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DYNAMICS, CAUSALITY, AND AGRICULTURAL PRODUCTIVITY

by

J. Antle

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The purpose of this paper is to explore the dynamic structure of agricultural production processes and the implications of this structure for the measurement and explanation of agricultural productivity. Underlying this approach is the view that changes in agricultural productivity occur over time as producers respond to the evolution of complex and interrelated natural, economic, technological, and institutional phenomena. Modern theories of economic development are consistent with this dynamic view of agricultural development.

Empirical agricultural productivity research, in contrast, is most often based on static models. An important case in point is the literature reviewed by Capalbo and Vo on the measurement of technical change in agriculture. Static dual cost and profit function models have been ued by many researchers to measure technological change and to draw inferences about the explanation of technological change. However, given that theory portrays technological change as a dynamic process, it can be questioned whether contemporaneous correlations between variables such as factor cost shares and factor prices can be used to draw valid inferences about the quantitative or qualitative properties of technological change in agriculture. It can be argued more generally that most of the existing empirical research has provided evidence that time trends and other measurable variables such as agricultural research, human capital, relative prices, and agricultural policies are <u>correlated</u> to some degree with agricultural productivity. However, it is unclear what the observed correlations between measured output, time, and other variables imply about the <u>causal</u> mechanisms governing agricultural productivity.

It is evident that all production processes occur over time and hence have temporal dimensions. Lucas (1967) introduced the time dimension into production using the cost-of-adjustment hypothesis that investment disrupts production and hence imposes costs on the firm. More recently Kydland and Prescott (1982) introduced the time dimension in production through the assumption that investment occurs over time. Antle (1983 a,b) suggests that agricultural production is fundamentally dynamic because it depends on biological processes and because farmers make production decisions sequentially over time.

These phenomena, however, all concern the <u>microdynamics</u> of production at the individual firm or farm level. Agricultural productivity at a point in time is a function of the individual producer's behavior within the existing natural, economic, technological, and institutional environment. But this environment itself is not static. Thus, as data are aggregated over producers and time, the <u>macrodynamics</u> of agricultural production involve both the microdynamics of the individual producer and the evolution of the environment within which the individual producer operates.

These observations suggest that it is necessary to begin with the microdynamics of production to understand the dynamic processes governing agricultural production. Therefore, the first section of the paper discusses the dynamic structure of farm-level production and the effects of aggregation. The second section addresses the causal relations in agricultural production implied by its dynamic structure. The third section then considers macrodynamics within a model of technological change, and implications for econometric measurement of technology structure and technological change. The concluding section discusses the implications of the analysis for future research on agricultural productivity.

I. The Dynamic Structure of Agricultural Production

Virtually all intraseasonal agricultural produciton processes are multistage, that is, they involve a sequence of inputs applied over time to a sequence of intermediate production stages. These intermediate stages lead to a final saleable output. Thus, intraseasonal agricultural production is characterized by output dynamics which are represented by a sequence of production functions in the autoregressive form

$$(1) \quad Q_t = f_t[x_t, Q_{t-1}, Q_{t-2}, \ldots, \varepsilon_t], \; t = 1, \ldots, T$$

where Q_t is output, x_t is an input vector, and ε_t is a random error and there are T stages. Interseasonal production may also exhibit output dynamics. This is exemplified by the crop rotation in which productivity in one season depends on the acreages and types of crops grown in preceeding seasons. The fundamental property of processes with output dyanmics is that they are time recursive. Thus production in period t depends on current and past inputs and production disturbances

$$\begin{aligned} Q_t &= f_t[x_t, Q_{t-1}, \varepsilon_t] \\ &= f_t[x_t, f_{t-1}[x_{t-1}, \ldots, \varepsilon_{t-1}], \varepsilon_t] \\ &= h_t[x_t, x_{t-1}, \ldots, \varepsilon_t, \varepsilon_{t-1}, \ldots]. \end{aligned}$$

Production also may be dynamic because a sequence of inputs affect output. In this case the process is characterized by input dynamics in the moving average form

$$(2) \quad Q_t = f_t[x_t, x_{t-1}, \ldots, \varepsilon_t].$$

An example of intraseasonal input dynamics is irrigation water which is applied over time. An example of interseasonal input dynamics is fertilizer carryover. More generally, all types of investment can be represented as input dynamics, investment in soil fertility through fertilization being just one example.

