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Technological Change in Illinois Agriculture, 1982–1984

Richard Grabowski[1], Steven Kraft[2], Seyed Mehdian[3] and Carl Pasurka[4]

[1]*Department of Economics*
and [2]*Department of Agribusiness Economics, Southern Illinois University at Carbondale, Carbondale, IL 62901 (U.S.A.)*
[3]*Department of Finance, Temple University, Philadelphia, PA (U.S.A.)*
[4]*Department of Economics, Loyola University, Chicago, IL (U.S.A.)*

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Abstract

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This paper has two main purposes: (1) to develop a method for measuring the extent and bias of technical change which involves the use of non-parametric production frontiers and does not require information on prices or factor shares; (2) to apply this method to individual farm data drawn from a sample of Illinois grain farms for the years 1982 and 1984. The results indicate that technical innovation is land using in nature and that the rate of technical change is related to the size of farm.

Introduction

This paper has two main purposes. First, a method for measuring the extent and bias of technical change is developed. Economists have become increasingly concerned with analyzing the process of technical change. Much of this work has centered on explaining the rate and bias of technical innovation. The main problem is that many of the methods require data on factor prices or shares which are often not available. This paper presents an alternative method for measuring the rate and bias of technical change which does not require information on factor prices or shares.

The second purpose of this paper is to apply this theoretical framework to individual farm data drawn from a sample of Illinois grain farms for the years 1982 and 1984. The extent and bias of technical innovation are determined. In addition, an analysis of the results assesses whether the rate of technical in-

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novation is related to: (1) the size of farm, (2) tenancy, or (3) the amount of land set aside in governmental programs. Given the problems confronting farmers in the United States, it is important to know which of these characteristics influence the rate of technological change.

In the next section, various methods which have been used in the past for measuring the extent and bias of technical change are discussed. The alternative theoretical framework used in this paper is presented in detail. Section 2 presents the empirical results.

1. Methodology

In a recent survey paper, Diewert (1980) discussed four basic approaches to measuring the rate of increase in total factor productivity or technical change. For ease of presentation in this paper, two of these approaches are combined so that three methods are discussed: the econometric approach, the index number approach, and the non-parametric programming approach. In order to make the discussion general, the last category is also modified to represent both parametric or non-parametric programming approaches to measuring productivity increases.

The multiple output econometric approach usually makes use of a joint cost function c defined as:

$$c(y, w, t) = \min_x \{w \cdot x (y, x) \in S_t\} \tag{1}$$

where $y \equiv (y_1, y_2, ..., y_m)$ is a vector of outputs, $w \equiv (w_1, w_2, ..., w_n)$ is a positive vector of input (rental) prices that the producer faces, $x \equiv (x_1, x_2, ..., x_n)$ is a non-negative vector of inputs utilized, $wx = \sum w_n x_n$, and S_t denotes the firm's period t production possibilities set. The econometric approach to measuring shifts in the production function rests on a number of assumptions: (1) that producers competitively minimize cost, and (2) that a conventional functional form for cost can be specified. Given the assumptions, a system of input demand equations is derived to which error terms are added. The resulting system of equations is then used to estimate econometrically the unknown parameters of c. Once c has been determined, summary measures of the shift in productivity ($\partial \ln c/\partial t$) can be calculated. A more detailed discussion of this approach is provided in the discussion below concerning the determination of the bias of technical change.

The second approach involves the use of index numbers. Let $y(t) = \mathrm{f}(x(t), t)$ be output at time t, and let $x(t) \equiv (x_1(t), x_2(t), ..., x_n(t))$ denote the vector of inputs utilized at time t. Assuming that the production function f is differentiable, differentiating $y(t) \equiv \mathrm{f}(x(t), t)$ with respect to t and dividing both sides by $\mathrm{f}(x(t), t)$ gives:

$$\frac{\dot{y}(t)}{y(t)} = \sum_{n=1}^{N} \left[\frac{\partial \ln \mathrm{f}(x(t), t)}{\partial x_n}\right] \dot{x}_n(t) + \frac{\partial \ln \mathrm{f}(x(t), t)}{\partial t} \tag{2}$$

where $\dot{y}(t)$ and $\dot{x}_n(t)$ are time derivatives. If the price of output is $p(t)$ at time t and the producer pays each input the value of their marginal product so that the nth input price $w_n(t)=p(t)\,\partial f(x(t),t)/\partial x_n$, then equation (2) can be rearranged to give:

