The Journal of Productivity Analysis, 4, 353-370 (1993)

Learning-By-Doing and the Sources of Productivity Growth: A Dynamic Model with Application to U.S. Agriculture*

YIR-HUEIH LUH
National Tsing Hua University, Hsin Chu, Taiwan, R.O.C.

SPIRO E. STEFANOU
Pennsylvania State University, University Park, PA 16802, USA

Abstract

The significance of learning to productivity grwoth is formulated within a dynamic adjustment-cost framework. Explicitly treating the acquisition of knowledge as a firm-specific capital good entering the production function along with other conventional inputs, the dynamic optimization model integrates the learning-by-doing hypothesis with technical change, scale, and disequilibrium input use effects in the aggregate productivity analysis. The theoretical framework is applied to examining the dynamic components accounting for the growth of U.S. production agriculture over the 1950-82 period. The results imply a less important role for technical change and assign a substantial role to the previously unmeasured contribution of learning-by-doing to the growth of aggregate agriculture industry.

1. Introduction

The measurement of productivity fluctuations in the U.S. has been the focus of attention in recent decades (Abramovitz [1956]; Solow [1957]; Fabricant [1959]; Jorgenson and Griliches [1967]; Christensen and Jorgenson [1970]; Hulten [1975, 1979]; Jorgenson [1988]). In examining the factors underlying productivity change, productivity growth is viewed as a broad measure capturing the influence of many effects including biased technical change, scale economies, temporary equilibrium and learning.

The significance of learning is generally discussed in three contexts in the literature. The progress or learning function describes the increased efficiency in direct labor requirement through the repetition of a task. Countering this approach, the endogenous theory of technical change in knowledge proposed by Arrow [1962] suggests learning as the underlying force driving the intertemporal shifts in production. Although the learning-by-doing formulation has the advantage of endogenously accumulating knowledge, one of its drawbacks is the exclusion of investment in research and development. More recently, the new economics of growth literature offers an alternative view of endogenously generated long-run growth. Lucas [1988] and Romer [1990], for instance, implictly allow the prospect of knowledge generating long-term growth without relying on exogenous changes

*The editor for this paper was Melvyn Fuss.

in technology or population. The third formulation of learning and productivity expresses the concept of learning in terms of improved knowledge regarding new technologies. Learning that enters the dynamics of the innovation adoption process has been modeled using the Bayesian approach or the innovation cycle hypothesis.

The dynamic aspects of learning are addressed in the literature. Oi [1967] indicates that learning-by-doing is a dynamic concept implying the existence of temporal linkages in production. The economies of scale resulting from knowledge accumulation is a logical outcome of intertemporal planning or production. However, very few studies incorporate the learning effect into a dynamic model applicable to long-run planning and optimization behavior. Past efforts employ the deterministic or expected intertemporal optimization framework in determining the optimal rate of learning (e.g., Rosen [1972]; Brueckner and Raymon [1983]); examine the effect of learning in the presence of entry and dynamic demand changes Devinney [1987], and model the stochastic learning process (Majd and Pindyck [1989]; Stefanou [1989]).

This paper develops a dynamic learning model where additional knowledge (flow of learning) is acquired through the production process within a long-run profit maximization framework. Within the dynamic adjustment-cost framework, knowledge stock enters the production function along with other conventional inputs while firms are penalized for rapid adjustment of quasi-fixed factors. The methodology developed here separates the learning effect from the scale, technical change and quasi-fixed factor disequilibrium effects in measuring changes in total factor productivity. The foundations of the dynamic adjustment model with learning is developed, followed by an empirical application to U.S. production agriculture employing the dynamic dual approach to derive a complete system of dynamic factor demand and output supply equations. The estimated parameters are reported and used to calculate policy-relevant elasticities. Productivity measurement explicitly accounting for the contribution of learning-by-doing is compared to the static and dynamic adjustment without learning cases.

2. The Dynamic Learning Model

The precise effect of learning is quite sensitive to changes in the definition of accumulated knowledge. Wright's [1936] study of production costs for airframes and others established that average and marginal input requirements reduce as the volume of accumulated output goes up. This suggests the possibility of using cumulative output as an index of experience. However, Arrow [1962] notes if the rate of output is constant, the stimulus to learning should be constant. Consequently, the learning that does take place is a gradual approach to equilibrium behavior. An alternative measure is the cumulative gross investment as the index of experience. Investment is capable of changing the environment in which production takes place and provides the continually new stimulus required for learning to take place (Sheshinski [1967]).

The evolution of productivity advancement over time based on the principles of optimum capital accumulation can be developed by allowing experience to be represented by accumulated gross investment, H. The change of experience over time ($\dot{H}$) is attributed to current gross investment (I^c); i.e., $\dot{H} = I_c$. With more than one capital input, an experience index is a weighted measure of gross investment for each quasi-fixed factor. Investment is aggregated through the choice of a weighting function, $Z_i(I)$, where I represents the vector of gross investments, $I = (I_1, \ldots, I_n)$. The transformation function describing the multiple-output production process is defined as $F(Y, X, K, \dot{K}, H, t)$, where Y represents the vector of outputs, X and K are the vectors of variable and quasi-fixed inputs, respectively, and $\dot{K}$ indicates the presence of internal adjustment costs. The argument t is a time trend serving as a proxy for the advancement of technology. The production technology is assumed to be characterized by jointness in inputs. Therefore, each input vector in the transformation function defines the total amount of that input type used in production of all outputs.

Within the economically relevant portion of the production surface where a profit maximizing firm operates, the transformation function is assumed to possess the following properties:

A.1 $F(Y, X, K, \dot{K}, H, t)$ is continuously twice differentiable, convex and closed set in Y, X, K, $\dot{K}$, and H in the non-negative orthant.
A.2 $F(Y, X, K, \dot{K}, H, t)$ is strictly increasing in Y and strictly decreasing, convex in X, K and H.
A.3 $F(Y, X, K, \dot{K}, H, t)$ is strictly increasing (decreasing) for increasing (decreasing) $\dot{K}$ and convex in $\dot{K}$.