Within a given season with t = 1, . . . , T stages, a risk-neutral farmer's objective function can be written as

$$(3)\quad \max_{\{x_t\}} E[p_T Q_T - \sum_{t=1}^{T} w_t x_t]$$

where P_T is the price of final output Q_T, and w_t is the input price. However, many of the farmer's decisions affect production both within and across seasons. In the case where the farmer's decisions span S seasons, this multiperiod decision problem is

$$(4)\quad \max_{\{x_t\}} E[\sum_{s=1}^{S} (P_{T_s} Q_{T_s} - \sum_{t=1}^{T_s} w_t x_t)].$$

This nesting of decisions is exemplified by the row-crop farmer in the Sacramento valley who rotates summer crops of processing tomatoes and corn. There are intraseasonal output dynamics associated with land preparation, planting, cultivating, irrigating, and harvesting operations. There are also interseasonal output dynamics due to the relation between soil fertility, diseases, and the crop rotation. In the longer run all processes exhibit input dynamics in the form of physical capital investment. Both output and input dynamics are characteristic of many other types of agricultural production, including perennial crops, livestock, and poultry. Thus, at the farm level, most production processes are likely to exhibit both input and output dynamics.

The farmer's decision making is intimately related to the structure of the production process. The general solution to a dynamic production problem such as (3) or (4) is given by the dynamic programming algorithm. Let $x^t = (x_1,\ldots, x_t)$ and $Q^t = (Q_1,\ldots, Q_t)$, ignoring the distinction between stages and periods for notational simplicity. Define μ_t as the parameter vector of the decision maker's subjective joint probability distribution function of current and future outputs, output prices, and input prices. The general form of the structural input demand functions implied by the solution to the multistage or multiperiod decision problem is

$$(5) \quad x_t = x_t[x^{t-1}, Q^{t-1}, \mu_t, w_t], \; t = 1,\ldots, T.$$

Equation (5) is the form of the solution for a technology with both input and output dynamics. If the technology had only input dynamics Q^{t-1} would not appear in (5); if the technology had only output dynamics x^{t-1} would not appear in (5). Note that (5) is a reduced-form equation since x^{t-1} and Q^{t-1} are predetermined and μ_t and w_t are exogenous.

A complete dynamic production model is a system of production functions such as (1) or (2) and input demand functions (5). One remarkable property of dynamic production models of this type is their recursive structure.[1] Processes characterized by output dynamics are recursive systems of both production functions and input demand functions, whereas processes with input dynamics are recursive only in the input demands [lagged outputs do not appear in equation (2)]. This recursive structure is central to the problem of econometric estimation of dynamic production models, and proves to be critical to the analysis of causality in section II.

It must be emphasized that the dynamics of agricultural production are intimately related to the time-dependent nature of the production process itself. This contrasts with the cost-of-adjustment theory underlying many dynamic production models in the economics literature. The cost-of-adjustment model is based on the idea that investment imposes costs on the firm in the form of reduced output [see Berndt, Morrison, and Watkins 1981 for a literature survey]. Since net investment can be expressed as the change in the capital stock, the cost-of-adjustment model is derived from a production function which is a special case of input dynamics given in equation (2). Thus, the cost-of-adjustment model does not exhibit output dynamics, and therefore cannot represent many of the dynamic relations in agricultural production at the farm level.

Most productivity analysis is conducted with data that have been aggregated to some degree. This raises the question of the dynamic structure of aggregate production, and more specifically, whether or not the recursive structures identified above are preserved in aggregation. Consider first farm-level data aggregated over a growing season, into total inputs and outputs for the season. For simplicity, assume there is only one (scalar) input x_t applied in each stage. Using (5), the total input use in the season is

$$(6) \quad X = \sum_{t=1}^{T} x_t[x^{t-1}, Q^{t-1}, \mu_t, w_t]$$

Substituting equation (1) for Q^t and equation (5) for x^{t-1} in equation (6) gives the final-form equation

$$X = X[\mu^T, w^T, \varepsilon^{T-1}],$$

showing that inputs aggregated across stages depend on the history of price expectations, input prices, and intermediate stage production shocks over the season. A production function defined in terms of seasonally aggregated inputs and production disturbances is

$$(7) \quad Q = f[X, \varepsilon^T]$$

Therefore, the production model consisting of the production function (7) and input demand functions (6) is also recursive because inputs explain final output and not vice versa. The final-form equation below (6) shows that inputs are correlated with final output, but are not functions of final output.

