Staff Paper P10-7
InSTePP Paper 10-03 August 2010

Staff Paper Series

CAPITAL USE INTENSITY AND PRODUCTIVITY BIASES

by

Matt A. Andersen, Julian M. Alston and Philip G. Pardey

Department of APPLIED ECONOMICS

INSTEPP INTERNATIONAL SCIENCE & TECHNOLOGY PRACTICE & POLICY

College of Food, Agricultural and Natural Resource Sciences

UNIVERSITY OF MINNESOTA

Staff Paper P10-7
InSTePP Paper 10-03 **August 2010**

CAPITAL USE INTENSITY AND PRODUCTIVITY BIASES

by

Matt A. Andersen, Julian M. Alston and Philip G. Pardey

Andersen is an Assistant Professor in the Department of Agricultural and Applied Economics at the University of Wyoming and a Research Fellow at the International Science and Technology Practice and Policy (InSTePP) Center at the University of Minnesota; Alston is a Professor in the Department of Agricultural and Resource Economics, University of California, Davis and a member of the Giannini Foundation; and Pardey is a Professor in the Department of Applied Economics, University of Minnesota and Director of InSTePP. *The authors dedicate this paper to their late friend and colleague Catherine Morrison Paul. They also gratefully acknowledge the financial support of the Minnesota Agricultural Experiment Station, the University of California, Agricultural Issues Center, the Institute of Governmental Affairs at UC Davis, and the Giannini Foundation.*

This is a substantially revised version of "Capital Use Intensity and Productivity Biases." Andersen, Matt A.; Alston, Julian M.; Pardey, Philip G., St. Paul, MN: University of Minnesota, Department of Applied Economics; University of Minnesota, International Science and Technology Practice and Policy (InSTePP), 2007. (Staff paper P07-06; InSTePP paper 07-02) 37p.

ABSTRACT

Measures of productivity growth are often pro-cyclical. This paper focuses on measurement errors in capital inputs, associated with unobserved variations in capital utilization rates, as an explanation for the existence of pro-cyclical patterns in measures of productivity. Recently constructed national and state-specific indexes of inputs, outputs, and productivity in U.S. agriculture for 1949–2002 are used to estimate production functions that include proxy variables for changes in the utilization of durable inputs. The proxy variables include an index of farmers' terms of trade and an index of local seasonal growing conditions. We find that utilization responses by farmers are significant and bias measures of productivity growth in a pro-cyclical pattern. We quantify the bias, adjust the measures of productivity for the estimated utilization responses, and compare the adjusted and conventional measures.

Key Words: U.S. agriculture; pro-cyclical productivity; capital utilization; primal productivity bias

JEL Classification: D24, C51, Q1, O4, O47

Capital Use Intensity and Productivity Biases

1. Introduction

A common observation is that measures of productivity growth are pro-cyclical, in the sense that measured productivity grows faster on average during periods of economic expansion than during periods of economic contraction (Basu 1996; Basu and Kimball 1997; Wen 2004). Does this observation imply that productivity actually changes in response to fluctuations in economic activity, or are we simply mismeasuring productivity in a systematic way? The literature on productivity measurement attributes these observed patterns to one or more of four primary sources: (i) increasing returns to scale in production; (ii) imperfect competition in output markets; (iii) exogenous technology shocks; and (iv) systematic errors in measuring either inputs or outputs (Basu and Fernald 2000). This paper focuses on the last of these, specifically on measurement errors related to capital inputs, as an explanation for the existence of pro-cyclical patterns in measures of agricultural productivity.

It is difficult to directly observe or measure annual variations in the rate of utilization of durable assets, and this difficulty has been widely cited by researchers as a potential source of significant measurement error for capital inputs. We begin with a detailed examination of how variable capital utilization can affect productivity measurement. The hypothesis that unmeasured changes in the utilization of capital can affect productivity measures is then illustrated using a model of production. Next, we estimate production functions in growth-rate form that include proxy variables for changes in the utilization of fixed assets. The proxy variables include an index of farmers' terms of trade and an index of local weather-related growing conditions. We find that utilization responses by farmers are significant and bias measures of productivity growth in a pro-cyclical pattern. We quantify the bias, adjust the measures of productivity for the estimated utilization responses, and compare the adjusted and conventional measures.

2. Primal Versus Dual Approaches

A number of studies have examined the concept of capital or capacity utilization and the implications for productivity measurement using either a restricted profit function approach or a dynamic, cost-adjustment framework. Fousekis and Papakonstantinou (1997) used a restricted profit function approach to estimate the economic utilization of capital in Greek agriculture and found an overutilization of the capital stock and subsequent overestimation of multi-factor productivity growth rates for the period 1971-1993. Morrison (1985 and 1986) examined capital utilization rates using a dynamic cost-adjustment approach. Also, Luh and Stefanou (1991) used a dynamic model that incorporates adjustment costs for capital inputs to calculate measures of productivity growth for the U.S. agricultural sector. The dynamic, cost-adjustment approach can account for variable capacity utilization with multiple quasi-fixed inputs in a general setting, and can be used to derive improved measures of input use and productivity.[1] This approach allows for the estimation of shadow values for quasi-fixed inputs, which are used instead of observed rental rates when calculating a utilization-adjusted measure of primal or dual productivity growth.

The cost-adjustment approach has some theoretical appeal owing to the strong links between the investment behavior of producers, the utilization of capital assets, and the

[1] For comparative purposes, we have also completed a preliminary examination of the issues raised in this paper using a dual, cost-adjustment approach. The productivity estimates we derived from using a standard Translog cost function versus variable Translog cost function with one quasi-fixed input (capital) support the findings in this paper obtained from using a conventional versus augmented primal, production function approach. Specifically, utilization responses are found to be statistically significant and to bias parametric measures of productivity growth irrespective of the approach taken.

resulting implications for productivity measurement. Moreover, from an empirical standpoint, input prices are commonly assumed to be exogenous, and if so, cost function models may avoid simultaneity problems associated with using quantity measures for inputs. However, the theoretical appeal of a dual approach stems from its use of explicit (and commonly held) behavioral assumptions conceived in the context of an individual firm. Thus a dual approach is probably most relevant when examining firm-level data. Its theoretical appeal is less compelling in the context of the highly aggregated, sector-level data used in this paper. In addition, the internal adjustment process in the dual approach is defined using an investment equation for capital inputs that relies on a measure of the rate of change of the quantity of capital, which might be measured with error in the case of U.S. agriculture.

Several additional reasons led us to opt for a primal approach here. First, this is a study of the U.S. agricultural sector, and a primal approach avoids imposing ex post cost-minimizing behavior for an application in which the use of aggregated data related to highly stochastic production processes makes this assumption questionable. Second, as described below, there is ample precedent in the literature for using a primal approach to estimate relationships between inputs and outputs in models that explicitly incorporate prices, although our reason for including prices differs from those in previous studies. Hence, an alternative interpretation of the prior literature is made possible in this context. Third, the influence of capital utilization rates on productivity measurement has been little studied using primal methods, making this application a useful complement to the prior capacity-utilization literature that has typically employed a dual approach.

The intent of this paper is to re-examine the potential errors introduced into measures of capital and productivity when assuming capital service flows are proportional to capital stocks. Fundamentally this is a problem related to measures of the quantity (not price) of capital, and so we opted to approach the problem by first defining a specific form for the measurement error, and then investigating the impacts in a primal setting. In this setting we can relax the assumption that capital service flows are proportional to capital stocks without having to rely on the assumption that prices are competitive or exogenous, or that the input quantities were chosen ex ante to minimize costs of the ex post output.

3. Prices as Proxy Variables for Changes in Utilization and Technology

In our models of production we use prices as proxies for unobserved changes in the utilization of capital. A number of alternative rationales have been offered in previous studies as justifications for including output prices or input prices in models of production. Consequently, alternative, potentially competing, explanations may be offered for a finding that prices make statistically significant contributions to production functions.