Assumption A.2 suggests the stock of knowledge and other inputs exhibit decreasing marginal returns in the production of output. Assumption A.3 assures the sluggish adjustment of the quasi-fixed factors. The firm producing with the production technology described by properties (A) solves the dynamic optimization problem of the form

$$J(p, w, c, k, h, t) = \max_{Y,X,\dot{K}} \int_t^{\infty} [p'Y - w'X - c'K]\, e^{-rs} ds, \quad (1)$$

subject to

$$\dot{K} = I - \delta K, \; K(t) = k,$$

$$F(Y, X, K, \dot{K}, H, s) = 0, \; t \leq s < \infty$$

$$\dot{H} = \sum_{i=1}^{n} Z_i\,(I)\, I_i, \; H(t) = h.$$

Here $J(\,)$ is the value function representing the optimal value of problem (1) when the interior solution exists. The value function is the maximized sum of discounted profit flow over the entire planning horizon and can be viewed as the long-run profit function for the competitive firm. Let the stocks of the quasi-fixed factors and the knowledge component at the beginning of the period be denoted by k and h, respectively. The value function also depends on time, t, the price vector of output, p, price vector of variable inputs, w, and the rental price vector for the quasi-fixed factor stocks, c. All vectors are taken to be conformably defined. The constant discount and depreciation rates are denoted by r and δ, respectively.

As the firm expects prices denoting actual market values at time t to persist indefinitely,[1] the dynamic optimization problem in (1) is transformed into a sequence of static optimization problems linked over time. The static optimization problem is expressed by the Hamilton-Jacobi equation

$$rJ(p, w, c, k, h, t) = \max_{Y,X,\dot{K},\lambda} \{p'Y - w'X - c'k + (I - \delta k)'J_x + \lambda F(Y, X, k, \dot{K}, h, t) + \dot{H}J_h + J_t\}, \qquad (2)$$

where $\lambda \geq 0$ is the Lagrangian multiplier associated with the production technology constraint.

The first-order conditions characterizing the interior solution for the long-run profit maximization problem in (1) are

$$F_{Y_i} = -\frac{p_i}{\lambda^*} \text{ for } i = 1, \ldots, m, \qquad (3a)$$

$$F_{X_\rho} = \frac{w_\rho}{\lambda^*} \text{ for } \rho = 1, \ldots, v, \qquad (3b)$$

$$\lambda^* F_{\dot{K}_j} = -\left[J_{k_j} + J_h\left(Z_j + \sum_{g=1}^{n} \frac{\partial Z_g}{\partial I_j} I_g\right)\right] \text{ for } j = 1, \ldots, n, \qquad (3c)$$

$$F(Y, X, k, \dot{K}, h, t) = 0. \qquad (3d)$$

Conditions (3a) and (3b) are simply the dynamic analog of the profit-maximizing conditions in the static setting. Condition (3c) states that the marginal cost of adjustment must equal the shadow value of capital. One of the distinctive features of the dynamic learning model is the firm's investment decision also determines its accumulation of knowledge. Consequently, optimal investment depends on the firm's marginal valuation of both capital stocks and knowledge stock.

The significance of learning to productivity growth is developed by decomposing the growth in output. The decomposition of output growth in the multiple-output production process is derived by totally differentiating $F(Y, X, k, \dot{K}, h, t)$ yielding

$$\sum_{i=1}^{m} F_{Y_i}\, dY_i + \sum_{\rho=1}^{v} F_{X_\rho}\, dX_\rho + \sum_{j=1}^{n} F_{k_j}\, dk_j + \sum_{j=1}^{n} F_{\dot{K}_j}\, d\dot{K}_j + \left(\frac{\partial F}{\partial t}\right) dt + \left(\frac{\partial F}{\partial h}\right) dh = 0. \qquad (4)$$

Dividing through $\Sigma_{i=1}^{m} F_{y_i} Y_i$ and dt and rearranging terms yields

$$\sum_{i=1}^{m} \frac{F_{Y_i} Y_i}{\sum_{i=1}^{m} F_{Y_i} Y_i} \hat{Y}_i = \sum_{\rho=1}^{v} \frac{-F_{X_\rho} X_\rho}{\sum_{i=1}^{m} F_{Y_i} Y_i} \hat{X}_\rho + \sum_{j=1}^{n} \frac{-F_{k_j} k_j}{\sum_{i=1}^{m} F_{Y_i} Y_i} \hat{k}_j$$

$$+ \sum_{j=1}^{n} \frac{-F_{\dot{K}_j} \dot{K}_j}{\sum_{i=1}^{m} F_{Y_i} Y_i} \hat{\dot{K}}_j + \frac{-\left(\frac{\partial F}{\partial t}\right)}{\sum_{i=1}^{m} F_{Y_i} Y_i} + \frac{-\left(\frac{\partial F}{\partial h}\right) h}{\sum_{i=1}^{m} F_{Y_i} Y_i} \hat{h} \tag{5}$$

where "$\hat{}$" indicates the proportional rate of change over time. The expressions for F_{k_j} and F_h are found by rearranging the first partial derivatives of the optimized Hamilton-Jacobi equation with respect to k_j and h, respectively.

Substituting the first-order conditions and the expressions of F_{k_j} and F_h into (5) yields

$$\sum_{i=1}^{m} \frac{p_i Y_i}{\sum_{i=1}^{m} p_i Y_i} \hat{Y}_i = \sum_{\rho=1}^{v} \frac{w_\rho X_\rho}{\sum_{i=1}^{m} p_i Y_i} \hat{X}_\rho + \sum_{j=1}^{n} \frac{(rJ_{k_j} + c_j) k_j}{\sum_{i=1}^{m} p_i Y_i} \hat{k}_j + \sum_{j=1}^{n} \frac{-J_{k_j} \dot{K}_j}{\sum_{i=1}^{m} p_i Y_i} \hat{J}_{k_j}$$

$$+ \sum_{j=1}^{n} \frac{-\left[J_{K_j} + J_h \left(Z_j + \sum_{g=1}^{n} \frac{\partial Z_g}{\partial I_j} I_g\right)\right] \dot{K}_j}{\sum_{i=1}^{m} p_i Y_i} \hat{\dot{K}}_j + \hat{A} + \frac{rJ_h h}{\sum_{i=1}^{m} p_i Y_i} \hat{h} + \frac{-J_h \dot{H}}{\sum_{i=1}^{m} p_i Y_i} \hat{J}_h \tag{6}$$

where $\hat{A} = -(\partial F/\partial t)/\Sigma_{i=1}^{m} F_{Y_i} Y_i$. By defining total revenue at time τ, $TR(\tau)$, and total shadow cost at time τ, $TSC(\tau)$, as