Aggregating across seasons to obtain annual data in the presence of interseasonal output dynamics gives aggregate inputs which depend on previous seasons' final outputs. For example, let annual farm output be measured as an output index $P[Q_{T_1}, \ldots, Q_{T_S}]$ where Q_{T_s} is final output in season s. With interseasonal output dynamics

$$(8) \quad Q_{T_s} = f_{T_s}[X_{T_s}, Q_{T_{s-1}}, Q_{T_{s-2}}, \ldots, \varepsilon_{T_s}]$$

so annual output aggregated over seasons can be expressed as

$$(9) \quad P = P[X_{T_1}, \ldots, X_{T_S}, \varepsilon_{T_1}, \ldots, \varepsilon_{T_S}],$$

where X_{T_s} is the input vector for season s aggregated across operations in season s. Solution of maximization problem (4) shows that X_{T_s} depends on prices, price expectations, and on previous seasons' inputs and production disturbances,

$$(10)\ X_{T_s} = X_{T_s}[X^{T_{s-1}}, \varepsilon^{T_{s-1}}, \mu_t, w_t].$$

Observe that the production model composed of equations (9) and (10) is recursive in inputs. Therefore, as in the case of input aggregation within a season, output aggregation across seasons preserves the recursive structure of production models.

Regional or national analyses typically deal with annual input and output data aggregated across operations, seasons, and farms. It is evident that aggregating annual farm output in equation (9) and inputs in equation (10) also preserves the fundamental recursive structure of production.

In concluding, the behavioral interpretation of these findings should be emphasized. Production at the farm level is recursive because of the logical time ordering of events in the production process: inputs must be chosen before output can be realized. Aggregation over time causes inputs and outputs to be <u>correlated</u> because some inputs and outputs are functions of the same production disturbances. However, it is not possible for inputs employed during a given time interval t to be functions of final output realized at the end of period t. Thus, in farm-level production and in aggregate data, the fundamental recursive structure of production is preserved.

II. Causality in Production

There are two approaches to the definition and measurement of causality in the economics literature, referred to as structural and nonstructural by Cooley and LeRoy (1982). The goal of this section is to relate the structure of dynamic production models to the causality concepts in the literature.

The structural approach is based on the traditional econometric concepts of endogeneity, identification, and structural form. What will be referred to here as structural causality is defined by Jacobs, Leamer, and Ward (1979, p. 403) as meaning that in an equation system, "y does not cause x" when "the disturbance in the y equation is never transmitted to x."[2] More specifically, consider the following example

(11) $Q_t = \Theta_1 x_t + \Theta_2 Z_t + \beta_{11} Q_{t-1} + \beta_{12} x_{t-1} + \beta_{13} Z_{t-1} + e_t$

(12) $x_t = \gamma_1 Q_t + \gamma_2 Z_t + \beta_{21} Q_{t-1} + \beta_{22} x_{t-1} + \beta_{23} Z_{t-1} + \delta_1 w_t + u_{1t}$

(13) $Z_t = \tau_1 Q_t + \tau_2 x_t + \beta_{31} Q_{t-1} + \beta_{32} x_{t-1} + \beta_{33} Z_{t-1} + \delta_2 r_t + u_{2t}$

where Greek symbols denote parameters, and e_t, u_{1t}, and u_{2t} are independent errors. The Q does not structurally cause x, for example, if $\gamma_1 = \gamma_2 = \beta_{21} = \beta_{23} = 0$.

Equations (11), (12) and (13) can be interpreted as a production model. Q_t is output in period t, x_t and Z_t are inputs chosen at the beginning of period t, and w_t and r_t are the input prices normalized by output price, so that (11) is a production function and (12) and (13) are input demand functions. By interpreting the variables as logarithms, a system of this form can be derived from a dynamic Cobb-Douglas model as in Antle (1983b). Viewed as a production model, it is known a priori that inputs x_t and Z_t are chosen before Q_t is realized, so $\gamma_1 = \tau_1 = 0$ with probability one. However, it is not necessarily true a priori that $\beta_{21} = \beta_{31} = 0$, i.e., that output in the previous period does not affect current input decisions. Indeed, it was argued in the previous section that output dynamics are present in most agricultural production, implying $\beta_{21} \neq 0$ and $\beta_{31} \neq 0$ so that causality does run from output to inputs.

In terms of causality from inputs to output, x does not structurally cause Q when the marginal productivity of both current and past inputs is zero. If the production process does not exhibit input dynamics, then $\beta_{12} = \beta_{13} = 0$, but positive marginal productivity of x_t implies $\Theta_1 \neq 0$ and $\Theta_2 \neq 0$. Thus, either nonzero marginal productivity or input dynamics imply inputs structurally cause output.