Similar issues arise when output prices are included in cost functions, which ordinarily would include quantities of fixed factors and output and prices of variable inputs, but not output prices. One reason for including output prices in cost functions, examined by Pope and Just (1996) and Moschini (2001), is to address a general 'errors in variables' problem. These authors were concerned with estimation bias that may result from including actual output as opposed to expected (or planned) output as an independent variable when estimating cost functions. This issue is important in cost functions based on an explicit or implicit assumption of cost minimization.[2] The same issue does not arise in the same way in the estimation of production functions, which is the focus here. On the other hand, pro-cyclical measurement bias in the capital input might be problematic in production function

[2] For an example and some more discussion of this point, see Jin et al. (2005).

studies, and it might be useful to consider this problem jointly with the problem studied by Just and Pope, and by Moschini.

The induced-innovation hypothesis originally proposed by Hicks (1932) has been used as a justification for including past input prices, output prices, or relative prices in primal models of production in a number of studies, including Fulginiti and Perrin (1993), Paris and Caputo (1995), Mundlak, Larson, and Butzer (1997), and Celikkol and Stefanou (1999).[3] Most of these studies include measures of input prices and output prices as right-hand-side variables. Mundlak (1988) argued that input and output prices are important 'state' variables in agriculture that induce technological change, and should be integrated into primal models of aggregate agricultural production. Commonly, the technology-changing impacts of past output prices are thought to occur with a long lag. Induced innovation entails induced research, the development of new technology, and induced adoption of existing technologies—some of which takes a very long time.

We suggest a third justification for prices to play a role in primal models of production and a new interpretation of the results from previous work that included past prices as explanatory variables in models of production. Specifically, recent or contemporaneous prices can be used to represent the effects of economic expansions and contractions, which are hypothesized to induce changes in the utilization of fixed assets in ways that have more immediate consequences for output and productivity, thus contributing to short-term pro-cyclical patterns in measures of productivity growth, holding technology constant. The previous studies, mentioned above, included prices in production functions to

[3] Hicks (1932) proposed that changes in relative factor prices induce entrepreneurs to find new, factor-saving methods of producing output. Hayami and Ruttan (1970) considered the innovation-inducing role of past output prices in determining the current state of technology in agriculture.

represent induced technical change, whereas we are suggesting a different rationale and one that is more compatible with short-lag responses in time-series data.

Transitory changes in output demand and input supply are hypothesized to cause unobserved and unmeasured changes in the utilization of fixed inputs in the short run. We wish to distinguish these short-run responses to contemporary price changes from the longer-run induced innovation responses to more-permanent price changes. In particular, observed increases in output that reflect changes in technology 'induced' by price changes should occur with a longer lag, be more enduring, and be asymmetrical for increases compared with decreases in output.[4] In the case of the utilization-changing effects of prices on production, any changes in observed output should be transient and symmetrical: output may change in either direction and the change will be temporary (no permanent rise in output for a given level of inputs). So there is a spectrum of likely responses to relative price changes:

1. Short-term—intensity of use of durable assets.
2. Medium-term—induced technical change (switching among existing technologies, many embodied in inputs).
3. Long-term—induced innovation (creating new technology options).

In the application that follows we focus on the short-term, utilization-changing effects of demand and supply shocks on productivity and output. Esposti (2000) found empirical evidence in Italian agriculture that short-term shocks to supply and demand greatly affect measures of productivity. In this study of U.S. agriculture we use of an index of farmers' terms of trade—the ratio of the aggregate prices received for output to the

[4] For example, an increase in the relative price of self-propelled combine harvesters is unlikely to cause farmers to revert to combines pulled by tractors or horse-drawn reapers. Adoption of self-propelled combines also induces other input changes associated with grain handling and storage (with their commensurate capital stock implications) that imply further adoption-disadoption asymmetries in response to price changes.

aggregate prices paid for aggregate inputs—to proxy utilization responses by farmers, which combines incentive effects of both changes in input supply and changes in output demand. We hypothesize that short-term movements in this measure provide a useful indication of changes in incentives facing farmers and, thus, capital utilization.

4. Corrections for the Consequences of Variable Capacity Utilization

Two closely related methods have been suggested for correcting for the consequences of variations in capacity utilization for the measurement of durable inputs and productivity. One common suggestion in the literature is to adjust the service flows of durable inputs using information on other inputs that are deemed easier to measure than capital and whose use changes in concert with the intensity of use of durable inputs. For instance, capital services could be adjusted according to changes in labor or materials inputs. When measured growth in the use of labor or materials is greater than the measured growth in capital services, this could be an indication that standard measurement procedures are underestimating the true growth in capital services. Griliches and Jorgenson (1967), for example, suggested estimating the utilization of physical capital based on the utilization of power. This procedure was originally conceived by Foss (1963) and can be used to adjust measures of (machinery-related) capital services directly for utilization changes. Baxter and Farr (2001) used materials inputs and energy inputs as proxies for capital services, and found that accounting for the variable utilization of the stock of capital substantially altered the productivity residual. Subsequently, Baxter and Farr (2005) incorporated variable capital utilization into a two-country business-cycle model, and showed that doing so substantially reduced the volatility and persistence of productivity shocks, as well as the correlation of productivity shocks among countries.

Another method to control for unobservable changes in the use of capital inputs when measuring productivity, suggested by Berndt and Fuss (1986), Morrison (1986), and Slade (1986), is to use a measure of the stock of capital and adjust the factor cost share of capital services by substituting estimated shadow values for observed market prices. The adjustment procedures are intended to control for the wedge that is created between market prices of capital goods and their shadow values when some (or all) assets are not fully utilized. This is subtly different from the service-flow adjustment approach proposed by Foss (1963), which focused on adjusting the quantity of capital.

The supply of services from capital inputs (and notably the specialized durable inputs most heavily used in agriculture, including many types of agricultural machinery) is neither fixed nor infinitely elastic in the short run, but upward sloping when considering agriculture as a sector. Figure 1 provides a simple illustration of this concept and the methods that have been suggested in the literature for adjusting the service flows or shadow values of capital services to incorporate unobservable variations in utilization. In Figure 1, K refers to the stock of capital, k is the flow of capital services from the stock, *VMP* is the value of the marginal product of capital, ρ is the rental rate of capital, and v is the shadow value of an additional unit of capital stock. In long-run equilibrium a given optimal rate of utilization of the stock, U^*, implies a flow of services equal to $k = U^*K$ that is proportional to the stock. For simplicity, we can choose units such that $U^* = 1$ and in long-run equilibrium the quantity measure of capital service flows corresponds to the quantity measure of the stock of capital. This proportional equivalence is embedded as an implicit assumption in much analysis that assumes constant capacity utilization.

[Figure 1: Demand Shock in the Market for Durable Assets]

Suppose the industry is in long-run equilibrium with a quantity of capital K_0 and a rate of capital service flows of $k_0 = U_0K_0 = K_0$ (for $U_0 = U^* = 1$), given a value of the marginal product of capital of VMP_0, a rental rate of capital equal to ρ_0, and a shadow value of capital equal to v_0 (and thus a ratio of the rental rate of capital to the shadow value of an additional unit of capital stock equal to $\varphi_0 = \rho_0/v_0 = 1$). Now, suppose the value of the marginal product of capital shifts down temporarily to VMP_1. In the short run, the quasi-fixity of capital implies the stock is fixed at K_0 and, through changes in the utilization rate, the supply of services from that stock is upward sloping as indicated by S_k. Hence, when capital is quasi-fixed, a temporary negative demand shock from VMP_0 to VMP_1 reduces the flow of services from k_0 to k_1, and the rental rate from ρ_0 to ρ_1, but these changes are unobserved. As a result, the following three things occur: (i) the ratio of the unobserved, actual flow of capital services to the observed stock no longer equals the long-run equilibrium ratio, U_0; (ii) the ratio of the observed rental rate of capital to the unobserved shadow value of the capital stock no longer equals the long-run equilibrium ratio, φ_0; and (iii) the measured quantity of capital services, k_0, temporarily exceeds the actual quantity of capital services, k_1.