$$TR(\tau) = p'Y^*$$

$$TSC(\tau) = w'X^* + c'k - \dot{K}' J_k - \dot{H}J_h - J_t,$$

(6) can be rewritten by multiplying and dividing through by $TSC(\tau)$ to yield

$$\hat{Y}(\tau) = \sum_{\rho=1}^{v} \frac{w_\rho X_\rho}{TSC(\tau)} \frac{TSC(\tau)}{TR(\tau)} \hat{X}_\rho + \sum_{j=1}^{n} \frac{(rJ_{k_j} + c_j)\, k_j}{TSC(\tau)} \frac{TSC(\tau)}{TR(\tau)} \hat{k}_j$$

$$+ \sum_{j=1}^{n} \frac{-J_{k_j} \dot{K}_j}{TSC(\tau)} \frac{TSC(\tau)}{TR(\tau)} \hat{J}_{k_j} + \sum_{j=1}^{n} \frac{-\left[J_{k_j} + J_h \left(Z_j + \sum_{g=1}^{n} \frac{\partial Z_g}{\partial I_j} I_g \right) \right] \dot{K}_j}{TSC(\tau)}$$

$$\frac{TSC(\tau)}{TR(\tau)} \hat{\dot{K}}_j + \hat{A} + \frac{-J_h \dot{H}}{TR(\tau)} \hat{J}_h + \frac{rJ_h\, h}{TR(\tau)} \hat{h}. \tag{7}$$

where

$$\hat{Y}(\tau) = \sum_{i=1}^{m} \frac{p_i Y_i}{TR(\tau)} \hat{Y}_i$$

represents the multiple output measure of the proportional growth in output at time τ. The ratio of $TSC(\tau)/TR(\tau)$ equals the inverse of the sum of the cost elasticity for each output in an intertemporal cost minimization problem, evaluated at the profit maximizing position. Further define

$$\hat{F}_v = \sum_{\rho=1}^{v} \frac{w_\rho X_\rho}{TSC(\tau)} \hat{X}_{\rho},$$

$$\hat{F}_{q_1} = \sum_{j=1}^{n} \frac{-\left[J_{k_j} + J_h \left(Z_j + \sum_{g=1}^{n} \frac{\partial Z_g}{\partial I_j} I_g \right) \right] \dot{K}_j}{TSC(\tau)} \hat{\dot{K}}_j,$$

$$\hat{F}_{ssk} = \sum_{j=1}^{n} \frac{(rJ_{k_j} + c_j)\, k_j}{TSC(\tau)} \hat{k}_j,$$

$$\hat{F}_{q_2} = \sum_{j=1}^{n} \frac{-J_{k_j} \dot{K}_j}{TSC(\tau)} \hat{J}_{k_j},$$

$$\hat{G}_{q_2} = \frac{-J_h \dot{H}}{TR(\tau)} \hat{J}_h,$$

$$\hat{G}_{ssl} = \frac{rJ_h \, h}{TR(\tau)} \hat{h},$$

$$SE(\tau) = \frac{TSC(\tau)}{TR(\tau)}.$$

Using the definitions above, decomposed output growth is expressed as

$$\hat{Y}(\tau) = \hat{A} + [SE(\tau) \, (\hat{F}_v + \hat{F}_{q_1} + \hat{F}_{q_2} + \hat{F}_{ssk})] + \hat{G}_{ssl} + \hat{G}_{q_2}, \tag{8}$$

where $\hat{Y}(\tau)$ is the multiple-output measure of the proportional output growth and $\hat{A}$ represents the shift in the multiple-output technology. The ratio of total shadow cost to total revenues at time τ, denoted by $SE(\tau)$, is a measure of scale in an intertemporal cost minimization problem evaluated at the profit maximizing position. $\hat{F}_v$ represents the proportional growth of the variable factors and $\hat{F}_{q_1}$ and $\hat{F}_{q_2}$ are disequilibrium components. The first disequilibrium component measures the proportional growth in net physical investment, and the second captures the proportional changes in the endogenously determined marginal values of quasi-fixed factor stocks. The component $\hat{F}_{ssk}$ reflects the proportional growth in quasi-fixed factor levels at long-run equilibrium.[2] The learning effects include the direct contribution of proportional changes in the endogenously determined shadow value of learning, $\hat{G}_{q_2}$, and the growth of the value of accumulated knowledge at long-run equilibrium,[3] $\hat{F}_{ssl}$. In addition to the direct learning effects, there are also indirect learning effects included in the components associated with the quasi-fixed factor disequilibrium effects, $\hat{F}_{q_1}$ and $\hat{F}_{q_2}$.

Total factor productivity growth ($T\hat{F}P$) is defined as the residual growth in outputs not explained by the growth in input use, input stock, valuation of the input stock, and learning and is expressed as

$$T\hat{F}P(\tau) = \hat{A} + [SE(\tau) - 1] \, [\hat{F}_v + \hat{F}_{q_1} + \hat{F}_{q_2} + \hat{F}_{ssk}] + \hat{G}_{ssl} + \hat{G}_{q_2}. \tag{9}$$

Therefore, growth in total factor productivity is decomposed into four components: technical change, scale, disequilibrium, and learning effects. Equation (9) has several important implications. First, even if there are no economies of scale ($SE(\tau) = 1$), the Divisia index of total factor productivity overstates the change in technology represented by the shift in the production function. This deviation is due mainly to the direct learning effects.

Second, with economies of scale, the total factor productivity growth index misrepresents the rate of technical change even if firms apply all inputs at their long-run equilibrium levels. This deviation is attributed to two components. The first component involves the direct effect of learning on efficiency gains, represented by $\hat{G}_{q_2}$ and $\hat{G}_{ssl}$. As long as the opportunity cost of learning, rJ_h, is greater than the instantaneous change in the long-run profit resulting from learning, dJ_h/dt, the combined effect of $\hat{G}_{q_2}$ and $\hat{G}_{ssl}$ is positive. The second component involves the measure of total shadow cost. Total cost in the Divisia indexing procedure is $w'X + (rJ_k + c)'k$, and the total shadow cost is defined as $w'X + c'k - \dot{K}'J_k - \dot{H}J_h - J_t$ in the dynamic setting. As long as the total opportunity cost of the quasi-fixed factor stocks, $rJ_k'k$, is not equal the negative shadow value of technical change, $-J_t$, total shadow cost differs from the total cost in the Divisia indexing procedure even at long-run equilibrium. However, the discrepancy can go either direction.