The nonstructural approach to causality is due primarily to Granger (see Granger 1969, 1980). Granger emphasized the existence of feedback and the direction of the flow of time in economic relationships. Granger's concept of causal ordering is based on "the notion that absence of correlation between past values of one variable X and that part of another variable Y which cannot be predicted from Y's own past implies absence of causal influence from X to Y" [Sims 1972, p. 544]. Whereas structural causality is based on identification of structural parameters, Granger causality is based on correlations between variables observed at different points in time. Jacobs, Leamer, and Ward note that Granger's definition of causality implies that Q does not cause x in a system such as (11), (12) and (13) if the coefficient of Q_{t-1} in the reduced form equation of x_t is zero. It is easily shown that this reduced form coefficient is $(\gamma_1 \beta_{11} + \gamma_2 \beta_{31} + \beta_{21})$. Note that to infer Granger causality, therefore, it is not necessary to identify the structural parameters γ_1, γ_2, β_{11}, β_{21}, and β_{31}.

Using system (11)-(13), Granger causality can be related to the dynamic properties of production systems. First, observe that output dynamics occurs when β_{11}, β_{21}, and β_{31} are nonzero. Thus, if the process does (not) exhibit output dynamics than Q does (not) Granger cause x or Z. Similarly, if the process does not exhibit input dynamics, it can be shown that neither x nor Z Granger cause Q. Second, observe that the condition $(\gamma_1 \beta_{11} + \gamma_2 \beta_{31} + \beta_{21}) = 0$

does not imply that any of the individual parameters is necessarily zero. It follows that if Q does not Granger cause x, it cannot be inferred that the production process does not exhibit output dynamics. But if Q does Granger cause x, it can be inferred that output dynamics exists. Similar results hold for input dynamics.

The discussion above shows that output (input) dynamics exists if and only if outputs (inputs) Granger cause inputs (outputs). Moreover, the absence of output (input) dynamics implies outputs (inputs) do not Granger cause inputs (outputs), but the converse is not generally true. The econometric implication of these results is that estimates of reduced-form dynamic factor demand models cannot be used to draw conclusive inferences about the dynamic structure of production processes. For example, Nerlovian partial adjustment models have been used to explain output and inputs as functions of lagged outputs, inputs, and prices. These models can be interpreted as reduced-form or final-form equations and therefore cannot be used to reject the null hypothesis of production dynamics. Only estimates of the structural production function parameters can be used to reject the hypothesis that a production process does not exhibit either input or output dynamics.

The causal relations between inputs and outputs can be translated into causal relations between quantities (either input or output) and prices. For example, recursive substitution of the demand functions in equation (5) to obtain the final-form equation shows that x_t generally depends on the parameters of expected future price distributions and on past prices. When the individual producer is a price taker, this means that causality runs from prices to quantities in microeconomic data. However, as data are aggregated, price exogeneity may be questionable. If market prices are endogenous in aggregated data, they may depend on past market quantities if the market takes more than one period to adjust to exogenous shocks. Thus aggregate data may exhibit feedback between quantities and prices.

III. The Dynamics of Innovation

The macrodynamics of agricultural productivity involves the farm-level dynamics discussed in section I, and the dynamics of the natural, economic, technological, and institutional environment within which the individual producer operates. Some factors that affect productivity, notably the natural environment, are clearly exogenous to the economic system, but influence it by determing the relative scarcity of resources and the productivity of a given technology. The production technology also has been assumed by some economists to be exogenous to the economic system, but Hicks (1932) argued that relative prices could influence the direction of technological change. More recently, Hayami and Ruttan (1971) hypothesized that relative prices could influence public sector institutions, such as agricultural research organizations, as well as the private sector.

Hayami and Ruttan emphasize that induced innovation is a dynamic process. They describe technical change in agriculture "as a dynamic response to the resource endowments and economic environment in which a country finds itself at the beginning of the modernization process" (Hayami and Ruttan, 1971, p. 26). In their analysis of changes in factor proportions during the Twentieth Century in Japan and the U.S., Hayami and Ruttan (1971, p. 133) "conclude that such changes in input mixes represent a process of dynamic factor substitution along a metaproduction function accompanying changes in the production surface induced primarily by changes in relative factor prices." Following the logic of the Hayami-Ruttan theory, this section outlines some elements of a stylized dynamic model of technological change, relates it to the dynamic structure of agricultural production, and discusses the implications for the empirical explanation of technological change.

The innovation process can be thought of as a sequence of interrelated investments. It begins with additions to the stock of basic scientific knowledge, followed by the transformation of that knowledge into technological (applied) knowledge, the embodiment of technological knowledge in physical inputs, and finally the diffusion of the inputs and related knowledge to producers. Thus the innovation process involves a sequence of individuals and institutions. The induced innovation hypothesis states that this process is influenced by relative factor prices such that the resulting technology saves relatively scarce resources and uses relatively abundant resources.