$$\frac{\partial \ln f(x(t),t)}{\partial t}=\frac{\dot{y}(t)}{y(t)}-\sum_{n=1}^{N} S_n(t)\frac{\dot{x}_n(t)}{x_n(t)} \tag{3}$$

where $S_n(t)\equiv w_n(t)\,x_n(t)/p(t)\,y(t)$. In other words, the left-hand side of equation (3) gives the rate of growth in output which is unexplained by the growth in inputs. If continuous data on output, inputs, and input prices are available, then equation (3) can be calculated.

The main difficulty with both approaches is that they require data on factor shares and/or input price data. Lacking such data makes it impossible to measure the extent of technological change using these approaches. Even assuming that such data are available, there is a more fundamental problem with using these approaches. Both procedures assume that individual operations or observations are efficient. As a result, all of the shift in the cost function and all of the difference between output and input growth is attributed to increased productivity or technological change. When one allows for the possibility that firms may not be efficient, then part of the increase in output may be due to improved efficiency of operation, not technical change.

Nishimizu and Page (1982) make this idea clear through the use of a simple diagram. In Fig. 1, g_1 and g_2 represent linear homogeneous Cobb–Douglas frontier production functions with technical progress between periods 1 and 2. A frontier production function gives the maximum possible output which can be produced from various quantities of a set of inputs. The word 'frontier' implies that points occur below or on the frontier, but never above it. Points A and C are observed levels of output y_1 and y_2 (in logarithms) for input x_1 and x_2 (in logarithms) at time periods 1 and 2 for the same observation. As can be seen, observation A lies below the frontier (g_1) for period one, i.e., it is producing less that its potential output in time period 1, $\hat{y}_1$. Line segment AB is a projec-

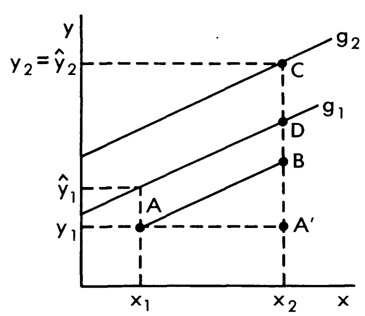

Fig. 1. Technical change and efficiency.

tion from point A assuming constant returns to scale. Finally, observation C (time period 2) lies on time period 2's frontier (g_2). Observation C is producing the maximum level of output $y_2 = \hat{y}_2$ ($\hat{y}_2$ is the maximum potential output of observation C).

The total increase in output between periods 1 and 2 is A′C. The total factor productivity approach attributes A′B of the increase to increased input usage while the rest, BC, is the result of technical change. Obviously, this is incorrect. The distance from B to D represents an improvement in technical efficiency and only DC represents technical change. In order to correctly measure technical change, Nishimizu and Page (1982) suggest that production frontiers be constructed for each year. Measuring the shift in the production frontier through time is used to calculate technical change.

In order to use the approach suggested above, production frontiers are constructed for a sample of observations at different points of time. There are four methods available for constructing these frontiers. The first method is the deterministic non-parametric approach (Farrell, 1957) which uses linear programming to construct the frontier. No parametric form is specified and the method uses the entire sample of observations, but constrains all points in output space to lie on or below the frontier. Although this technique corresponds most closely to the theoretical concept of a frontier, empirically it is sensitive to errors in observations (the outlier problem). More will be said below concerning this method.

The second approach involves constructing a deterministic parametric frontier. The only difference between this method and the deterministic non-parametric method is that the frontier is constructed using a specific functional form. This method was first suggested by Farrell and has been extended by Aigner and Chu (1968). The principle advantages of this method are the ability to characterize frontier technology in a simple mathematical form and the ability to easily accommodate non-constant returns to scale. There are two main drawbacks. First, the method is deterministic and thus no allowance is made for noise, measurement error, etc. The second drawback is the inability to deal easily with multiple outputs.

The third method, in contrast to the previous two, uses statistical techniques to construct a deterministic frontier. The technique was first proposed by Afriat (1972) and has been extended by Richmond (1974) and Greene (1980). This method involves assuming some sort of functional form for the frontier and estimating it. The easiest way to estimate it is by using corrected ordinary least squares (COLS). The functional form chosen (usually Cobb–Douglas) is first estimated using OLS and then the constant term is corrected by shifting it up until no residual is positive and at least one is zero.