The flow of capital services (or, equivalently, the return to capital in equilibrium) is typically estimated as the rental rate of capital multiplied by the productive stock of capital, ρ_tK_t, under the assumption that the flow of services is proportional to the stock of capital and $k_t = K_t$. This is because the actual flow of services is unobservable to the researcher. As noted above, two approaches have been used to approximate the true return to capital services, ρ_1k_1, when the proportion between the stock and flow varies over time. The first, as proposed by Foss (1963), is to make a utilization adjustment to the capital service flow using information on changes in the intensity of use of other inputs. The second approach, which is closely related, controls for the unobservable change in utilization by using parametric or other methods to estimate the shadow value of an additional unit of capital stock, v_1, and $v_1 K_0$ is used as an approximation of the cost of capital services. However, as shown in Figure 1, in this simple illustration the shadow value, v_1, understates the rental rate of capital, ρ_1, and using $K_0 = k_0$ overstates the true quantity of services, k_1, leaving the potential for additional measurement problems (these errors in price and quantity will be exactly offsetting only if the demand for capital is unit elastic, in which case the total cost of capital services does not change with changes in quantity or price).

5. Production Functions Augmented with Variable Capital Utilization

We consider two specifications of a production function, augmented for the variable utilization of durable assets. The first specification is a modified Cobb-Douglas production function in which the quantities of some factors of production are measured with error. The second is a modified Translog production function that represents a generalization of the Cobb-Douglas model.

Start by assuming the existence of an aggregate production function for U.S. agriculture of the Cobb-Douglas form:

$$Q_t = f(\tilde{X}_t, Y_t; \beta) = G_t(Y_t) \times \prod_{i=1}^{n} \tilde{X}_{it}^{\beta_i}, \tag{1}$$

where $\tilde{X}_i = (\tilde{X}_1, ..., \tilde{X}_n)$ denotes a vector of conventional inputs like land, labor, capital, and materials; $Y_k = (Y_1, ..., Y_s)$ denotes a vector of variables that determine the current state of technology; and β represents a vector of parameters. Assume we only observe only a proxy, X_i, for some $\tilde{X}_i$, (for instance a capital stock as a proxy for a capital flow), which is assumed to be related to the true quantity according to a variable rate of utilization, U_i, such that $\tilde{X}_i = X_i \times U_i$. The rate of utilization is a latent unobserved variable. However, we do observe variables, Z_h, that determine the current rate of utilization, $U_i = U_i(Z)$.

Taking logarithms (and using lower case italics to denote variables in logarithms) we can write equation (1) as

$$q_t = g_t(y_t) + \sum_{i=1}^{n} \beta_i (x_{it} + u_{it}). \tag{2}$$

Now, expressing productivity, g_t, as a linear function of the logged technology-changing variables, y_k, yields

$$g_t = \alpha_0 + \sum_{k=1}^{s} \alpha_k y_{kt} + \varepsilon_{0t}, \tag{3}$$

and expressing the utilization rate as a linear function of the utilization-changing variables, z_h, yields,

$$u_{it} = \sum_{h=1}^{m} \lambda_{ih} z_{ht}. \tag{4}$$

In these equations the Greek letters α, β, and λ, are used to represent the fixed parameters to be estimated and ε_0 is a random error term, assumed to be distributed independently of the explanatory variables, x_i, z_h, and y_k. Substituting equations (3) and (4) into (2) results in the following augmented Cobb-Douglas production function for estimation:

$$q_t = \alpha_0 + \sum_{k=1}^{s} \alpha_k y_{kt} + \sum_{i=1}^{n} \beta_i x_{it} + \sum_{i=1}^{n} \sum_{h=1}^{m} \beta_i \lambda_{ih} z_{ht} + \varepsilon_{0t}. \tag{5}$$

The second specification is a modified Translog production function that incorporates measurement error and represents a generalization of the Cobb-Douglas model:

$$q_t = g_t(y_t) + \sum_{i=1}^{n} \beta_i (x_{it} + u_{it}) + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} (x_{it} + u_{it})(x_{jt} + u_{jt}). \tag{6}$$

Substituting equations (3) and (4) into (6) results in the following augmented Translog production function for estimation:

$$q_t = \alpha_0 + \sum_{k=1}^{s} \alpha_k y_{kt} + \sum_{i=1}^{n} \beta_i x_{it} + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} x_{it} x_{jt} + \ldots$$

$$\sum_{i=1}^{n} \sum_{h=1}^{m} \lambda_{ih} z_{ht} \left(\beta_i + \sum_{j=1}^{n} \gamma_{ij} x_{jt} + \frac{1}{2} \sum_{j=1}^{n} \gamma_{ij} \sum_{h=1}^{m} \lambda_{jh} z_{ht} \right) + \varepsilon_{0t} \,. \tag{7}$$

Two simplifying assumptions were made prior to estimating equations (5) and (7). First, we consider only measurement errors associated with variable utilization of capital. While unobservable utilization changes may be important for other inputs such as land and labor, the problem is likely to be much less pronounced with these inputs, especially given the methods we used to construct the corresponding measures of them.[5] Second, the utilization term is assumed to follow a specific form. Details on the utilization term and a list of the specific production functions to be estimated are provided in the next section.

6. Empirical Analysis

The main data used in this paper are state-specific Fisher Ideal indexes of inputs, outputs, and multifactor productivity (MFP) in U.S. agriculture in the 48 contiguous states for the period 1949–2002.[6] As an illustration, the corresponding national indexes of inputs, outputs, and productivity are presented in Figures 2 and 3.

[Figure 2: Indexes of the Quantity of Land, Labor, Capital, and Materials, 1949–2002]
[Figure 3: Indexes of the Quantity of Output, Input, and MFP, 1949–2002]

---

[5] Specifically, we measured labor in terms of hours on farms (rather than counts of operators and others), adjusting for significant changes in the part-time farming patterns of farmers. The land variable is an estimate of the quantity of land in farms, accounting for policy induced set-aside acres in agriculture and changes in the mix of pasture- and range-land and irrigated and non-irrigated crop land.

[6] These data are the latest in a series of InSTePP production accounts developed under the leadership of Philip Pardey at the University of Minnesota's International Science and Technology Practice and Policy (InSTePP) center. These data, the Pardey, Andersen, Craig, and Alston (2010) series, represent a revised and updated version of data published by Acquaye, Alston, and Pardey (2003) and originally developed and used by Craig and Pardey (1996).

We use the following variables, which are all state-specific except for the annual time trend.

1. Output, q: the logarithm of the index of the quantity of agricultural output.
2. Inputs, x_i: the logarithms of indexes of the quantities of quality-adjusted land, x_1, labor, x_2, capital, x_3, and materials, x_4.
3. An annual time trend, y_1: 1949 = 1.
4. Seasonal growing conditions, y_2: the logarithm of the index of pasture and range conditions expressed in deviations from the mean of the logarithm of the index.[7]
5. Terms of trade, z_1: the logarithm of the ratio of the index of the price of aggregate output to the index of the price of aggregate input.

When specified in logarithms the state-level indexes of output are non-stationary, which might result in spurious parameter estimates.[8] However, when the same measures are first differenced and thus specified as rates of growth, they are stationary; therefore, we have specified the estimating equations in rates of growth as well as in undifferenced logarithmic form. Descriptive statistics for all of the variables used in the analysis are presented in Table 1 for the period 1949–2002.

[Table 1: Descriptive Statistics for Variables in the Regression Analysis]

The analysis proceeds using a two-step procedure, where the first step involves constructing appropriate proxy variables to represent utilization, and the second step involves estimating various production functions augmented with the utilization variables.

[7] In all of the regressions the growing conditions index enters as a technology shifter, but in some of the regressions it also enters as a utilization-changing variable. This is done to separate the direct effects of weather from the indirect effects of changes in the utilization of capital resulting from changes in weather. For example, a drought will have direct impacts on current output, but it may also have indirect effects if farmers choose to leave machinery idle.