A model of the innovation process begins with the stock of basic scientific knowledge, K_t.[3] Assume K_t evolves over time as

$$(14)\quad K_{t+1} = \delta_t K_t + k_t + \kappa_t$$

where δ_t is a depreciation rate (reflecting knowledge obsolescence), k_t is systematic investment in basic research, and κ_t is a random term representing scientific discoveries that are not explained by purposeful investment. There has been little if any research on the influence prices have on basic research, although the induced innovation hypothesis suggests that there may be some influence. On the other hand, noneconomic forces (e.g., World War II) clearly do affect both the amount and type of investment in basic research.

The Hayami-Ruttan theory is more closely related to the subsequent stages of the innovation process in which basic knowledge is transformed into on-farm technology. The next step in the innovation process is the transformation of basic knowledge into applied or technological knowledge. The equation of motion for technological knowledge, T_t, is

$$(15)\ T_{t+1} = \rho_t T_t + I_t[R_t, K_t, w_t, \mu_t] + \tau_t,$$

where ρ_t is a depreciation rate; I_t is gross investment as a function of research funding R_t, basic knowledge K_t, factor prices w_t and price expectations μ_t; and τ_t is a random term. In this formulation, the induced innovation hypothesis enters throught the presence of w_t and μ_t in the gross investment term I_t. If T_t and I_t are thought of as vectors whose elements measure stocks of knowledge in different fields, then the induced innovation hypothesis can be interpreted as saying that μ_t determines how applied research funding R_t is utilized to transform basic knowledge K_t into specific types of technological knowledge T_{t+1}.

The stock of technological knowledge is next embodied in physical inputs by private industry and public institutions, and diffused to producers. This process depends on T_t and price expectations μ_t. Technology diffusion also may be constrained by such factors as the farmer's human capital, government spending on technology diffusion (extension), and transportation and communication infrastructure; denote these factors by D_t. Let the on-farm technology be expressed as a function $A_t[T_t, \mu_t, D_t]$. Now a general model of on-farm production can be written as the production function

$$(16)\ Q_t = f_t[x^t, Q^t, A_t, \varepsilon_t]$$

and the input demand functions

$$(17)\ x_t = x_t[x^{t-1}, Q^{t-1}, \mu_t, w_t, A_t],$$

where A_t is an argument in the production function and input demand functions to represent the state of on-farm technology. Note that the existence of either input or output dynamics makes the input demand functions recursive, so that a final-form demand equation system can be written as

$$(18)\ x_t = x_t[w^t, \varepsilon^t, \mu^t, A^t]$$

to show that the input decisions in period t are functions of the histories of prices, price expectations, technologies and production shocks.

The structure of the model represented by equations (16) and (17) has important implications for testing the induced innovation theory and for modeling agricultural production. First, observe that the final-form factor demand equations (18) depend on the histories of prices, expectations, and technologies if the production process is dynamic _whether or not the induced innovation hypothesis is true_. That is, the final form has the same general structure whether or not w_t and μ_t influence I_t and A_t, because lagged prices also enter the final form through input and output dynamics. Thus, the final form generated by an induced innovation model is observationally equivalent to the final form generated by a model with exogenous technological change, and the two models therefore cannot be distinguished in the final form. For example, consider the alternative hypothesis that the evolution of T_t and A_t is exogenous, and that the technology is nonhomothetic such that factor proportions respond to relative factor prices in the same qualitative manner as they would if T_t and A_t were functions of prices. Both models could generate time series that would be consistent with the reduced form equation (18). Therefore, if production dynamics cannot be ruled out _a priori_, final-form factor demand equations cannot be used to test the induced innovation hypothesis. However, note that if production is static, the induced innovation model generates a final form with lagged prices due to equation (15), whereas the model of exogenous technological change implies a final form without lagged prices. The final form, therefore, could be used to test the induced innovation hypothesis under the assumption of static production.

The above results have strong implications for econometric measurement of agricultural productivity and testing of hypotheses about the structure of technology and technological change. Consider the use of dual cost or profit functions for these purposes. Dual functions and their derivatives have been advocated for econometric studies because they directly yield estimation equations with only exogenous variables on the right-hand side (Lau 1978), that is, because they directly yield factor demand and product supply equations in final form. Given the above results on final form equations, it is clear that the dual approach is of limited usefulness for identifying parameters needed to differentiate between theories of technological change and dynamic production, unless sufficiently strong a priori structure is imposed on the technology. To illustrate, consider one element x_{it} of the final form system (18). Multiplying x_{it} by its price and dividing by total variable profit gives a system of profit "share" equations