3. Empirical Model of Learning: The Case of U.S. Agriculture

The dynamic model providing empirically tractable estimates of the contribution of technical change, returns to scale, disequilibrium input use and the learning effect is applied to the U.S. production agriculture. Annual data for aggregate U.S. agriculture over the period 1948–82 is taken from Capalbo, Vo, and Wade [1985]. The data base consists of six output groups (small grains, coarse grains, field crops, fruits, vegetables, and animal products) and five input groups (labor, land, intermediate and material inputs, structure, and other capital). To gain degrees of freedom, the first five output groups are further aggregated into one single crop output applying the Tornqvist discrete approximation to the Divisia indexing procedure. The implicit price for crop output is calculated using the translog quantity indices and the implicit prices for the first five output groups. Land, capital, and other capital (including durable equipment, livestock, and livestock inventory) are further aggregated into one single capital input applying the same aggregation rule.

Assuming investment in durable equipment and labor improves the skills and technical knowledge, current gross investment used to index the change of experience over time is calculated using a linear aggregation rule. The assumption differentiates the present model from earlier learning models by allowing gain in efficiency through accumulation in both physical and human capital. Arrow's [1962] and others progress function type models basically assume productivity improvement from experience with existing heavy, durable capital goods. Emphasizing the ability to organize and maintain complex production processes, Rosen [1972] and others identify knowledge with "entrepreneurial capacity." Including investment in durable equipment and labor to represent the improvement in skills encompasses both contributions to learning.

Data for gross investment in durable equipment is also taken from Capalbo, Vo and Wade [1985]. Gross investment for labor is calculated by using a 10 percent straight-line depreciation rate. The prices of the gross investment inputs are assumed to equal the rental prices.

3.1. Model Specification

The value function is specified as a modified generalized Leontief function. In addition to the regularity properties of the value function,[4] two additional assumptions are incorporated into the theoretical model in order to conform with the restrictions imposed by observed data. The first involves restricting the second derivative of the value function with respect to the initial capital stock, J_{kk}, to equal zero, which is the necessary condition for consistent aggregation for the intertemporal profit-maximizing firm (Blackorby and Schworm, [1982]). The second assumption concerns the approximated discrete measure for the net investment. The approximated discrete measure for net investment is based on the difference between the current and lagged capital stock; i.e., $K(\tau)$ is approximated as $K_\tau - K_{\tau-1}$.

Let p represent the (2×1) vector of output prices, subscript 1 denotes crop output, and 2 denotes animal output. k is the (2×1) vector of quasi-fixed factor stocks where k_1 is the stock of capital input and k_2 is that of labor. h represents knowledge stock. The (2×1) vector, c, is the corresponding rental prices, X denotes the quantity of the only variable input, intermediate input, and w is its corresponding price. Also, let the effect of disembodied technological changes be represented by the time trend variable, t. The modified generalized Leontief value function with two outputs (Y_1, Y_2), one variable input (X), and two quasi-fixed inputs (k_1, k_2) is of the following form:

$$J = [p'\ w]\begin{bmatrix} A_{pk} \\ A_{wk}\end{bmatrix} k + c'Bk + [p^{\frac{1}{2}\prime}\ w^{\frac{1}{2}}]\begin{bmatrix} A_{pc} \\ A_{wc}\end{bmatrix} c^{\frac{1}{2}} + c^{\frac{1}{2}\prime} F c^{\frac{1}{2}}$$

$$+ [p^{\frac{1}{2}\prime}\ w^{\frac{1}{2}}]\begin{bmatrix} A_{pp} & A_{pw} \\ A_{wp} & A_{ww}\end{bmatrix}\begin{bmatrix} p^{\frac{1}{2}} \\ w^{\frac{1}{2}}\end{bmatrix} + t[A_p\ A_w\ A_c]\begin{bmatrix} p \\ w \\ c\end{bmatrix}$$

$$+ [p'\ w\ c']\begin{bmatrix} A_{ph} \\ A_{wh} \\ A_{ch}\end{bmatrix} h, \tag{10}$$

where

$$\begin{array}{llll} B^{-1} = [A_{ij}]_{2\times 2} & A_{pp} = [H_{ij}]_{2\times 2} & A_{pk} = [B_{ij}]_{2\times 2} & A_{ww} = [J_{\rho\rho}]_{1\times 1} \\ A_{wk} = [D_j]_{1\times 2} & A_{pw} = [I_i]_{2\times 1} & A_{wc} = [F_j]_{1\times 2} & A_p = [M_{1i}]_{1\times 2} \\ A_{pc} = [E_{ij}]_{2\times 2} & A_w = [M_{21}]_{1\times 1} & F = [G_{ij}]_{2\times 2} & A_c = [M_{3i}]_{1\times 2} \\ A_{ph} = [N_{1i}]_{1\times 2} & A_{wh} = [N_{21}]_{1\times 1} & A_{ch} = [N_{3i}]_{1\times 2} & \end{array}$$

The dynamic factor demand and output supply equations reflecting the importance of learning-by-doing on decision making are derived by applying the envelope theorem to the value function (Epstein [1981]) to yield

$$\dot{K}_i^* = \frac{r}{2}\sum_{j=1}^{2} A_{ij}\left[\sum_{\rho=1}^{2} E_{\rho j}\left(\frac{p_\rho}{c_j}\right)^{\frac{1}{2}} + F_j\left(\frac{w}{c_j}\right)^{\frac{1}{2}} + 2\sum_{\alpha=1}^{2} G_{\alpha j}\left(\frac{c_\alpha}{c_j}\right)^{\frac{1}{2}}\right]$$

$$+ (r + A_{ii})k_i + A_{i\gamma}k_\gamma + \sum_{j=1}^{2} A_{ij}M_{3j}(rt - 1) + rh\left(\sum_{j=1}^{2} A_{ij}N_{3j}\right), \text{ for } i \neq \gamma, \tag{11}$$

$$X^* = -\frac{r}{2}\left[\sum_{j=1}^{2} F_j \left(\frac{c_j}{w}\right)^{1/2} + 2\sum_{\alpha=1}^{2} I_\alpha \left(\frac{p_\alpha}{w}\right)^{1/2} + 2\,J_{\rho\rho}\right]$$

$$+ \sum_{j=1}^{2} D_j(\dot{K}_j^* - rk_j) + M_{21}(1 - rt) - N_{21}\,rh, \tag{12}$$

$$Y_i^* = -\frac{r}{2}\left[\sum_{j=1}^{2} E_{ij} \left(\frac{c_j}{p_i}\right)^{1/2} + 2\sum_{j=1}^{2} H_{ij} \left(\frac{p_j}{p_i}\right)^{1/2} + 2\,I_i \left(\frac{w}{p_i}\right)^{1/2}\right]$$

$$+ \sum_{j=1}^{2} B_{ij}(rk_j - \dot{K}_j^*) + M_{1i}(rt - 1) - N_{1i}\,rh. \tag{13}$$