Another way of estimating the frontier is by maximum likelihood techniques. However, there are several difficulties involved. First, the estimated parameters depend on the particular distribution assumed for the error term.

Second, not just any one-sided error term will do. The usual desirable asymptotic properties of maximum likelihood estimators hold only if the density of the error term satisfies certain conditions. Greene has shown that the gamma density satisfies these conditions. However, it is disturbing that the assumption regarding the distribution of technical inefficiency is governed by statistical convenience.

Overall, the advantage of using the deterministic statistical method to construct frontiers is the possibility of statistical inference based on the results. The disadvantages are that all deviations in the frontier are attributed to technical inefficiency and that a functional form must be specified.

The final method involves the estimation of a stochastic frontier. This involves specification of a functional form and uses statistical techniques (maximum likelihood) to estimate the frontier. However, in contrast to the deterministic statistical frontier method, this method allows the frontier to be stochastic. The essential idea is that the error term is composed of two parts. A symmetric component permits random variation of the frontier across observations and captures the effects of measurement error, random shocks, etc. A one-sided component of the error term captures the effects of inefficiency. This method was first proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977), and has been extended by Schmidt and Lovell (1980) and Huang (1984), among others.

There are a number of drawbacks to using this method. First, considerable structure is usually imposed on the technology. In addition, the distribution of the one-sided error term must be specified when the model is estimated. Thus, additional structure is imposed on the distribution of technical inefficiency. Finally, the method has difficulty in dealing with multiple outputs.

Nishimizu and Page (1982) constructed a deterministic parametric frontier. This required them to specify a functional form and they chose the translog production function. This function imposes fewer restrictions on the structure of production than does the Cobb–Douglas. However, it still imposes a structure on the technology. They chose not to use the stochastic method because the distribution of the one-sided component of the error term must be specified and there is little guidance concerning the appropriate specification.

This paper presents a theoretical framework to measure technological change which is an improvement over that derived by Nishimizu and Page. A non-parametric deterministic method, based on the work of Diewert (1980) and Diewert and Parkan (1983), will be used in constructing the frontiers. The advantage of the non-parametric method is that no structure is imposed upon the technology.

A number of different approaches have been used to measure the bias of technical innovation. The most popular method involves estimating the translog cost function. For example, Nghiep (1979) estimated a translog cost function:

$$\ln C = v_0 + v_Y \ln Y + v_T \ln T + \sum_{i=1}^{n} V_i \ln P_i + 1/2 \sum_{i=1}^{n} \sum_{j=1}^{n} \sigma_{ij} \ln P_i \ln P_j \qquad (4)$$

$$+ \sum_{i=1}^{n} \sigma_{iY} \ln P_i \ln Y + \sum_{i=1}^{n} \sigma_{iT} \ln P_i \ln T + \sigma_{YT} \ln Y \ln T$$

where $\sigma_{ij} = \sigma_{ji}$, $\sum_i v_i = 1, \sum_i \sigma_{ij} = 0$, $\sum_i \sigma_{iY} = 0$, and $\sum_i \sigma_{iT} = 0$. The terms C, Y and T are respectively, cost, output, and time. The share equations are what are actually estimated and these are written as:

$$\frac{\partial \ln C}{\partial \ln P_i} = v_i + \sum_{j=1}^{n} \sigma_{ij} \ln P_j + \sigma_{iT} \ln T \qquad (5)$$

where P_j represents input prices, and T is time. The latter serves as a proxy for technical change. As a consequence, the bias of innovation is determined by examining the signs and relative sizes of the coefficients for the time variable in each of the share equations.

Hayami and Ruttan (1985) attempted to measure the bias of technical change by using a two-level constant elasticity of a substitution (CES) production function. They specify factor augmenting technical change. Output is assumed to be produced by n inputs $(X_1, ..., X_n)$ with corresponding factor augmenting coefficients $(E_1, ..., E_n)$, where E_i represents the efficiency of X_i. The production function is written as:

$$Q = f(E_1 X_1, ..., E_n X_n) \qquad (6)$$

where the production function is assumed to be linear homogeneous and well-behaved.