(19) $\pi_{it} = \pi_{it} [w^t, \varepsilon^t, \mu^t, A^t] \ , \ i = 1,\ldots, n \ .$

Alternatively, consider the system of equations

(20) $\pi_{it} = \pi_{it} [w_t \ , \ t] \ .$

System (20) (or its cost share analog) has been used in the studies cited by Capalbo and Vo to measure biased technological change and technology structure. System (20) can be derived from (19) by assuming static, nonstochastic production, static expectations, and $A_t = t$. If the true process generating the data is given by (19), it is clear that the interpretation of the time trend in (20) as representing technological change could lead to spurious inferences about the structure of the technology and the nature of technological change. Moreover, if the induced innovation hypothesis is entertained so that A_t is a function of past prices and price expectations, the profit shares can be expressed as a system depending on w^t, ε^t, and μ^t. Estimation of this final-form system clearly could not be used to differentiate the effects on profit shares of production dynamics from those of induced innovation.

In contrast, a structural production model can be used to distinguish the hypotheses of induced and exogenous technological change in the presence of production dynamics. The production function (15) shifts over time as a function of the on-farm technology which, according to the induced innovation theory, is a function of the history of prices and other variables influencing the innovation process. The induced innovation theory also implies that factor proportions should be functions of the history of prices, given current prices, price expectations, and the histories of input use and output. Therefore, the structural form of a dynamic production model can be used to test the induced innovation hypothesis by inferring causality from past prices to present productivity.

In conclusion, the analysis of a dynamic production model with technological change shows that both the dynamic structure of production and the dynamics of innovation may lead to observationally equivalent final forms. Therefore, unless production dynamics can be ruled out *a priori*, which seems unreasonable, final-form parameter estimates cannot be used to differentiate between production dynamics and alternative induced models of technological change. If production dynamics cannot be ruled out a priori, it is necessary to identify the structural parameters in the model to test the induced innovation theory.[4]

IV. Policy and Productivity

This section considers the implications of the above analyses for measuring and explaining agricultural productivity. Two sets of issues are considered. The first is the measurement of the productivity of investments in agricultural research, human capital, and physical infrastructure. The second is the relation of agricultural price and production policies to productivity.

A. Measuring Productivity of Public Sector Investments in Agriculture.

The innovation model outlined in the previous section shows that the evolution of on-farm technology is a function of the histories of agricultural investments, both private and public. If the demand for and supply of public sector investments is a function of agricultural productivity, then they would not be exogenous to production and causality between them and productivity would be bi-directional. If this were true, would measured static productivity of the investments be biased?

To explore this issue, suppose agricultural research spending in year t in region i, R_{it}, is a function of the region's history of average land productivity, $P_i^{t-1} = (P_{it-1}, P_{it-2}, \ldots)$. Consider the estimation of a regional production function using pooled regional cross section and time series data. Equations (14) and (15) suggest that a production function for region i could be specified as

(18) $Q_{it} = f_{it}[x_i^t, Q_i^{t-1}, R_i^{t-1}, D_{it}, \varepsilon_{it}]$,

where the technology index A_{it} has been substituted out of the model, and the unobservable histories of the variables K_t, μ_t, and τ_t are subsumed in the error term ε_{it}. The measured productivity of R_i^{t-1} would be biased if it is correlated with the unmeasured effects represented by the error term ε_{it} in the production function. Such correlation could be due to autocorrelated outputs, but this seems unlikely because annual agricultural output autocorrelations typically are small and of low order. Correlation between R_i^{t-1} and ε_{it} is much more likely to be due to omitted variables or measurement error. For example, the stock of basic knowledge in region i, K_{it}, may also be a function of past productivity. Since the K_{it-1}, K_{it-2},..., are subsumed into the error term of (18), ε_{it} and R_i^{t-1} would be correlated and the measured productivity of R_i^{t-1} would be biased upward. Another likely possibility is that the regions in the sample differ in land quality, and hence in their past productivity. If the data are not accurately adjusted for quality differences, then ε_{it} and R_i^{t-1} would be correlated. Again the marginal productivity of agricultural research would be biased upward because high levels of research would be associated with high levels of productivity, regardless of true research productivity.