The optimal net investment demand equations are consistent with the multivariate flexible accelerator model, thus can be rewritten as

$$\dot{K}^* = \begin{bmatrix} r + A_{11} & A_{12} \\ A_{21} & r + A_{22} \end{bmatrix} (K - \bar{K}^*), \tag{14}$$

where $\bar{K}^*$ is the vector of desired or long-run equilibrium levels of quasi-fixed factors. The long-run demand equations for the quasi-fixed inputs are solved by setting $\dot{K}^*$ equal to zero yielding

$$\bar{K}^* = -\begin{bmatrix} r + A_{11} & A_{12} \\ A_{21} & r + A_{22} \end{bmatrix}^{-1} \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$$

$$\cdot \begin{bmatrix} \frac{r}{2}\left(\sum_{\rho=1}^{2} E_{\rho 1}\left(\frac{p_\rho}{c_1}\right)^{1/2} + F_1\left(\frac{w}{c_1}\right)^{1/2} + 2\sum_{\alpha=1}^{2} G_{\alpha 1}\left(\frac{c_\alpha}{c_1}\right)^{1/2}\right) + M_{31}(rt - 1) + rhN_{31} \\ \frac{r}{2}\left(\sum_{\rho=1}^{2} E_{\rho 2}\left(\frac{p_\rho}{c_2}\right)^{1/2} + F_2\left(\frac{w}{c_2}\right)^{1/2} + 2\sum_{\alpha=1}^{2} G_{\alpha 2}\left(\frac{c_\alpha}{c_2}\right)^{1/2}\right) + M_{32}(rt - 1) + rhN_{32} \end{bmatrix} \tag{15}$$

3.2. The Empirical Results

The iterated seemingly unrelated regression method (ITSUR) is used to estimate (11), (12), and (13) jointly, assuming a constant real discount rate of 6 percent and a linear disturbance vector with mean vector zero and variance-covariance matrix Σ. The asymptotically efficient parameter estimates along with the corresponding approximate standard errors of (10) are reported in Table 1. The R^2 measure for output supply and input demand

Table 1. Coefficient estimates of the full and reduced model.

Parameter	Estimate	Standard Error	Estimate	Standard Error
A_{11}	−0.89071	0.19616	−1.05103	0.17713
A_{22}	−0.17183	0.05075	−0.17176	0.04923
A_{12}	0.01125	0.02874		
A_{21}	0.83777	0.40400		
E_{11}	−6.65838	3.68379	−6.29166	3.74795
E_{12}	−35.29989	12.96348	−33.79819	13.20801
E_{21}	13.07524	5.50934	11.14321	5.07121
E_{22}	18.26024	16.90078	9.58556	16.51311
F_1	8.68496	4.37343	8.09540	4.44827
F_2	17.38891	9.94630	17.99864	10.40858
G_{11}	−34.42561	7.62625	−31.83506	5.67918
G_{12}	−11.41954	5.78947	−12.54243	5.91087
G_{22}	13.49522	35.28617	6.78995	29.16303
M_{11}	−1.37570	0.39952	−1.29678	0.45177
M_{12}	0.42758	0.41652	0.47120	0.48182
M_{21}	−1.34104	0.42041	−1.31693	0.38878
M_{31}	0.17113	0.49820	0.33030	0.21752
M_{32}	−0.69378	5.29724	−0.41110	4.05027
I_1	4.26524	3.06682	4.12082	3.12863
I_2	−26.87836	3.65951	−26.76519	3.63167
$J_{\rho\rho}$	−27.53901	7.33431	−28.07872	7.49088
D_1	−0.42885	0.27701	−0.12571	0.12307
D_2	−0.16518	0.16420	−0.14220	0.14053
H_{11}	−13.89010	16.60726	−14.19856	15.16405
H_{12}	13.69439	2.59571	12.87927	2.79943
H_{22}	32.01765	15.66808	17.75833	13.22102
B_{11}	0.31607	0.24750	0.27611	0.18713
B_{12}	−0.11344	0.16202	−0.07881	0.18079
B_{21}	0.03575	0.25440	0.25422	0.16634
B_{22}	0.11124	0.13875	0.11096	0.14924
N_{11}	1.30680	0.22119	1.26012	0.27110
N_{12}	−0.08379	0.25388	−0.14689	0.30479
N_{21}	0.33404	0.25228	0.32561	0.23930
N_{31}	−0.23483	0.29646	−0.33888	0.15168
N_{32}	0.44197	2.86178	0.30303	2.23840

equations are, 0.978 for crops, 0.940 for animals, 0.989 for intermediate inputs, 0.401 for capital, and 0.735 for labor. The test of independent adjustment yields a chi-square test statistic of 4.03 with 2 degrees of freedom, indicating that capital and labor adjust independently. Therefore, independent adjustment is maintained in the remaining analysis. Parameter estimates for the reduced model are listed in Table 1. Results indicate capital adjusts instantaneously with an adjustment rate of −0.99 while labor adjust rather sluggishly with an adjustment rate of −0.11.

The short-, intermediate-, and long-run elasticities derived from (11), (12), (13), and (15) are used to summarize the dynamic behavior of output supplies and input demands. Following the definition provided in Morrison and Berndt [1981], short-run elasticities are those obtained when quasi-fixed factors are held fixed, and intermediate-, and long-run behavior are the response given quasi-fixed factors have partially or fully adjusted to their respective long-run optimal or desired levels.

The short-run response of any quantity, Q_i, to the change in price, R_j, is defined as

$$\epsilon^S_{Q_iR_i} = \left(\frac{\partial Q_i}{\partial R_i} \bigg|_{k_1=\bar{k}_1, k_2=\bar{k}_2} \right) \left(\frac{R_i}{Q_i} \right), \tag{16}$$

the corresponding intermediate-run elasticity maintaining independent adjustment is

$$\epsilon^I_{Q_iR_i} = \left[\frac{\partial Q_i}{\partial R_i} \bigg|_{k_1=\bar{k}_1, k_2=\bar{k}_2} + \sum_{j=1}^{2} (r + A_{jj}) \frac{\partial Q_i}{\partial \bar{K}_j^*} \frac{\partial \bar{K}_j^*}{\partial R_i} \right] \left(\frac{R_i}{Q_i} \right), \tag{17}$$

and the corresponding long-run elasticity is

$$\epsilon^L_{Q_iR_i} = \left[\frac{\partial Q_i}{\partial R_i} \bigg|_{k_1=\bar{k}_1, k_2=\bar{k}_2} + \sum_{j=1}^{2} \frac{\partial Q_i}{\partial \bar{K}_j^*} \frac{\partial \bar{K}_j^*}{\partial R_i} \right] \left(\frac{R_i}{Q_i} \right), \tag{18}$$

where $\bar{k}_i$ represents the fixed stock of quasi-fixed factor in the short-run.