The factor using bias of the technology is evaluated by examining changes in factor shares. The expression for the rate of change in factor shares is:

$$\frac{\dot{S}_i}{S_i} = \sum_{j \neq i} S_j (\sigma_{ij} - 1) \left(\frac{\dot{P}_j}{P_j} - \frac{\dot{P}_i}{P_i} \right) + \sum_{j \neq i} S_j (1 - \sigma_{ij}) \left(\frac{\dot{E}_j}{E_j} - \frac{\dot{E}_i}{E_i} \right) \qquad (7)$$

where the dot denotes the time derivative, P_i is the price of input i, S_i is the factor share of input i, and σ_{ij} is the Allen partial elasticity of substitution between input i and j. All other variables are as defined above. It follows that the rate of change in the ith factor share is decomposed into the price induced factor substitution effect (the first term on the right-hand side) and the biased technical change effect (the second term).

The major difficulty with the approaches to measuring the bias of technical innovation discussed above is that they require data which are often not available. Specifically, factor input prices and/or factor share data are required in order to be able to measure the bias of technical change. The approach specified in this paper does not require that information. Instead, the approach outlined below only requires data on outputs and inputs.

As discussed earlier, the method used here to construct the production frontier is based upon he work of Nishimizu and Page (1982). However, in constructing the production frontier no parametric specification is imposed on the technology. In other words, a non-parametric deterministic approach is used to construct the frontier. In addition, instead of constructing an output based frontier, an input based frontier is used.

The method developed here is an extension of Farrell's (1957) work on measuring technical efficiency as well as extensions of his work (Färe, Grosskopf and Lovell, 1985). In this type of analysis technical efficiency is defined as producing the maximum of output for any particular combination of inputs, holding technology constant. Farrell provided a methodology by which technical efficiency is measured. Consider a firm using two inputs x_1 and x_2 and producing output y_1. Assume that the firms production function (frontier) is written as $y = f(x_1, x_2)$ and that it is characterized by constant returns to scale. As a result, the production function is written as $1 = f(x_1/y, x_2/y)$. This frontier technology is characterized by the unit isoquant which is labeled I_o in Fig. 2. Assume that A represents an observation for a particular firm. Then the ratio OB/OA measures technical inefficiency. This is an input based measure of technical inefficiency because it measures the proportional reduction in inputs that could occur while still producing the same level of output (Førsund, Lovell and Schmidt, 1980).

The efficient unit isoquant is not directly observable. However, the free disposal convex hull of the input–output ratios can be constructed using linear programming techniques. In this case, a linear programming technique is used to envelope all of the observations. All of the observations must lie on or above the unit isoquant. The methodology is non-parametric in the sense that no

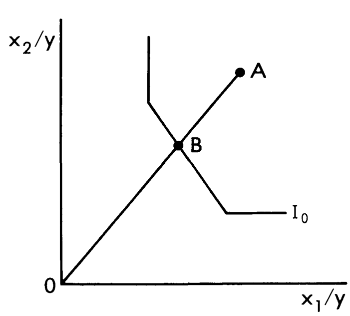

Fig. 2. Measuring technical efficiency.

functional form is specified to construct the efficiency frontier. This programming approach is the last of the approaches mentioned earlier for measuring the rate of increase in productivity.

Given this introduction, several points need to be made. First, this approach can be utilized for either pooled data (cross-sectional and time series data) or strictly time series data. Second, the assumption of constant returns to scale is rather restrictive. However, this assumption has been relaxed in recent work on constructing efficiency frontiers (Färe and Lovell, 1978).

A methodology for measuring the extent and bias of technical innovation can now be developed. We assume that cross-sectional data are available for years 1 and 2 (a later year) for the same set of firms. Isoquant I_1 in Fig. 3 is constructed by using the cross-sectional data for year 1. I_2 is constructed using the pooled data for years 1 and 2. Point A represents an observation for a specific farm in year 1. Labor (N) and capital (K) are measured on the horizontal and vertical axis, respectively.

It is possible to determine the extent of technical change for observation A in Fig. 3 by measuring:

$$\frac{OB-OC}{OB}=1-\frac{OC}{OB} \tag{8}$$

This gives the proportional shift inward of the isoquant along ray OA. Equation (8) is derived by calculating the technical efficiency of observation A relative to isoquant I_1, OB/OA, and then calculating the technical efficiency of observation A relative to isoquant I_2, OC/OA. Dividing the latter by the former yields OC/OB. Substituting this result into equation (8) yields the proportional shift inward of the isoquant, given the factor proportions of observation A. This procedure is used to calculate the proportional shift in the isoquant for each observation in year 1's data set.