The preceding analysis shows that bias in the measured research productivity is not due to the dynamic structure of production or to the causal relations between research and productivity _per se_. In a correctly specified model with accurately measured inputs, ε_{it} and R_i^{t-1} are not correlated if output is not autocorrelated, whether causality between productivity and research is uni-directional or bi-directional. Therefore, the biases that exist are most likely due to common measurement and specification problems. The same analysis could be conducted for other public sector investments, including human capital and physical infrastructure. The recursive structure of the dynamic production model ensures that the productivity of these investments is unbiased as long as output is not autocorrelated, the model is not misspecified, and input measurement error is not severe.[5]

Causality is important to the measurement of the productivity of public sector investments also because these investments themselves are often interrelated. These investments have a logical time ordering in the process of agricultural growth: physical infrastructure such as roads is a necessary precondition for development of certain other physical and institutional infrastructure such as education, extension, and marketing systems. Diffusion of agricultural technology also depends on related physical and institutional investments. Thus, agricultural investments have a logical causal ordering in their relation to each other and to productivity.

The pervasiveness of these interrelations between public sector investments means that it is extremely difficult to measure the distinct productivity effects of agricultural research, human capital, and related physical and institutional infrastructure. For example, in estimating a production function similar to (18) with aggregate U.S. time series, the author found research, human capital, and physical infrastructure data to be highly correlated. Indeed, it has been argued elsewhere (Antle 1984), that interdependence of agricultural investments is so pervasive that it is questionable whether it is meaningful to discuss the productivity of individual investments. Rather, it was argued that only the productivity of

<u>sets</u> of interrelated investments can be measured. This conclusion, if true, has important implications for existing research which has used production models to measure the productivity of agricultural research, human capital, and other public sector investments. Since many such studies include only one or two variables of the potentially many that would be required to represent the full set of interrelated investments, it seems probable that the measured productivity of these investments is biased, most likely upwards.

B. Production and Price Policy

The model of innovation outlined in the previous section shows that innovation can come from both the demand and supply sides of the "technology market." Induced innovation can be initiated through the effects relative prices have on the demand for technology that saves scarce resources, and subsequent suppply response by public institutions and private firms. Technological change can also come about through exogenous shifts in the supply of a particular type of technology without being induced by prices. One of the important policy questions is, therefore, to what degree agricultural price and production policies do influence the innovation process. The answer to this question clearly depends on the validity of the induced innovation theory. Price policies have the potential to influence productivity through the demand side only if induced innovation is a significant factor in the innovation process. Public subsidization of research and diffusion can stimulate the supply side of the technology market whether or not induced innovation is operative.

The model of induced innovation shows that the transformation of basic knowledge into on-farm technology is influenced by price expectations. Therefore, a necessary condition for agricultural policies to affect productivity is that price policies must alter the long-run price expectations of farmers on the demand side and of the institutions on the supply side of the technology market. The implication, very much in the spirit of the rational expectations theory, is that erratic or unanticipated government policies do not modify expectations and hence do not influence technological change; whereas established long-term policies or credible announced changes in policy may influence price expectations and thus alter the direction and rate of technological change.

Specific examples of both unanticipated and long-term policies are the Payment-in-Kind (PIK) program and the milk price support program. PIK was announced as a temporary program and thus would not be expected to alter long-term expectations. In contrast, the long-term, stable character of milk price supports appears to have significantly influenced producers' demand for capital intensive milking technology and related biological research, as well as the allocation of both public and private research resources. For example, the California Milk Advisory Board provides several hundred thousand dollars of private research funding for dairy research. The University of California recently established a multi-million dollar teaching and research center in Tulare County, California. An important policy question is the degree to which this commitment of research resources has been influenced by the milk price supports.

The milk price support example is also of interest because it suggests that <u>relative output prices</u> may influence the direction of innovation just as much as input prices. Induced innovation theorists have emphasized the role of input prices in influencing scarce-factor-saving technology. But there seems to be nothing in the logic of the induced innovation theory contradicting the possibility that relative product prices influence the overall relative rates of technical change in different industries or in specific inputs in certain industries. In the case of dairy production, it seems likely that increasing relative wage rates encouraged mechanized milking. But it seems equally plausible that dairy mechanization continued beyond what would have been profitable without government intervention because of output price and tax policies.

Production and related nonprice policies also may influence the direction of innovation by altering the perceived opportunity costs of resources and technologies. Production policies such as PIK clearly affect product and input prices just as direct price support programs do. But other policies only indirectly related to production may also have significant impacts on opportunity costs. One example is pesticide regulation and the commitment of research resources to integrated pest management (IPM). Modern chemical pesticides were a spinoff of scientific developments during World War II (see Flint and van der Bosch, 1979). Advances in related biological technology, mechanical technology, and increases in wage rates helped stimulate the development and diffusion of the new chemical technology. But as pollution and health externalities became a serious concern, government regulations and restrictions began to increase the on-farm opportunity costs of pesticides, and public institutions began to respond to society's demand for less chemical intensive agricultural technologies. IPM, because it emphasizes the use of all available methods of pest control, biological and chemical, therefore was seen as a means to reduce agricultural pesticide pollution. It is not yet clear that government policy has raised the opportunity cost of chemical control of pests to the point that major technological change is forthcoming.