[8] Dickey-Fuller tests of a unit root were used to verify that most of the state-level indexes of output are non-stationary when expressed in logarithms, but stationary after first differencing (logarithmic differences).

As previously mentioned the index of farmers' terms of trade—the ratio of the aggregate price of output to the aggregate price of variable inputs—combines incentive effects of both changes in input supply and changes in output demand. Cyclical movements in this measure may provide a useful indication of short-term changes in incentives facing farmers, and hence in the utilization of capital.

In the regression analysis the terms of trade measures for each state, z_1, are trend-filtered and lagged one period, thereby representing cyclical movements in farmers' expectations about terms of trade. To obtain these measures, we began by regressing each of the state-specific terms-of-trade measures on the annual time trend, y_{1t}. The residuals, $\hat{\varepsilon}_t$ from the regressions were retained, and a 'pre-determined' or 'expected' terms of trade measure was then defined as the residuals from these regressions lagged one period, $\hat{z}_{1t} = \hat{\varepsilon}_{t-1}$. The de-trending and lag procedures are based on the widely used 'naïve' expectations model and our hypothesis that changes in capital utilization are linked to short-run cyclical movements in farmers' terms of trade (not long-run trends in this measure).

Next, capital utilization is assumed to depend on economic and environmental circumstances, and is therefore specified as a function of the terms of trade measure, $\hat{z}_{1t}$, and the index of growing conditions expressed in deviations from the state-specific long-run mean, y_{2t}.

$$u_t = \lambda_{31}\hat{z}_{1t} + \lambda_{32}y_{2t} \tag{8}$$

When the utilization term (in logarithms) is equal to zero, this implies that farmers are using a constant proportion of the stock of capital in production each period, the proportionality assumption holds, and capital services are measured without error.

We estimate production functions with the variables in logarithms and rates of change (first differences in logarithms). In each case a base model is estimated, representing a conventional Cobb-Douglas or Translog production function, as well as an augmented version with variable utilization. The base (conventional) models are nested in the utilization models as shown in Table 2, which lists the different specifications.

[Table 2: Specifications of the Production Functions in the Empirical Analysis]

The following estimation results were obtained using STATA software. For the purpose of this analysis the data set consists of observations for 48 states over the years 1950–02, resulting in a sample of 2,544 observations (2,496 observations in rates of change) of the variables. Regression estimates for equations A to D in Table 2 were obtained using Ordinary Least Squares (OLS) or Non Linear Least Squares (NLLS), where applicable.[9]

Estimation results from the Cobb-Douglas models are shown in Table 3, where a total of 28 parameter estimates are presented, of which 22 are statistically significantly different from zero at the 1 percent level, and two at the 5 percent level.[10] Most of the estimated elasticities of production with respect to inputs seem too small for land and labor and too large for materials inputs. The fact that conventionally measured capital, labor and land inputs were shrinking (as well as the quality-adjusted measures used here), while output was rapidly expanding in U.S agriculture during most of 1950–02, makes estimating a production function for this period challenging. This fact is reflected in the mostly small (probably downward-biased) and often statistically insignificant values for the estimated production elasticities for land and labor in the regression results.

[9] The utilization-adjusted Translog models involve non-linear parameters and therefore (NLLS) regression results are reported for these models.

[10] The 28 parameters do not include the estimates of the R^2 and the measure of returns to scale, which are at the bottom of the table.

[Table 3: Cobb-Douglas Models: Ordinary Least Squares (OLS) and Fixed-effects (within) Estimates]

The results for the Translog specifications are presented in Table 4, which contains a total of 70 parameter estimates, 29 of which are statistically significant at the 1 percent level, 12 at the 5 percent level, and 6 at the 10 percent level. The added flexibility of the Translog specification comes hand-in-hand with imposing less (and potentially too little) structure on the production technology, which can result in unreasonable parameter estimates (such as negative production elasticities). In the case of the base model Translog production function, the results are mostly consistent with prior expectations about agricultural production. The production elasticities from this model are all positive and statistically significant, except for labor. The estimate of returns to scale is 0.919, which is statistically significantly less than 1.0 but close nonetheless.

[Table 4: Translog Models: Ordinary Least Squares (OLS) and Non-linear Least Squares Estimates (NLLS)]

Table 5 shows the estimates of annual MFP growth from the different model specifications. All of the estimates of productivity growth rates are statistically significantly different from zero at the 1 percent level of significance. The parametric estimates in Table 5 are all smaller than the (non-parametric) estimate of the average annual growth in U.S. MFP over 1950–2002, 1.69 percent, which was calculated as the sample average of the annual rates of change of the index of productivity among all states and years.[11] The parametric estimates are also generally lower than recently published non-parametric estimates of productivity growth in U.S. agriculture for a similar period that were calculated

[11] If we calculate the national average MFP growth as the average of the annual rates of change of the index of productivity among all states and years, we assign an equal weight to each state in the calculation. This is in contrast to first calculating a national index of MFP, which is weighted by the value shares of the different states, and then taking the annual average. If MFP growth was relatively higher (lower) in large agricultural producing states, then the simple average among states would understate (overstate) MFP growth. Generally, we want to compare averages using one method or the other.

as the annual average of a national index of MFP. For example, Ball, Butault, and Nehring (2001) estimated that U.S. agricultural productivity grew by 1.94 percent per year on average for the years 1960–1996, while Acquaye, Alston, and Pardey (2003) estimated that it grew on average by 1.90 percent per year for the years 1949–1991. We surmise that some additional specification error exists (such as omitted variables) is probably biasing the econometric measures downward. Other studies that used a production function approach to obtain parametric estimates, such as Capalbo and Denny (1986) and Jorgenson (1990), also found comparatively small rates of productivity growth in U.S. agriculture.

[Table 5: Annual MFP Growth in U.S. Agriculture 1951–2002]

We are now in a position to answer two important questions. Are the estimates of productivity growth pro-cyclical? Did changes in the intensity of use of capital contribute to pro-cyclical patterns in these measures? The elasticities in Table 6 represent the percentage increase in productivity growth that would result from a 1 percent increase in the given variable, holding all other factors constant, calculated at the sample means of the variables.

[Table 6: Elasticity of Productivity with Respect to Expected Terms of Trade and Growing Conditions]

The regression results for the different specifications indicate that changes in the terms of trade and growing conditions variables have a significant and positive effect on productivity growth. These results support the hypothesis that measured productivity growth is pro-cyclical, and that unobserved changes in the utilization of capital in response to short-run fluctuations in farmers' terms of trade and growing conditions have contributed to these patterns. Furthermore, the results using the full sample are similar in magnitude across models (except the undifferenced Translog model), indicating that a 10 percent increase in farmers' terms of trade would cause between a 1.18 and 1.43 percent increase in measured productivity. Similarly, a 10 percent increase in the index of growing conditions above the long-run average would cause a 1 percent increase in measured productivity. As indicated in the descriptive statistics in Table 1, year-to-year proportional changes in the measure of terms of trade ranged between -0.50 and 0.53, and year-to-year proportional changes in our measure of growing conditions ranged between -2.28 and 2.26, sufficient to contribute significantly to year-to-year changes in measured productivity.