The actual derivation involves solving two linear programming problems. Since there are n observations in year 1's data set, the first linear programming problem is:

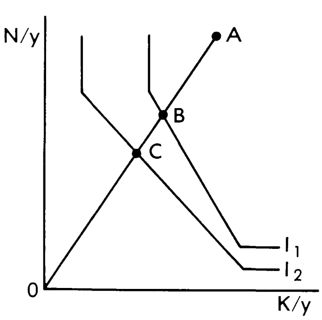

Fig. 3. Technological change.

$$\text{Min } \lambda$$

subject to

$$N_1^1 z_1^1 + N_2^1 z_2^1 + N_A^1 z_A^1 + \ldots + N_n^1 z_n^1 \leq \lambda N_A^1$$

$$K_1^1 z_1^1 + K_2^1 z_2^1 + K_A^1 z_Z^1 + \ldots + K_n^1 z_n^1 \leq \lambda K_A^1$$

$$y_1^1 z_1^1 + y_2^1 z_2^1 + y_A^1 z_A^1 + \ldots + y_n^1 z_n^1 \geq y_A^1$$

The subscripts refer to a specific observation and the superscript indicates that all observations are drawn from year 1. This program calculates the efficiency of observation A relative to I_1. The first two constraints are input constraints for labor, *N*, and capital, *K*. The constraint for capital is discussed in detail in order to give the reader an economic interpretation of the constraint. The left-hand side of the constraint represents the theoretically technically efficient observation. This is composed of a weighted sum of all observations, including observation A. The *z*'s are weights assigned to each observation by the LP problem. The right-hand side is the actual level of K_A^1, for observation A in the year 1, multiplied by the level of inefficiency, λ. If the observation is technically efficient, then $\lambda = 1$ and the left and right-hand sides are equal. In this case, level of usage of capital, K_A^1, is the same as the theoretically efficient level ($\lambda = 1$). If the observation is inefficient, $\lambda < 1$, meaning that capital actually used can be reduced without reducing output.

The last constraint in (9) is the output constraint. In this model, a single output approach is used, there is only one *y*-product by *n* observations. The left hand side is the theoretically technically efficient level of output to which the actual output of observation A in year 1, y_A^1, is compared. The theoretically efficient observation is a linear combination of all observations in the data set, including observation A. This constraint says that the efficient level of output must be equal to or greater than the amount produced by observation A. In summary, the solution to this program will give, in Fig. 2, OB/OA.[1]

The above linear programming procedure could be easily expanded to the case of multiple outputs. For each additional output an additional output constraint is added to (9). Thus if two outputs *y* and *w* were used, an additional output constraint for *w* is added and the linear programming problem is:

$$\text{Min } \lambda$$

subject to (10)

$$N_1^1 z_1^1 + N_2^1 z_2^1 + N_A^1 z_A^1 + \ldots + N_n^1 z_n^1 \leq \lambda N_A^1$$

[1]In this simple one output, two input case the isoquant could actually be plotted graphically. However, in the multiple input case used in this paper this will not be possible.

$$K_1^1 z_1^1 + K_2^1 z_2^1 + K_A^1 z_A^1 + ... + K_n^1 z_n^1 \leq \lambda K_A^1$$

$$y_1^1 z_1^1 + y_2^1 z_2^1 + y_A^1 z_A^1 + ... + y_n^1 z_n^1 \geq y_A^1$$

$$w_1^1 z_1^1 + w_2^1 z_2^1 + w_A^1 z_A^1 + ... + w_n^1 z_n^1 \geq w_A^1$$

The second program measures the technical efficiency of observation A relative to isoquant I_2. The linear programming problem is:

Min β

subject to (11)

$$N_1^1 z_1^1 + ... + N_A^1 z_A^1 + ... + N_n^1 z_n^1 + N_1^2 z_1^2 + ... + N_A^2 z_A^2 + ... + N_n^2 z_n^2 \leq \beta N_A^1$$

$$K_1^1 z_1^1 + ... + K_A^1 z_A^1 + ... K_n^1 z_n^1 + K_1^2 z_1^2 + ... + K_A^2 z_A^2 + ... + K_n^2 z_n^2 \leq \beta K_A^1$$

$$y_1^1 z_1^1 + ... + y_A^1 z_A^1 + ... y_n^1 z_n^1 + y_1^2 z_1^2 + ... + y_A^2 z_A^2 + y_n^2 z_n^2 \geq y_A^1$$

where the subscript refers to the specific observation and the superscript indicates the sample year. Thus N_A^1 and N_A^2 represent the amount of labor used by observation A in year 1 and year 2, respectively. The first two constraints are again input constraints. However, note that the linear programming problem involves pooling the observations for the same set of firms for two different years. As a result, the solution to this program yields OC/OA.[2] Note that this procedure also can handle additional outputs by adding additional output constraints.

Taking β and dividing by λ yields OC/OB. Substituting this into equation (8) determines the proportional shift in the isoquant along ray OA. If equation (8) is positive, then the isoquant has shifted inwards and technical change has occurred. The same procedure is used for each observation and the rate of technical change is calculated for each observation.

Once the above procedures are completed, it is possible to investigate the bias of innovation. This involves estimating regression equations in which the rate of technical change for each observation is specified as the dependent variable, while measures of relative factor intensities are used as independent variables. In the two input (N and K) example, labor and capital intensities are writen as $N/(N+K)$ and $K/(N+K)$ (N and K are measured in dollars). By examining the sign and level of significance for each coefficient, one could determine whether technical change is in any way related to factor intensities.

2. Empirical analysis

The data used in this paper consist of information on production for a sample of 92 grain farms in central Illinois. The data contain information on input

[2]Note that the z's are constant across all observations in (9). In other words, as the efficiency measure for each observation is calculated the weights used to construct the frontier isoquant remain unchanged. This also holds for the z's in (10) and (11).

and output for these farms for 2 years, 1982 and 1984. A farm is considered a grain farm if the value of feed fed to livestock is less than 25% of the value of crop returns and if the value of feed fed to dairy and poultry is not more than one-sixth of the crop returns. The data source was the Illinois Farm Business Farm Management Farm Business Analysis 1982 and 1984 data tape *Annual Summary of Illinois Farm Business Records*.

The farms in the sample produce a variety of grains including: corn, soybeans, wheat, and double crop soybeans. The inputs in this sample are land, labor, fertilizer, pesticides, seeds, equipment, and buildings. The land variable is defined as tillable acres multiplied by a soil productivity index (Fehrenbucher et al., 1978). This gives a measure of effective land. Labor is defined as annual paid and unpaid farm labor costs (wages are imputed for family labor). Fertilizer, pesticides, and seed are also defined in terms of annual costs. The equipment variable includes annual power and equipment fixed costs and the building variable is annual building costs. These two are combined and labeled capital. Table 1 contains summary statistics of the variables.

One of the difficulties with the approach outlined in the previous section is the existence of outliers which may result from errors in measurement. There is no established procedure for dealing with this problem. Timmer (1971) suggested deleting an arbitrary percentage of the observations. However, there is no underlying statistical rationale for implementing this procedure. In this paper, the observations were individually examined to determine whether there

TABLE 1

Summary statistics for sample farms inputs and outputs

Variable	Mean		Standard deviation	
	(bu/acre)	(t/ha)	(bu/acre)	(t/ha)
Corn	141	8.87	25	1.57
Soybeans	42	2.82	5.98	0.40
Wheat	53	3.56	9.29	0.62
Double crop soybeans	28	1.88	8.08	0.54
	($/acre)	($/ha)	($/acre)	($/ha)
Capital	41.07	101.50	17.44	43.10
Labor	36.78	90.88	12.97	32.05
Fertilizer	34.08	84.21	11.18	27.63
Pesticide	15.81	39.07	7.46	18.43
Seed	16.01	39.56	8.00	19.77

bu, bushel for wheat and soybeans = 60 lb ≈ 27.2155 kg; for corn = 56 lb ≈ 25.4545 kg.
acre ≈ 0.404686 ha ≈ 4047 m^2.
t, metric tonne = 1000 kg.