V. Implications for Research

The preceding sections suggest that productivity change in agriculture is a complex dynamic process. Measurement and explanation of this process requires an understanding of how individual producers, private industry, and public institutions respond to incentives to innovate. Econometric productivity measurement can contribute to our understanding of this complex process, but it seems that there rarely will be data adequate for estimation of many of the behavioral relations involved. Therefore, careful description and analysis of the unquantifiable institutional and behavioral components of the system will always be needed to evaluate policy options. Given this caveat, the above discussion suggests serveral directions for fruitful research.

1) Measurement of farm-level production dynamics. This area of research is especially important for analysis of farm-level decision making, and can provide information on the behavioral lags due to microdynamics. The recursive structure of microproduction greatly simplifies the estimation problem. However, farm-specific time series data are needed for this research and are rarely available. Microcomputer technology promises to facilitate the collection of consistent micro time series.

2) The relation between microdynamics and aggregate dynamics has received little attention (one exception is Day 1984). It was found in section 1 that the recursive structure of farm-level production is preserved in aggregation. This fact can be used to study the causal relationships between aggregate quantities and prices, and to study aggregate production dynamics. One important research question is the importance of aggregate input and output dynamics, since this determines whether or not the cost-of-adjustment theory could be used as the basis for aggregate dynamic models.

3) The analysis in section III showed that bi-directional causality between agricultural research, human capital, and infrastructure investments does not bias the measured productivity of these investments. However, the causal interrelations between these investments themselves is not well understood and is important in identifying the productivity of individual investments.

4) A host of questions related to the dynamics of innovation need to be answered before the relation of agricultural price and production policies to agricultural productivity can be fully understood. First, the dynamic approach suggests an understanding of farmers' expectations may be important to the evaluation of agricultural policy. A second related need is for a better understanding of the dynamics of innovation. The analysis in section III showed that structural dynamic models are needed to test the induced innovation hypothesis. For policy analysis, evidence is needed on the period of time required for relative price changes to be translated into productivity changes through the induced innovation process. There is a need for estimates of what might be called "the price elasticity of the supply of innovations." Casual empiricism suggests, for example, that producers adjust their factor proportions rapidly to price changes, to the degree possible with the existing technology; but that public institutions adjust slower and less predictably to relative price changes. Research into the relative speed of adjustment of the various organizations involved in the innovation process could provide much insight into the dynamics of technological change.

5) The welfare implications of the links between policy and productivity are largely unexplored. For example, in the case of the milk price support policy, there appear to have been income transfers from consumers and tax payers to certain asset owners and producers, given the technology that was in

place when the policy was instituted. However, it is less clear what the welfare implications are as the milk price support began to influence the allocation of research resources and dairy productivity. This effect can be interpreted as an additional distortion in resource allocation induced by the policy, but it differs from the usual distortion because it also generates scientific research which presumably increases social welfare.

FOOTNOTES

[1]These systems are referred to as recursive without specifying the structure of the error covariance matrix. If the covariance matrix is not diagonal, then the system is either block recursive or triangular.

[2]There is a remarkable similarity in the models and terminology used by Jacobs, Leamer, and Ward to define causality and the model and terminology used by Mundlak and Hoch (1965) in their classic article on estimation of the Cobb-Douglas production function. Mundlak and Hoch considered the case of production disturbances being "transmitted" from output to inputs. Thus, Mundlak and Hoch clearly recognized the importance of structural causality in production function estimation.

[3]The stock of knowledge is difficult to define and more difficult to measure. For some creative work in this direction see Evenson and Kislev (1975).

[4]Similar results on reduced-form equations of dynamic models have been noted in the rational expectations literature. For example, Eckstein (1984) finds that a dynamic rational expectations model and a Nerlovian partial adjustment model give observationally equivalent reduced-form acreage response equations. However, the rational expectations model's structural form implies overidentifying restrictions which can be used to differentiate the two models.

[5]In this connection Chaudhri's (1979) study of education and agricultural productivity is worth mentioning. Chaudhri argued that education is an endogenous variable and estimated a static aggregate production model in which education was endogenous. However, it is clear that education (a measure of the <u>stock</u> of farmers' human capital) in year t <u>cannot</u> be a function

of agricultural output in t. Thus Chaudhri's model contradicts the logic underlying the recursive structure of production, and must be misspecified.

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