The average values of estimated short-, intermediate-, and long-run elasticities summarizing the dynamic behavior of output supplies and input demands when the learning effect is considered are presented in Table 2. Output supply elasticities are negative, both for crops and animals. The downward sloping output supply is not theoretically inconsistent nor empirically implausible. Treadway [1970] demonstrates that due to the internal adjustment cost associated with changing the stock of quasi-fixed factors, firms may behave as having a determinate production scale and thus, increase output in response to a fall in price even in the long run (Treadway [1970, pp. 341–343]). Similarly, Caputo [1990] indicates that output supply or input demand behavior inconsistent with static maximization theory at a particular point of time is plausible in the adjustment-cost model of the firm.

The dynamic learning model with experience indexed by accumulated gross investment predicts downward sloping input demands, which have the expected signs indicating that quantity demanded for both variable and quasi-fixed inputs reduces in response to rising prices. The cross-price elasticities imply a gross complementary relationship between intermediate input and capital, and between intermediate input and labor. Capital and labor are substitutes. The normal/inferior nature of production factors is inferred from the estimated cross-price elasticities of input with respect to output prices. Capital and labor are normal factors in the production of crops, while the intermediate input is not. However, the only factor that can be regarded as a normal input in the production of animals is the intermediate input.

The elasticities indicate a generally inelastic pattern in the output supply and input demand response to price changes. Only the response of labor to its own price and the price of crops in the long run approach unitary elasticity. All of the estimated elasticities have consistent signs throughout, independent of whether the quasi-fixed factors have adjusted to their respective long-run equilibrium levels.

Table 2. Short-run, intermediate-run, and long-run elasticities.

	Price				
Quantity	Crops	Animals	Inter. Input	Capital	Labor
Short-Run					
Crops	−0.046	0.132	0.035	−0.029	−0.092
Animals	0.234	−0.026	−0.272	0.060	0.031
Inter. Input	−0.085	0.415	−0.200	−0.055	−0.074
Intermediate-Run					
Crops	−0.026	0.104	0.019	−0.038	−0.059
Animals	0.255	−0.049	−0.286	0.054	0.055
Inter. Input	−0.074	0.402	−0.209	−0.058	−0.062
Capital	0.058	−0.076	−0.047	−0.026	0.092
Labor	0.085	−0.018	−0.029	0.044	−0.082
Long-Run					
Crops	−0.037	0.106	0.023	−0.043	−0.048
Animals	0.270	−0.052	−0.291	0.061	0.043
Inter. Input	−0.055	0.398	−0.215	−0.049	−0.080
Capital	0.058	−0.077	−0.047	−0.027	0.092
Labor	0.764	−0.163	−0.258	0.394	−0.737

3.3. Learning and the Growth in U.S. Agriculture

The proportional growth of output over time and the scale-related components constituting the growth are presented in Table 3. Over the entire time span, aggregate agriculture output grew at an average annual rate of 1.45 percent. The scale-related components constituting the growth in agricultural output involve the growth in variable factors, $\hat{F}_v$, the growth in the quasi-fixed factor levels at the long-run equilibrium, $\hat{F}_{ssk}$, and the growth in net physical investment, $\hat{F}_{q_1}$.[5] Variable inputs and net physical investment grew at an average annual rate of 0.59 and 0.17 percent, respectively. The long-run equilibrium quasi-fixed factor reduced 0.61 percent per annum. Estimates of the scale elasticities reveal the decreasing-returns-to-scale characteristic of U.S. agriculture production structure. However, the upward trend indicates the production structure transforms gradually into increasing returns-to-scale in the 1980s.

Table 3. Proportional growth of output over time and the scale-related components (average values).

Year	$\hat{Y}$	$SE(\tau)$	$\hat{F}_v$	$\hat{F}_{ssk}$	$\hat{F}_{q_1}$
1950–59	0.009033	0.57953	0.008942	−0.017728	0.00598
1960–69	0.009465	0.68812	0.007064	−0.006487	−0.00044
1970–82	0.022664	0.76562	0.002634	0.003031	−0.00006
1950–82	0.014534	0.68574	0.005888	−0.006144	0.00166

Capalbo indicates that the Divisia input index in the agricultural data base reflects adjustments for changes in composition and education of the labor force, the use of service prices for capital and land, and adjustments to the pesticides and fertilizer inputs (Capalbo [1988, p. 61]). Therefore, the bracketed term at the right-hand-side of (8) represents the combined effect of scale, quality adjusted growth in variable and quasi-fixed inputs, and disequilibrium input use. This combined effect is found to account for 19.08 percent of the growth of aggregate agricultural output over the 1950–82 period. The remaining portion of the growth, which is attributed to the effect of technical change and learning, is significantly smaller than the observed residual reported in Ball [1985], Capalbo [1988], and Luh and Stefanou [1991]. Emphasizing the efficiency growth associated with the accumulated experience indexed by accumulated gross investment, the estimated contribution of technical change to the output growth of U.S. agriculture over the 1950–82 period is overestimated in both the static and the dynamic no-learning frameworks.

The dynamic measures of total factor productivity for the dynamic learning model are presented in Table 4. Under the assumption of indexing experience through accumulated gross investment, total factor productivity is found to grow at 1.31 percent per annum. This total factor productivity measure is in general less than those obtained under the assumption that no learning is involved (also shown in Table 4).

Table 5 presents the quantitative decomposition of the dynamic total factor productivity measure consistent with (9). The direct learning effect involving the growth of the value of accumulated knowledge at long-run equilibrium is represented by $\hat{G}_{ssl}$.[6] The combined effect of scale, quality-adjusted input growth, and disequilibrium input use accounts for 10.47 percent of the total factor productivity growth. Learning and technical change constitutes the remaining 89.53 percent of growth. The component associated with technical change is calculated as the residual. Because of the dominant contribution of learning-by-doing in the growth of total factor productivity, less than one-third of the observations have a positive residual leading to negative averages over some time span. This result implies a less important role for technical change and assigns a substantial role to the previously unmeasured contribution of learning-by-doing to the growth of aggregate agriculture industry.