Our preferred model is the utilization-adjusted Translog model, with the variables specified in rates of change. This is the most general specification, and avoids the potential for spurious regression results by transforming the non-stationary productivity series (in logs) to a stationary series in logarithmic differences. Also, as previously mentioned, in all of the regressions the growing conditions index enters as a technology shifter, but in some of the regressions it also enters as a utilization-changing variable. This model allows for the estimation of the direct effects of weather, as well as from the indirect effects of changes in the utilization of capital induced by changes in weather.[12]

Short-term cyclical measurement errors in indexes of input quantities of the types identified in this paper have consequences for studies that use the indexes as data. Any of the given annual estimates may be significantly biased. However, the transitory nature of the errors means they have a smaller impact on (non-parametric) estimates of productivity

[12] The sum of the direct and indirect effects is positive as we expected, but the indirect effect, as captured by the estimated parameter, λ_{32}, is statistically significant and negative. The estimated elasticity of productivity with respect to the indirect weather effect is equal to -0.040, meaning that above-average weather causes a slight underutilization of the capital stock compared with normal years. This results in a slightly negative impact on output, although the overall effect of good weather on output is still positive. At first blush the finding of a negative indirect effect seems odd, but we can suggest some plausible reasons for such an effect. Planting and cultivating activities may be more burdensome in years with adverse weather, spurring higher-than-normal rates of capital use to counteract the effects of poor weather. Conversely, in above-average years, the favorable weather conditions may ease planting and cultivating activities thus causing farmers to cut back on the use of their capital stock relative to a normal year.

growth based on averages of index numbers over a sufficiently long sample, because the errors tend to average out over time. In other words, estimates of long-run productivity growth based on averages are not so susceptible to cyclical utilization bias, but could be biased nonetheless. The implications may be more serious for parametric studies of production that can be sensitive to measurement errors in individual observations of the variables. Specifically, transitory measurement error in the independent variables will cause attenuation to the null (or zero) in parameter estimates in a regression analysis; the parameter estimates will be biased and the bias will not average out over a sufficiently long sample as with non-parametric estimates.

Evidence on Productivity Biases

We quantify the resulting bias in parametric estimates of productivity growth by examining the differences between estimates of productivity growth obtained using a standard approach and a utilization-adjusted approach. Our comparison begins by re-estimating our preferred base and utilization-adjusted models specified in rates of change of the variables. The first set of estimates were obtained from the base Translog model estimated using OLS, and the second set from the utilization-adjusted Translog model estimated using NLLS. The intercept terms from each of these regressions represent the parametric estimate of annual average productivity growth, and the residuals from each regression represent the remaining part of output growth that is unexplained by the traditional factors (land, labor, capital, and materials) as well as weather conditions and, in the case of the utilization model, the expected terms of trade. After running each regression we added the residuals back to the estimated intercept terms to get a parametric estimate of productivity growth for each model that varies over time and among states. The averages of the estimates across the 48 states for each year (state-average estimates), and the annual averages of the estimates for each state, are presented in Table 7, along with the absolute difference between the measures.

[Table 7: Average Productivity Growth by Year and by State]

The base model implicitly assumes that capital utilization is constant, and the utilization model relaxes this assumption. Therefore the base model estimates potentially reflect utilization bias, whereas the utilization model controls for these effects. When the base estimate of productivity growth is larger (smaller) than the utilization adjusted estimate, this is an indication of an unmeasured over-utilization (under-utilization) of the capital stock. The difference between the estimates is an indication of the utilization bias. Table 7 shows the substantial differences between the parametric estimates in terms of the annual and state-averages. The difference between the parametric estimates is largest when considering annual estimates of state-average productivity growth, and this is particularly true during turbulent economic periods such as the 1970s. The difference between the annual estimates of state-average productivity growth is largest in 1979, where the base estimate of productivity growth for that year is 4.37 percent, and the utilization-adjusted estimate is 2.63 percent, indicating an unmeasured overutilization of capital. We also performed paired data *t*-tests of the equality of the means of the annual estimates of state-average productivity growth (assuming equal variances) indicating that in thirty-three of the fifty-two annual estimates the means were statistically significantly different (26 at the 1 percent level, four at the 5percent level, and three at the 10 percent level).

The differences between the state estimates of average-annual productivity growth over the period 1951–2002 are less substantial, but relatively large for certain states with capital-intensive production, like Montana, Nebraska, and North Dakota. For example, the annual average productivity growth in North Dakota was 1.83 percent per year from the base model and 2.23 percent per year from the utilization model, with the difference in productivity growth averaging 0.4 percent per year. Compounded over a 52 year period (1951–2002) the difference in these growth rates is sizeable.[13] Table 7 shows that in certain states and during certain time periods the estimated bias in productivity growth is large, and ignoring this bias could result in substantial errors in interpreting rates of productivity growth among different states and time periods. This is especially true when considering annual estimates of state-average productivity growth. Econometric models of production and productivity are susceptible to this bias.

7. Conclusion

The quantity of U.S. agricultural output more than doubled during the years 1950–2002, reflecting increased use of materials inputs along with changes in technology, combined with reductions in the use of capital, land and labor inputs. The overall growth in output is essentially entirely attributable to productivity growth, since the aggregate index of inputs did not change appreciably.

Like other studies of other sectors, we have shown that U.S. agricultural productivity growth was procyclical throughout the second half of the 20th century. This paper has focused on one possible reason for these observed productivity patterns— measurement error in the capital variable when estimates of changes in the capital stock (assuming constant utilization rates) are used to represent changes in the flows of services from the capital stock. Our hypothesis is that the assumption of constant utilization rates gives rise to

[13] An index of productivity (MFP) would increase from a base of 100 in the year 1951, to 319 in the year 2002 with a 2.23 percent growth rate, and 259 in the year 2002 with a 1.83 percent growth rate. In percentage terms 319 is approximately 21 percent higher than 259, implying 21 percent more output for the same measured inputs.

year-to-year, or cyclical errors in estimates of the quantity of capital and productivity, contributing to pro-cyclical productivity patterns.

We augmented conventional production function models, to allow for the variable utilization of capital assets, and estimated the augmented model to test the hypothesis that cyclical movements in demand for agricultural outputs and inputs affect measures of agricultural productivity. The results indicate that a portion of the pro-cyclical patterns observed in measures of productivity growth can be attributed to errors in measuring durable inputs like physical capital. In many of the regression results the finding was for significant and positive utilization effects related to changes in farmers' terms of trade as well as changes in growing conditions.

The most important effect of the utilization bias discussed in this paper is that unobservable cyclical movements in the utilization of durable assets have the potential to introduce significant bias in studies of production, especially in parametric studies that are sensitive to measurement error in the input quantities. It is quite possible that the utilization problem analyzed in this paper may be more pronounced in capital-intensive sectors of the economy such as construction, manufacturing, and mining.

References

Acquaye AK, Alston JM, Pardey PG (2003) Post-War Productivity Patterns in U.S. Agriculture: Influences of Aggregation Procedures in a State-Level Analysis. American Journal of Agricultural Economics 85: 59-80.

Ball VE, Butault JP, Nehring R (2001) U.S. Agriculture, 1960-96: A Multilateral Comparison of Total Factor Productivity. USDA Technical Bulletin Number 1895.

Basu S (1996) Procyclical Productivity: Increasing Returns or Cyclical Utilization? The Quarterly Journal of Economics 111: 719-751.

Basu, S, Kimball MS (1997) Cyclical Productivity with Unobservable Input Variation. NBER Working Paper Number 5915. Washington D.C.: National Bureau of Economic Research.

Basu S, Fernald J (2000) Why Is Productivity Procyclical? Why Do We Care? NBER Working Paper Number 7940. Washington D.C.: National Bureau of Economic Research.

Baxter M, Farr D (2001) The Effects of Variable Capital Utilization on the Measurement and Properties of Sectoral Productivity: Some Underlying International Evidence. NBER Working Paper 8475. Washington D.C.: National Bureau of Economic Research.

Baxter M, Farr D (2005) Variable Capital Utilization and International Business Cycles. Journal of International Economics 65: 335-347.

Berndt ER, Fuss MA (1986) Editors' Introduction. Journal of Econometrics 33: 1-5.

Berndt ER, Fuss MA (1986) Productivity Measurement with Adjustments for Variations in Capacity Utilization and Other Forms of Temporary Equilibrium. Journal of Econometrics 33: 7-29.

Capalbo SM, Denny, M (1986) Testing Long-run Productivity Models for the Canadian and U.S. Agricultural Sectors. American Journal of Agricultural Economics 68: 615-25.

Celikko P, Stefanou SE (1999) Measuring the Impact of Price-Induced Innovation on Technological Progress: Application to U.S. Food Processing and Distribution Sector. Journal of Productivity Analysis 12: 135-151.