TABLE 2

Results of linear programming

Observation	(1)	(2)	(3)	Observation	(1)	(2)	(3)
1	1.00	0.96	0.04	46	0.87	0.86	0.01
2	0.67	0.52	0.23	47	0.92	0.87	0.05
3	0.77	0.57	0.26	48	0.82	0.66	0.19
4	0.99	0.78	0.22	49	1.00	1.00	0.00
5	0.90	0.61	0.32	50	1.00	1.00	0.00
6	0.85	0.74	0.13	51	1.00	1.00	0.00
7	0.89	0.82	0.07	52	0.79	0.74	0.06
8	1.00	0.90	0.10	53	0.69	0.67	0.03
9	0.89	0.66	0.26	54	0.83	0.74	0.11
10	0.71	0.71	0.00	55	0.79	0.79	0.00
11	0.93	0.83	0.11	56	0.70	0.69	0.02
12	0.93	0.66	0.29	57	1.00	1.00	0.00
13	0.89	0.66	0.27	58	1.00	1.00	0.00
14	0.88	0.72	0.18	59	0.70	0.70	0.00
15	0.87	0.66	0.24	60	0.86	0.70	0.18
16	0.96	0.96	0.00	61	1.00	1.00	0.00
17	0.70	0.62	0.11	62	1.00	1.00	0.00
18	1.00	1.00	0.00	63	0.70	0.70	0.00
19	0.95	0.95	0.00	64	1.00	1.00	0.00
20	1.00	1.00	0.00	65	0.87	0.84	0.03
21	0.57	0.48	0.15	66	1.00	1.00	0.00
22	0.84	0.71	0.16	67	1.00	0.98	0.02
23	0.98	0.67	0.32	68	0.76	0.62	0.18
24	0.93	0.88	0.05	69	0.92	0.72	0.22
25	1.00	1.00	0.00	70	0.85	0.85	0.00
26	0.80	0.73	0.08	71	1.00	0.98	0.02
27	1.00	1.00	0.00	72	1.00	1.00	0.00
28	1.00	1.00	0.00	73	1.00	0.85	0.15
29	0.83	0.62	0.26	74	0.85	0.62	0.27
30	1.00	0.82	0.18	75	0.89	0.70	0.22
31	0.85	0.62	0.27	76	1.00	1.00	0.00
32	0.71	0.56	0.22	77	0.85	0.69	0.19
33	1.00	1.00	0.00	78	1.00	0.77	0.23
34	1.00	1.00	0.00	79	0.89	0.87	0.03
35	0.97	0.91	0.06	80	0.79	0.77	0.03
36	1.00	0.99	0.01	81	0.80	0.67	0.16
37	1.00	0.87	0.13	82	1.00	0.75	0.25
38	0.77	0.74	0.04	83	0.85	0.64	0.25
39	1.00	1.00	0.00	84	0.91	0.68	0.26
40	1.00	1.00	0.00	85	1.00	0.80	0.20
41	1.00	1.00	0.00	86	1.00	0.85	0.15
42	0.89	0.84	0.06	87	0.89	0.73	0.18
43	0.99	0.98	0.01	88	1.00	0.84	0.16
44	1.00	0.99	0.01	89	1.00	1.00	0.00
45	0.89	0.88	0.01	90	0.85	0.70	0.17
				91	0.71	0.53	0.25
				92	0.92	0.71	0.24
				Mean	0.90	0.81	0.10
				Standard deviation	0.11	0.15	0.10

were any farms producing output while using zero quantities of an input or several inputs. These observations were then deleted.[3]

The results of solving the linear programs, given in (9) and (10), modified to incorporate additional inputs and outputs are presented in Table 2. Column (1) contains the results of calculating the efficiency of each observation in 1982 relative to a production frontier constructed by using only the 1982 sample. In terms of Fig. 2, this would give us OB/OA for each observation. Column (2) represents the results of calculating the efficiency of each observation in 1982 relative to a production frontier constructed by pooling the 1982 and 1984 sample for the 92 farms (total number of observations would then be 184). In terms of Figure 2, this gives us OC/OA for each observation in 1982. Finally, column (3) contains the measure of technical change which is calculated using equation (8).

As can be seen from examining Table 2, the average efficiency level for the farms in 1982 is 0.90. This means that the output level of these farms in 1982 could have been produced with 90% of the total inputs actually used. In addition, the average rate of technical change from 1982 to 1984 was 10%.