4. Conclusion

This study develops a theoretical methodology to build the learning effect into a dynamic model applicable to long-run planning and optimization behavior. Integrating the gain in efficiency associated with learning into the adjustment-cost model of the firm, the model provides a theoretically consistent framework to formulate the concept of learning-by-doing as a major component in explaining the overall growth in output. By evaluating the major factors affecting the pattern of productivity growth, the empirical application to U.S. production agriculture increases the accuracy and policy relevance of productivity analysis for the aggregate agriculture industry.

The estimated rates suggest capital adjusts almost instantaneously. Other adjustment-cost models for U.S. agriculture (Vasavada and Chambers [1986]; Vasavada and Ball [1988]; Howard and Shumway [1988]; Taylor and Monson [1985]; and Luh and Stefanou [1991]) predict a much slower capital adjustment. The results imply that learning plays an important

Table 4. Dynamic measures of total factor productivity for U.S. agriculture, 1950–1982.

Year	Total Factor Productivity (1977 = 100) No-Learning Model	Learning Model
1951	83.23	86.66
1952	84.96	74.53
1953	85.58	72.48
1954	83.75	66.86
1955	85.79	68.04
1956	72.21	65.27
1957	107.58	109.46
1958	92.66	83.08
1959	85.70	74.00
1960	78.75	79.77
1961	80.80	81.85
1962	81.85	81.28
1963	87.58	89.75
1964	89.81	90.38
1965	84.38	84.14
1966	90.79	93.22
1967	88.33	86.54
1968	85.04	80.90
1969	88.47	86.52
1970	79.29	75.59
1971	90.74	90.10
1972	88.44	86.39
1973	89.30	89.35
1974	93.90	94.47
1975	94.98	94.16
1976	97.26	94.44
1977	100.00	100.00
1978	92.52	92.71
1979	101.02	99.81
1980	100.76	99.96
1981	107.98	105.02
1982	113.14	108.70

Notes: The dynamic measures of total factor productivity growth for the no-learning model is taken from Luh and Stefanou [1991].

Table 5. Components of dynamic total factor productivity growth (average values).

Year	$\hat{TFP}$	Scale	$\hat{G}_{ssl}$	$\hat{A}$
1950–59	0.01183	0.006870	0.0289420	−0.02398
1960–69	0.00933	0.000055	0.0273385	−0.01807
1970–82	0.01706	−0.001836	0.0294897	−0.01059
1950–82	0.01313	0.001375	0.0286718	−0.01691

Note: The "Scale" component is calculated using the expression $[SE(\tau) - 1]\ (\hat{F}_v + \hat{F}_{q_1} + \hat{F}_{ssk})$.

role in facilitating the adjustment process for quasi-fixed inputs, especially capital. Empirical estimates of agricultural labor adjustment rate indicate a similar long lag in labor adjustment compared to other studies. The much longer lag in the adjustment of labor compared to capital supports the view that slow labor adjustment is a major part of the farm adjustment problem. In addition, the substantially different adjustment rates between the two quasi-fixed factors suggest a long duration for wage-oriented policies to fully achieve desired results, while investment-oriented policies may work must faster.

The learning models yield negative output supply elasticities. These results are not theoretically inconsistent nor empirically implausible. Moreoever, with experience indexed by aggregate gross investment, the result of reducing output supply, and thus contracting the production capacity, restricts the accumulation of experience and thereby imposes an additional penalty on producers. Therefore, it is not irrational to have an increase in supply in response to falling prices. This study suggests the problem of surplus production and over-commitment of farm resources may be addressed by the sluggish input adjustment behavior of the substantial learning effect.

Technical change is often referred to as the main engine of the growth in the aggregate U.S. production agriculture. This study demonstates a less important role for technical change and assigns a substantial role to the previously unmeasured contribution of learning to the growth of U.S. agriculture industry. This result has two distinctive implications concerning investment-oriented policy analysis. First, the significant influence of learning on overall growth suggests the need to examine the possible biases in policy analysis. LeBlanc and Hrubovcak [1986] conclude that tax policies are effective in promoting agricultural investment, which counters farm policy efforts to restrict supply. The results of this study suggest the offsetting effect of tax policies may even be greater since stimulated investment contributes to the accumulation of knowledge, which in turn leads to a higher level of output.

The second implication concerns the effectiveness of tax policies in influencing the level of agricultural investments. The work of Hall and Jorgenson [1967], and LeBlanc and Hrubovcak [1986] indicate the most dramatic change in net investment induced by instantaneous tax policy changes occurs in the first year and then diminishes over time. Explicitly recognizing the potential influence of learning on investment decisions, the dramatic change in investment induced by changes in tax policies is carried over to the future through the learning effect. Consequently, even if the changes in investment in response to policy changes diminish over time, these changes diminish at a lower speed.

Notes

1. This assumes firms form their price expectations statically. That is, firms expect relative prices observed in each base period to persist indefinitely, and expectations are altered when the base period changes (Epstein and Denny [1983]). For functions homogenous in prices, real prices are assumed to be static as well.
2. To see this notice that using the first-order conditions (3a) through (3d) in the arbitrage equation leads to

$$rJ_{k_j} = -c_j + \gamma^* F_{k_j} + \frac{dJ_{kj}}{dt}.$$

At the long-run equilibrium, $\dot{K} = \dot{J}_k = \dot{H} = \dot{J}_h = 0$. The necessary conditions in (3) must still hold along with

$$rJ_{k_j} = \gamma^* F_{k_j} - c_j.$$

This states that at the long-run equilibrium, the value of the marginal product of capital must equal the service price which is the opportunity cost of an additional unit of capital plus the rental rate on capital. Substituting into equation (7) leads to

$$\hat{Y}(\tau) = \sum_{p=1}^{v} \frac{w_p X_p}{TSC(\tau)} \frac{TSC(\tau)}{TR(\tau)} \hat{X}_p + \sum_{j=1}^{n} \frac{(rJ_{k_j} + c_j) k_j}{TSC(\tau)} \frac{TSC(\tau)}{TR(\tau)} \hat{k}_j + \hat{A} + \frac{rJ_h h}{TR(\tau)} \hat{h}.$$

Therefore, $\Sigma[(rJ_{k_j} + c_j)k_j]\hat{k}_j/TSC$ is interpreted as the proportional growth in quasi-fixed factor levels at the long-run equilibrium.