Craig BJ, Pardey PG (1996) Productivity Measurement in the Presence of Quality Change. American Journal of Agricultural Economics 78: 1349-1354.

Esposti R (2000) Stochastic Technical Change and Procyclical TFP the Case of Italian Agriculture. Journal of Productivity Analysis 14: 119–141.

Foss MF (1997) The Utilization of Capital Equipment: Postwar Compared with Prewar. Survey of Current Business Washington D.C.: Bureau of Census: 8-16.

Fousekis P, Papakonstantinou A (1997) Economic Capacity Utilization and Productivity Growth in Greek Agriculture. Journal of Agricultural Economics 48: 38-51.

Fulginiti LE, Perrin RK (1993) Prices and Productivity in Agriculture. The Review of Economics and Statistics 75: 471-482.

Griliches Z, Jorgenson DW (1967) The Explanation of Productivity Change. Review of Economic Studies 34: 249-283.

Hayami Y, Ruttan VW (1986) Agricultural Productivity Differences Among Countries. American Economic Review 60: 895-911.

Helliwell JF, Chung A (1986) Aggregate Output with Variable Rates of Utilization of Employed Factors. Journal of Econometrics 33: 285-310.

Hicks J (1932) The Theory of Wages. London: Macmillan 1963 edition (Original printing 1932).

Jin S, Rozelle S, Aston JM, Huang J (2005) Economies of Scale and Scope and the Economic Efficiency of China's Agricultural Research System. International Economic Review 46: 1033-1057.

Jorgenson DW (1990) Productivity and Economic Growth. Chapter in E. Berndt and J. Triplett, eds. Fifty Years of Economic Measurement: The Jubilee Conference on Research in Income and Wealth. University of Chicago Press: 19-118.

Jorgenson DW, Gollop FM (1992) Productivity Growth in U.S. Agriculture: A Postwar Perspective. American Journal of Agricultural Economics 74: 745-50.

Lau LJ, Yotopoulos PA (1971) A Test for Relative Efficiency and Application to Indian Agriculture. American Economic Review 61: 94-109.

Luh YH, Stefanou SE (1991) Productivity Growth in U.S. Agriculture Under Dynamic Adjustment. American Journal of Agricultural Economics 73: 1116-1125.

Morrison CJ (1985) On the Economic Interpretation and Measurement of Optimal Capacity Utilization with Anticipatory Expectations. Review of Economic Studies 52: 295-310.

Morrison CJ (1986) Productivity Measurement with Non-Static Expectations and Varying Capacity Utilization: An Integrated Approach. Journal of Econometrics 33: 51-74.

Moschini G (2001) Production Risk and Estimation of Ex-Ante Cost Functions. Journal of Econometrics 100: 357-380.

Mundlak Y (1988) Endogenous Technology and the Measurement of Productivity. Chapter in S.M. Capalbo and J.M. Antle, eds. Agricultural Productivity: Measurement and Explanation. Washington D.C.: Resources for the Future: 316-331.

Mundlak Y (1996) Production Function Estimation: Reviving the Primal. Econometrica 64: 431-438.

Mundlak Y (2000) Agriculture and Economic Growth: Theory and Measurement. Cambridge MA: Harvard University Press.

Mundlak Y, Larson D, Butzer R (1997) The Determinants of Agricultural Production: A Cross-Country Analysis. World Bank Policy Research Working Paper 1827 Washington D.C.

Pardey PG, Andersen MA, Craig BJ, Alston JM (2010) The InSTePP Accounts: U.S. Agricultural Input, Output, and Productivity Series Primary Data Documentation, 1949–2002 (Version 4). University of Minnesota: International Science and Technology Practice and Policy Center.

Paris Q, Caputo M (1995) The Rhetoric of Duality. Journal of Agricultural and Resource Economics 20: 195–214.

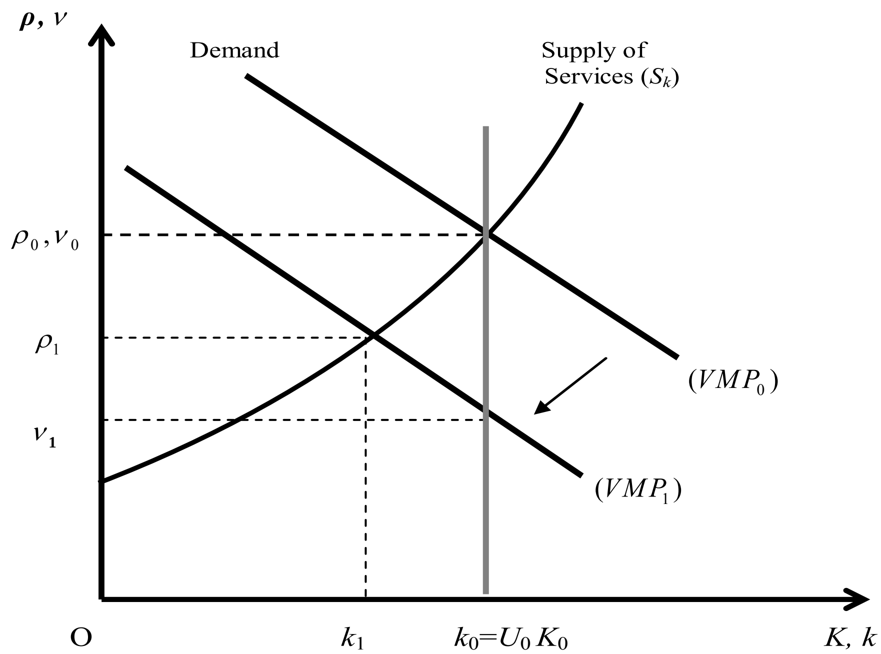
Pope RD, Just RE (1996) Empirical Implementation of Ex Ante Cost Functions. Journal of Econometrics 72: 231-249.

Pope RD, Just RE (2003) Distinguishing Errors in Measurement from Errors in Optimization. American Journal of Agricultural Economics 85: 348-358.

Slade ME (1986) Total-Factor-Productivity Measurement When Equilibrium is Temporary: A Monte Carlo Assessment. Journal of Econometrics 33: 75-95.

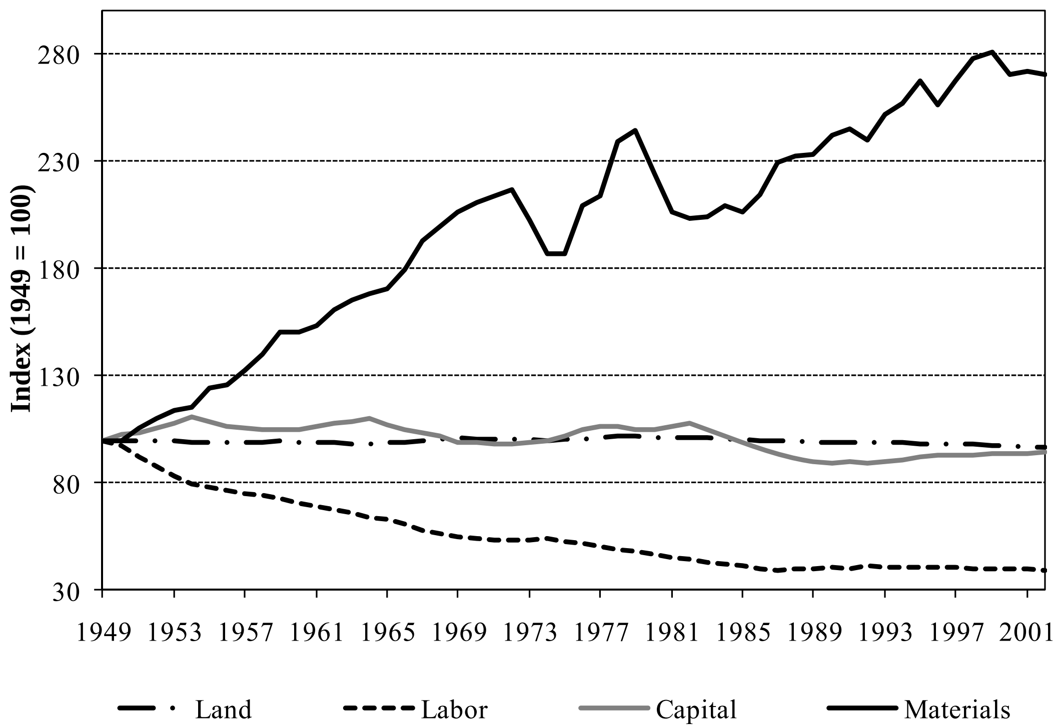
Wen Y (2004) What Does It Take to Explain Procyclical Productivity? Contributions to Macroeconomics 4: 1-38.