In order to determine the bias of innovation, a regression equation was estimated with the rate of technical change (column 3 in Table 2) as the dependent variable and measures of the various factor intensities as independent variables. In order to measure land intensity, the average of the beginning and ending land values for the year 1982 for each farm is used as the measure of land. This result is then divided by the sum of the expenditures on all inputs, including land. This same approach was followed with each input. Since all of the variables on the right-hand side must sum to 1, the regression equation was estimated without an intercept. The results are presented in Table 3.

There is some suspicion that strong multicollinearity among fertilizer, pesticide, and seed intensity exists. In order to avoid this problem, all three variables are combined into one intensity variable, which is labeled chem-seed intensity. The regression analysis is repeated, again without an intercept, and the results are presented in Table 4.

The results indicate that technological change is positively related to the land intensity of production. None of the coefficients for the other factor intensities are significantly different from zero. Based upon these results, technical innovation during this time period is land using in nature.

In addition to the above, we determine whether the extent of technical change is related to the size of the farm, the tenure status of the farm, and the extent to which farm operators participated in governmental programs as indicated

[3]An alternative approach would be to construct stochastic frontiers. This would eliminate the errors in measurement problem. However, this gain comes at significant cost. Specifically, a functional form must be specified for the production technology and for the one-sided error term. The authors are currently engaged in research on this topic.

TABLE 3

Factor intensity regression results

Variable	Estimate	Standard error	T-ratio
Capital intensity	0.004	0.9742	0.03
Land intensity	0.374	0.0004	3.71
Labor intensity	0.089	0.5839	0.55
Fertilizer intensity	−0.042	0.8231	−0.22
Pesticide intensity	0.004	0.9888	0.01
Seed intensity	−0.481	0.1959	−1.30

$R^2=0.55$.

TABLE 4

Factor intensity regression results

Variable	Estimate	Standard error	T-Ratio
Capital intensity	−0.027	0.128	−0.21
Land intensity	0.329	0.100	3.79
Labor intensity	0.093	0.158	0.59
Chem-seed intensity	−0.114	0.116	−0.99

$R^2=0.55$.

by set asides for land. Regression analysis is again used with the rate of technical change, as determined above, being the dependent variable and farm size, tenure status, and the extent of land set aside (for year 1982) as independent variables. Farm size is measured in two different ways: gross farm revenue and area of land. Tenure is measured as the percent of owned farm land divided by the total land farmed. The extent of participation in governmental programs is measured by the proportion of total land on each farm which is set aside as

TABLE 5

Role of farm size (revenue and area), tenure, and farm set aside in technical change

Variable	Estimate	Standard Error	T-Ratio
Constant	0.1402	0.02626	5.34
Gross revenue	0.0004	0.00001	2.03
Area (acres)	−0.0001	−0.00007	−2.19
Land set aside	−0.0064	0.01158	−0.56
Tenure	−0.0533	0.03892	−1.37

$R^2=0.10$.

a result of participation in governmental programs. The results are presented in Table 5.

The larger farms, in terms of gross revenue are associated with more rapid rates of technical change. However, farm size measured in area is inversely related to the rate of technical change. None of the other variables are significant.

Summary and conclusions

In this paper, an alternative method for measuring the extent and bias of technical change was presented. It involved the construction of several non-parametric production frontiers. These frontiers were constructed using data on 92 Illinois grain farms for both 1982 and 1984. The first step involved the construction of an input based production frontier using only 1982 data for the 92 farms. The technical efficiency of each farm was then measured relative to this frontier. The second step involved the construction of an input-based production frontier by pooling data for 1982 and 1984 for the 92 farms. The technical efficiency of each farm, given by the 1982 data, was then measured relative to this pooled frontier. Using the above information it was possible to determine the extent of technical change for each farm from 1982 to 1984.

The next step was to determine the bias of technical change. This was accomplished by estimating regression equations in which the extent of technical innovation was the dependent variable, and the various factor intensities of production, one for each input, were used as independent variables. The results indicated that technical innovation was land using in nature. In addition, regression analysis was used to determine whether or not the extent of technical innovation was significantly related to the size of farm, tenure status, or the extent of the farm's participation in governmental land set aside programs. The results indicate that farm size, measured by gross revenue, was significantly and positively related to the extent of technical change; while farm size, measured in area, was negatively related to technical change.

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