3. At the long-run equilibrium, the only learning component involved is $rJ_h h/TR(\tau)\, \hat{h}$, therefore, this component is interpreted as the growth of the value of accumulated knowledge at the long-run equilibrium.
4. The value function is twice continuously differentiable, concave in quasi-fixed inputs, and convex in prices.
5. The postulated form of the value function restricts the changes of the endogenously determined marginal valuation of the quasi-fixed factor stocks over time to $dJ_k/dt = 0$. Therefore, the second disequilibrium component, $\hat{F}_{q_2}$, involving the proportional changes in J_k vanishes.
6. The postulated form of the value function restricts the changes of the endogenously determined shadow value of learning, $\hat{G}_{q_2}$, to be zero. Therefore, the direct learning effect is only involved with the growth in the value of accumulated knowledge at the long-run equilibrium, $\hat{G}_{ssl}$.

References

Abramovitz, M. (1956). "Resource and Output Trends in the U.S. Since 1807." *The American Economic Review* 46, 5–23.

Arrow, K.J. (1962). "The Economic Implications of Learning by Doing." *Review of Economic Studies XXIX*, 154–174.

Ball, V.E. (1985). "Output, Input, and Productivity Measurement in U.S. Agriculture, 1948–1979." *American Journal of Agricultural Economics* 67, 475–486.

Blackorby, C. and W. Schworm. (1982). "Aggregate Investment and Consistent Intertemporal Technologies." *Review of Economic Studies* 49, 595–614.

Brueckner, J.K. and N. Raymon. (1983). "Optimal Production with Learning by Doing." *Journal of Economics Dynamic and Control* 6, 127–135.

Capalbo, S.M. (1988). "Measuring the Components of Aggregate Productivity Growth in U.S. Agriculture." *Western Journal of Agricultural Economics* 13, 53–62.

Capalbo, S.M., T.T. Vo, and J.C. Wade. (1985). "An Econometric Data Base for Measuring Agricultural Productivity and Characterizing the Structure of U.S. Agriculture." Discussion Paper Series, No. RB85-01, National Center for Food and Agricultural Policy.

Caputo, M.R. (1990). "Comparative Dynamics via Envelope Methods in Variational Calculus." *Review of Economic Studies* 57, 689–697.

Christensen, L.R. and D.W. Jorgenson. (1970). "U.S. Real Product and Real Factor Input, 1929–1967." *Review of Income and Wealth* 16, 19–50.

Devinney, T.M. (1987). "Entry and Learning." *Management Science* 33, 706–724.

Epstein, L.G. (1981). "Duality Theory and Functional Forms for Dynamic Factor Demands." *Review of Economic Studies XLVIII*, 81–95.

Epstein, L.G. and M.G.S. Denny. (1983). "The Multivariate Flexible Accelerator Model: Its Empirical Restrictions and an Application to U.S. Manufacturing." *Econometrica* 51, 647–674.

Fabricant, S. (1959). *Basic Facts on Productivity Change.* New York: Columbia University Press for the National Bureau of Economic Research.

Hall, R. and D. Jorgenson. (1967). "Tax Policy and Investment Behavior." *The American Economic Review* 57, 391–414.

Howard, W.H. and C.R. Shumway. (1988). "Dynamic Adjustment in the U.S. Dairy Industry." *American Journal of Agricultural Economics* 70, 837–847.

Hulten, C.R. (1975). "Technical Change and the Reproducibility of Capital." *The American Economic Review* 65, 956-965.

Hulten, C.R. (1979). "On the Importance of Productivity Change." *The American Economic Review* 69, 126–136.

Jorgenson, D.W. and Z. Griliches. (1967). "The Explanation of Productivity Growth." *Review of Economic Studies* 34, 249–283.

Jorgenson, D.W. (1988). "Technological Innovation and Productivity Change in Japan and the United States." *The American Economic Review* 78, 217–222.

LeBlanc M. and J. Hrubovcak. (1986). "The Effects of Tax Policy on Aggregate Agricultural Investment." *American Journal of Agricultural Economics* 68, 767–777.

Luh, Y.H. and S.E. Stafanou. (1991). "Productivity Growth in U.S. Agriculture Under Dynamic Adjustment." *American Journal of Agricultural Economics* 73, 1116–1125.

Lucas, R.E. Jr. (1988). "On the Mechanics of Economic Development." *Journal of Monetary Economics* 22, 3–42.

Majd, S. and R.S. Pindyck. (1989). "The Learning Curve and Optimal Production Under Uncertainty." *RAND Journal of Economics* 20, 331–343.

Morrison, C.J. and E.R. Berndt. (1981). "Short-Run Labor Productivity in the Dynamic Model." *Journal of Econometrics* 16, 339-365.

Oi, W. (1967). "The Neoclassical Foundations of Progress Functions." *The Economic Journal LXXVII*, 579–594.

Romer, P.M. (1990). "Endogenous Technological Change." *Journal of Political Economy* 98, 71–102.

Rosen, S. (1972). "Learning by Experience as Joint Production." *Quarterly Journal of Economics* 86, 366–382.

Sheshinski, E. (1967). "Tests of the Learning By Doing Hypothesis." *Review of Economics and Statistics XLIX*, 568–578.

Solow, R.M. (1957). "Technical Change and the Aggregate Production Function." *Review of Economics and Statistics* 39, 312–320.

Stefanou, S.E. (1989). "Learning, Experience, and Firm Size." *Journal of Economics and Business* 7, 1–14.

Taylor, T.G. and M.J. Monson. (1985). "Dynamic Factor Demands and the Effects of Energy Price Shocks." *Southern Journal of Agricultural Economics* 17, 1-9.

Treadway, L.G. (1970). "Adjustment Costs and Variable Inputs in the Theory of the Competitive Firm." *Journal of Economic Theory* 2, 329–347.

Vasavada, U. and V.E. Ball. (1988). "A Dynamic Adjustment Model for U.S. Agriculture: 1948-79." *Agricultural Economics* 2, 123–137.

Vasavada, U. and R.G. Chambers. (1986). "Investment in U.S. Agriculture." *American Journal of Agricultural Economics* 68, 950–960.

Wright, T.P. (1936). "Factors Affecting the Cost of Airframes." *Journal of the Aeronautical Sciences* 3, 122–128.