Figure 1: Demand Shock in Market for Durable Assets



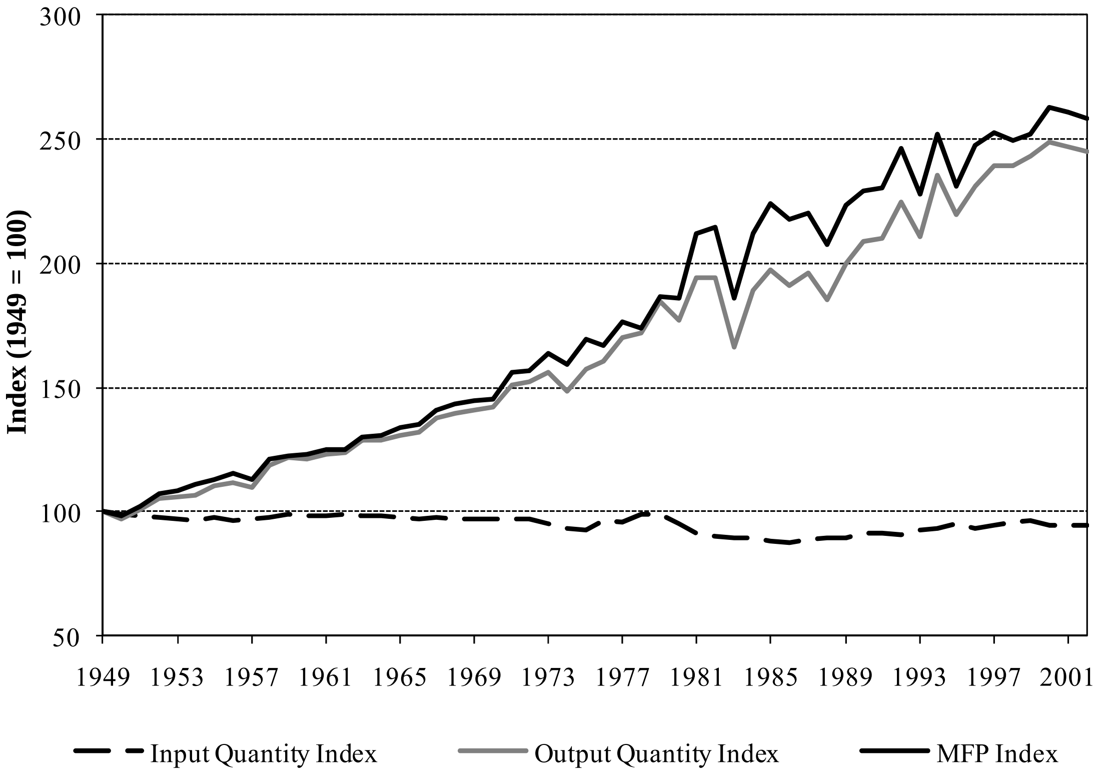
Source: Authors.

Figure 2: Indexes of the Quantity of Land, Labor, Capital, and Materials in U.S. Agriculture, 1949–2002



Source: InSTePP production accounts.

Figure 3: Indexes of the Quantity of Input, Output, and Productivity in U.S. Agriculture, 1949–2002



Source: InSTePP production accounts.

Table 1: Descriptive Statistics

	Mean	Minimum	Maximum	Standard Deviation
Natural Logs				
Output	5.006	4.121	6.158	0.405
Labor	3.928	2.833	4.615	0.421
Land	4.452	3.235	4.892	0.308
Capital	4.571	3.535	5.423	0.293
Materials	5.135	3.664	6.321	0.505
Growing conditions	0.000	-2.205	0.388	0.231
Terms of trade	-0.001	-0.738	0.591	0.168
Rate of Growth (percent per year)				
Output	0.014	-0.528	0.492	0.081
Labor	-0.018	-0.209	0.244	0.037
Land	-0.005	-0.074	0.046	0.015
Capital	-0.002	-0.121	0.090	0.026
Materials	0.016	-0.293	0.309	0.060
Growing conditions	-0.005	-2.277	2.264	0.304
Terms of trade	0.000	-0.497	0.532	0.086

Note: The estimates in logarithms include 2,544 observations. The estimates in growth rates include 2,496 observations.

Table 2: Specifications of the Production Functions in the Empirical Analysis

Equation Type and Specification
A. Conventional Cobb-Douglas
$q_t = \alpha_0 + \alpha_1 y_{1t} + \alpha_2 y_{2t} + \sum_{i=1}^{n} \beta_i x_{it}$
B. Utilization Augmented Cobb-Douglas
$q_t = \alpha_0 + \alpha_1 y_{1t} + \alpha_2 y_{2t} + \sum_{i=1}^{n} \beta_i x_{it} + \beta_3 (\lambda_{31} \hat{z}_{1t} + \lambda_{32} y_{2t})$
C. Conventional Translog
$q_t = \alpha_0 + \alpha_1 y_{1t} + \alpha_2 y_{2t} + \sum_{i=1}^{n} \beta_i x_{it} + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} x_{it} x_{jt}$
D. Utilization Augmented Translog
$q_t = \alpha_0 + \sum_{k=1}^{s} \alpha_k y_{kt} + \sum_{i=1}^{n} \beta_i x_{it} + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} x_{it} x_{jt} + (\lambda_{31} \hat{z}_{1t} + \lambda_{32} y_{2t}) \left[\beta_3 + \sum_{j=1}^{4} \gamma_{3j} x_{jt} + \frac{1}{2} \gamma_{33} \lambda_{31} \hat{z}_{1t} \right]$

Note: Two equations were estimated for each specification, one in logarithms and the other in rates of change of the variables.

Table 3: Cobb-Douglas Models: Ordinary Least Squares (OLS) Estimates

		Logs		Growth rates	
		Base	Utilization	Base	Utilization
Production Elasticities					
Land	β_1	0.205	0.223	0.190	0.223
		(0.026)	(0.026)	(0.092)	(0.092)
Labor	β_2	0.024	-0.008	0.046	0.017
		(0.019)	(0.019)	(0.035)	(0.034)
Capital	β_3	0.206	0.218	0.240	0.256
		(0.024)	(0.025)	(0.064)	(0.063)
Materials	β_4	0.391	0.396	0.226	0.232
		(0.016)	(0.017)	(0.024)	(0.024)
Trend	α_1	0.012	0.011		
		(0.000)	(0.000)		
Growing Conditions	α_2	0.077	0.084	0.102	0.103
		(0.017)	(0.018)	(0.007)	(0.007)
TOT Elasticity	$\lambda_{31}\beta_3$		0.205		0.118
			(0.041)		(0.019)
Constant	α_0	-22.126	-21.289	0.013	0.013
		(0.848)	(0.870)	(0.002)	(0.002)
RTS		0.825	0.829	0.701	0.728
R^2		0.794	0.796	0.182	0.198

Note: Robust standard errors in parentheses calculated using the Huber-White sandwich estimator of variance. TOT = Terms of trade. RTS = Returns to scale.

