entire period. The second and third time periods capture the productivity dynamics between two sub-periods (i.e., 1993 to 2002 and 1996 to 2005) when real output was at its lowest and highest, respectively. Also, the 1996 to 2005 sub-period reflects labor productivity changes after the 1996 farm policy legislation.

[6] Samples were grouped by year and only one frontier was estimated for each year.

Table 4. Decomposition of Cummulative Labor Productivity Growth Relative to 1993

Period	Annual Growth Rate of Change in ... Output/Worker (g_Y)	Efficiency (g_{EFF})	Technology (g_{TECH})	Factor Intensity (g_{FI})
1993–1994	-0.52	0.37	-4.79	3.89
1993–1995	-2.48	-5.43	1.55	1.40
1993–1996	6.91	-2.06	7.13	1.84
1993–1997	7.59	0.43	3.97	3.19
1993–1998	0.47	-0.05	-2.03	2.55
1993–1999	2.52	-2.94	2.82	2.64
1993–2000	2.79	0.38	-0.26	2.67
1993–2001	2.65	0.35	-0.29	2.59
1993–2002	1.49	-0.88	0.25	2.12
1993–2003	3.04	-2.08	2.79	2.33
1993–2004	3.66	-0.17	1.40	2.43
1993–2005	3.47	-2.08	3.29	2.26
1993–2006	3.54	-1.26	2.02	2.78
1993–2007	5.00	-0.98	2.77	3.21

Notes: The reported estimates are growth rates and the following equality holds: $g_Y = g_{EFF} + g_{TECH} + g_{FI}$.

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

	Productivity Growth (g_Y)			Efficiency Change (g_{EFF})			Technical Change (g_{TECH})			Factor Intensity (g_{FI})		
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 Farms	5.00	1.34	2.09	-0.98	-0.79	-1.87	2.79	0.29	1.79	3.20	1.91	2.18
Very Small Farms	0.92	-1.20	-0.27	-2.98	-2.35	-4.04	2.14	0.35	1.97	1.75	0.80	1.81
Small Farms	3.81	1.52	1.85	-1.11	-0.69	-2.06	2.20	0.14	1.86	2.72	2.07	2.06
Medium-Sized Farms	5.63	3.23	3.01	-0.34	0.32	-0.97	2.63	0.25	1.64	3.34	2.66	2.33
Large Farms	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: The reported estimates are growth rates and the following equality holds: $g_Y = g_{EFF} + g_{TECH} + g_{FI}$.

By comparing the results for each sub-period, it is evident that productivity growth was high in the 1996 to 2005 sub-period (2.09 percent) due to the high rates of advancement in technology (1.79 percent) and factor intensity (2.18 percent). In contrast, productivity growth was low in the 1993 to 2002 period (1.34 percent), due mainly to the slow rate of technical change (0.29 percent). A breakdown of the results by farm size provides evidence that productivity growth varies by farm size. Deterioration in efficiency was the norm in the three periods; it was inversely related with farm size, with very small farms deteriorating at a higher rate relative to small farms, medium-sized farms, and large farms. The annual rate of growth in productivity was high in the 1993 to 2007 period (5 percent) compared to the 1993 to 2002 period (1.34 percent) and the 1996 to 2005 period

(2.09 percent). Very small farms achieved higher growth rates in technical change in the 1993 to 2002 and 1996 to 2005 periods compared to small farms and medium-sized farms. Medium-sized farms achieved higher growth in factor intensity in the 1993 to 2002 and 1996 to 2005 periods compared to small farms and very small farms (0.80 percent and 1.81 percent, respectively). Large farms had relatively higher levels of productivity change, efficiency change, technical change, and factor intensity rates during the 1993 to 2007 period.

Overall, the finding that productivity varied by farm size category supports evidence of consolidation of farms during the study period. Large farms were associated with high productivity growth, over the entire period and the two sub-periods, which was driven by high growth in factor intensity, while small farms were characterized with low productivity growth due to higher rates of efficiency deterioration and low growth in factor intensity. Factor intensity seems to be the primary driver of consolidation. Efficiency change deterioration was particularly problematic during the 1996 to 2005 sub-period or following the 1996 farm policy legislation. Without technical change and changes in factor intensity, the productivity difference between very small farms and large farms would have been even larger.

Summary and Conclusions

This article focused on decomposing labor productivity growth in the Kansas farm sector into components attributable to efficiency change, technical change, and factor intensity. Changes in productivity were computed sequentially for two subsequent years (i.e., from 1993/1994 to 2006/2007) and cumulatively by using 1993 as the reference base year (i.e., from 1993/1994 to 1993/2007) using the Kumar and Russell (2002) tripartite decomposition approach.

The main findings are that the Kansas farm sector experienced growth in labor productivity over the sample period, although the growth varied by year and farm size. The significant year-to-year fluctuations in productivity can be attributed to weather, policy interventions, general economic conditions, and other factors. Factor intensity and technical change were found to be the main sources of productivity growth. On average, output per worker grew at an annual rate of 5.0 percent, with factor intensity and technical change accounting for 3.2 percent and 2.8 percent of the growth, respectively. Efficiency change, on average, accounted for an annual productivity decline of about 1 percent. This implies that, on average, farms were further away from the best-practice frontier in 2007 than in 1993. 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 factor intensity, suggesting that innovation is embodied in factor intensity (i.e., use of purchased inputs and capital).

The annual growth rate in output per worker was found to vary with farm size, an indication that farm size is an important component of productivity growth. Potential policies and educational endeavors related to improving productivity should take this into account. Very small farms experienced a decline in productivity over the sample period. In contrast, large farms experienced relatively high growth rates in productivity and its components. The role played by technical change in productivity growth is important because changes in efficiency alone cannot sustain productivity growth. Once the farms are able to achieve technical efficiency, productivity can be increased only by innovation (i.e., upward shift of the frontier). As noted by Fuglie, MacDonald, and Ball (2007), agriculture is more dependent on improvements in technology as a source of growth than is the rest of the U.S. economy. Technical change was high across farms and occurred at high levels of factor intensity. Large farms experienced notably higher rates of technical change and factor intensity over the study period than small farms.

Finally, the measures of labor productivity growth and its components provide insight into the dynamic nature of production processes. In addition to providing useful benchmarks to agricultural producers, the measures reported in this study also have important policy implications. For example, policy actions intended to improve the rate of productivity growth might be misdirected if they focus on accelerating the rate of innovation (technical change) in circumstances where the cause of low productivity growth is due to the low rate of technical efficiency improvements (efficiency change). Declining performance in technical efficiency indicates a great potential for the Kansas farm sector to increase labor productivity by eliminating mistakes in the production process through, for example, education and training programs.

At least two issues not addressed in this study warrant further research. The persistently low rates of technical efficiency suggest that it might be more difficult (i.e., expensive) to diffuse technologies than to shift the production frontier. Therefore, an extension of this study would be to further analyze the cost of increasing efficiency versus the cost of shifting the technological frontier. Also, it would be interesting to explore how the quantity and quality of inputs across geographic locations impact efficiency.

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