Table 4: Translog Models: OLS and Non-linear Least Squares Estimates (NLLS)

		Logs		Growth rates	
		Base (OLS)	Utilization (NLLS)	Base (OLS)	Utilization (NLLS)
Parameters					
Land	β_1	-0.979	-1.035	-0.039	0.036
		(0.378)	(0.321)	(0.131)	(0.129)
Labor	β_2	0.252	0.514	0.078	0.048
		(0.270)	(0.239)	(0.042)	(0.043)
Capital	β_3	-0.743	0.297	0.199	0.139
		(0.400)	(0.134)	(0.079)	(0.046)
Materials	β_4	0.206	-0.357	0.236	0.229
		(0.248)	(0.152)	(0.026)	(0.027)
Cross-Product Terms					
Land/Labor	γ_{12}	0.260	0.507	3.089	2.582
		(0.150)	(0.130)	(2.080)	(1.964)
Land/Capital	γ_{13}	0.290	0.242	0.362	-3.266
		(0.126)	(0.076)	(3.359)	(1.544)
Land/Materials	γ_{14}	-0.264	-0.172	5.019	4.553
		(0.131)	(0.105)	(1.601)	(1.486)
Labor/Capital	γ_{23}	-0.095	-0.185	-2.658	-0.206
		(0.112)	(0.057)	(1.493)	(0.384)
Labor/Materials	γ_{24}	-0.069	-0.191	-1.231	-0.842
		(0.077)	(0.065)	(0.521)	(0.517)
Capital/Materials	γ_{34}	-0.398	-0.130	-2.117	0.797
		(0.093)	(0.045)	(0.984)	(0.333)
Land/Land	γ_{11}	0.035	-0.196	-7.945	-17.323
		(0.133)	(0.247)	(2.946)	(5.892)
Labor/Labor	γ_{22}	-0.078	-0.211	-0.236	-0.061
		(0.051)	(0.086)	(0.347)	(0.703)
Capital/Capital	γ_{33}	0.228	0.013	-1.662	-0.188
		(0.110)	(0.014)	(1.528)	(0.260)
Materials/Materials	γ_{44}	0.333	0.560	-0.062	- 0.093
		(0.036)	(0.057)	(0.193)	(0.417)
Intercept Terms					
Trend	α_1	0.012	0.012		
		(0.000)	(0.001)		
Growing Conditions	α_2	0.099	0.088	0.101	0.145
		(0.017)	(0.021)	(0.007)	(0.025)
Utilization Terms					
Terms of Trade	λ_{31}		-6.002		0.824
			(2.107)		(0.263)
Growing Conditions	λ_{32}		0.327		-0.254
			(0.389)		(0.140)
Constant	α_0	5.279	-20.026		0.015
		(0.719)	(1.392)		(0.002)
RTS		0.919	0.863	0.577	0.575
R^2		0.817	0.821	0.190	0.210

Note: Standard errors in parentheses. RTS = Return to scale.

Table 5: Annual MFP Growth in U.S. Agriculture 1951–2002

	Logs		Growth rates	
	Base	Utilization	Base	Utilization
	-------------- *percent per year* -------------			
Cobb-Douglas models	1.17	1.13	1.34	1.30
Translog models	1.18	1.24	1.55	1.53

Note: All estimates are significantly different from zero at the 1 percent level of significance.

Table 6: Elasticity of Productivity of Expected Terms of Trade and Growing Conditions

	Cobb-Douglas models		Translog models	
	Logs	Growth rates	Logs	Growth rates
Terms of Trade	0.205	0.118	-0.226	0.143
	(0.041)	(0.019)	(0.093)	(0.046)
Growing Conditions	0.084	0.103	0.100	0.101
	(0.018)	(0.002)	(0.018)	(0.015)

Note: Standard errors in parentheses.

Table 7: Average Productivity Growth by Year and by State

State-average by year				Annual average by state			
Year	Base	Utilization	Abs. Diff.	State	Base	Utilization	Abs. Diff.
		percent per year				*percent per year*	
1951	3.87	2.43	1.44	Alabama	2.14	2.16	0.02
1952	1.90	0.84	1.06	Arizona	1.90	1.94	0.04
1953	3.74	4.55	0.81	Arkansas	2.66	2.63	0.03
1954	-0.43	0.64	1.06	California	2.29	2.19	0.10
1955	-0.70	0.28	0.99	Colorado	1.65	1.63	0.02
1956	2.80	2.72	0.08	Connecticut	1.09	1.01	0.08
1957	-1.70	-1.25	0.45	Delaware	2.92	2.91	0.01
1958	3.22	3.48	0.25	Florida	2.00	2.03	0.03
1959	1.38	0.98	0.41	Georgia	2.90	2.96	0.06
1960	-0.53	-0.07	0.45	Idaho	2.13	2.12	0.02
1961	0.86	0.87	0.01	Illinois	1.65	1.59	0.06
1962	1.49	1.47	0.02	Indiana	1.42	1.50	0.08
1963	2.76	2.65	0.10	Iowa	1.75	1.77	0.02
1964	0.72	1.19	0.47	Kansas	1.66	1.79	0.13
1965	2.22	1.76	0.46	Kentucky	0.46	0.43	0.03
1966	0.36	0.05	0.31	Louisiana	1.57	1.61	0.04
1967	1.86	1.58	0.28	Maine	1.18	1.08	0.10
1968	2.16	2.55	0.39	Maryland	1.86	1.89	0.03
1969	1.56	1.09	0.46	Massachusetts	0.72	0.46	0.26
1970	1.49	1.02	0.46	Michigan	1.58	1.51	0.07
1971	4.88	4.61	0.27	Minnesota	1.85	1.80	0.05
1972	-1.11	-0.64	0.47	Mississippi	2.11	2.06	0.05
1973	2.60	1.65	0.95	Missouri	0.89	1.02	0.12
1974	2.24	1.61	0.63	Montana	0.83	1.11	0.28
1975	2.44	3.75	1.31	Nebraska	1.87	2.03	0.16
1976	1.91	2.62	0.70	Nevada	1.07	1.20	0.13
1977	0.65	0.42	0.23	New Hampshire	0.84	0.66	0.18
1978	-1.30	0.38	1.69	New Jersey	1.15	0.52	0.63
1979	4.37	2.63	1.75	New Mexico	2.29	2.19	0.10
1980	2.08	2.60	0.52	New York	0.83	0.77	0.07
1981	8.20	7.89	0.31	North Carolina	1.99	1.76	0.22
1982	1.72	3.09	1.37	North Dakota	1.83	2.23	0.40
1983	-6.79	-6.98	0.19	Ohio	1.15	1.22	0.08
1984	7.68	6.86	0.82	Oklahoma	1.51	1.52	0.01
1985	3.79	3.79	0.00	Oregon	1.85	1.81	0.04
1986	-3.15	-2.50	0.65	Pennsylvania	1.54	1.52	0.01
1987	2.16	1.93	0.24	Rhode Island	1.79	1.53	0.26
1988	-1.32	-2.02	0.70	South Carolina	1.53	1.52	0.01
1989	3.07	2.30	0.78	South Dakota	1.45	1.70	0.25
1990	3.81	3.83	0.01	Tennessee	0.68	0.72	0.05
1991	1.69	1.63	0.06	Texas	1.73	1.87	0.14
1992	3.38	3.73	0.36	Utah	1.33	1.31	0.02
1993	-3.52	-3.35	0.17	Vermont	1.23	1.01	0.22
1994	8.61	7.91	0.70	Virginia	0.85	0.75	0.10
1995	-4.76	-4.69	0.07	Washington	2.10	2.07	0.02
1996	3.90	3.43	0.47	West Virginia	0.80	0.64	0.16
1997	0.67	0.62	0.04	Wisconsin	1.12	1.12	0.00
1998	0.09	0.13	0.04	Wyoming	0.69	0.70	0.01
1999	2.52	3.07	0.55	**Average**	**1.55**	**1.53**	**0.02**
2000	2.02	2.17	0.14				
2001	0.01	0.24	0.22				
2002	-0.98	-1.82	0.84				
Average	**1.55**	**1.53**	**0.02**				

Source: Authors' calculations.

Note: The column labeled 'Abs. Diff.' is the absolute value of the difference between the estimates.