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# Toward a Behavioral Approach to Modelling Dynamic Production Choice Structures

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## Introduction

Given the stable position in applied literature now held by static, duality models of choice, the focus of innovation has shifted to development of models of dynamic economic behavior. However, before jumping into this stream it is important to assess 1) the objectives and empirical relevance of study of such behavior, and 2) the characteristics of observed behavior which might help us resolve the specification of such models. The objective of empirical study of dynamic behavior seems clear. An accurate descriptive model is desired which could provide the basis for prediction and comparative analysis of behavior. The relevance of any such study is limited, as usual, by the accuracy and consistency with which the theory of behavior upon which the model is based simulates observed behavior. A prerequisite of relevance is an understanding of the elemental characteristics of observed dynamic behavior which might suggest the primitive elements of a theory of behavior and motivate model specification.

In the same spirit that Weaver (1982) considered the essential characteristics of the static choice problem faced by agricultural producers, the nature and characteristics of the dynamic problem must be described and enumerated to serve as a foundation for model specification. The theme of this paper is that such an assessment establishes that the empirical researcher is in an even weaker position concerning dynamic model specification than in the static case. Not only are an extensive variety of specification issues left unresolved in the dynamic case, but theoretical and empirical tractability require strong prior restrictions which find little justification in observed

behavior. If, indeed, the objective of empirical modelling is to describe (i.e. learn about) dynamic behavior, then it would seem apparent that data should be approached and analyzed with the clearest lenses possible, one which maximizes the probability of learning.

The paper will proceed by briefly enumerating the dynamic and stochastic characteristics of the agricultural choice problem in the second section. This will provide the foundation for a general assessment of the appropriateness of received theoretical models of dynamic behavior and for the suggestion of possible strategies for learning. Specifically, in the third and fourth sections two approaches will be presented. The first will involve extension of reduced form dynamic choice functions to accommodate a fundamental characteristic of dynamic behavior: use of information by decision makers. The second approach presents a means of learning from observed histories of behavior in a way which imposes minimal prior structural restrictions on the empirical model.

## An Assessment of the Potential Role of Economic Theory in the Specification of Models of Dynamic Production Behavior

### *Possible Approaches*

Empirical study of any observed phenomena may proceed in one of two ways. If little is known about the phenomena, observations might be recorded and considered in order to generate hypotheses concerning its occurrence. Alternatively, what might be labelled consistent modelling methods might be adopted in which a detailed specification of a model is motivated by a specific theoretical hypothesis which attempts to explain the phenomena's occurrence.

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Past empirical models of dynamics of production choice have focused on:

- 1) inertia in adjustment or implementation of plans,
- 2) the output sacrificed (or opportunity cost) due to adjustment of quasi-fixed input flows, and
- 3) inertia in adaptation of information motivating choices.

In an important sense, these early approaches were consistent with the feeling that dynamic choices were not simply the result of fully rational decision-making that is free of a variety of constraints not normally considered by neoclassical optimization models. Such constraints and alternative choice problems were reviewed by Griliches and Nerlove as a basis for providing some justification for what had otherwise been labelled as *ad hoc* models. In other words, the early dynamics literature attempted to be descriptive, and importantly, to acknowledge the complexity and subjectivity of such decisions and the possible inappropriateness of adoption of an approach where a specific rational choice model is imposed on the data. This approach employed a very general theory of dynamic choice to suggest that expected output prices might affect choice and that adjustment of expectations and choices might not be instantaneous. Although these early empirical models were freed of detailed restrictions motivated by a more precise theoretical hypothesis, empirical tractability required a variety of prior restrictions on the form of the dynamic relationships. In this sense the models were *ad hoc*.

Most recent work, however, has adopted the consistent modelling approach. Static or stochastic optimal control problems have been specified in neoclassical form where discounted intertemporal preferences are maximized subject to dynamic constraints on adjustment and current endowments, see e.g. McLaren and Cooper, Epstein, Merton, Loury. The mechanics of these problems are by now well-known and have been extended, at least in theoretical form, to agricultural problems, see e.g., Burt, Koo and Dudley; Antle; Dixon and Howitt; Noel, Gardner and Moore. However, empirical applicability of these models has been severely limited by the appropriateness of assumptions (e.g., single output, risk neutrality, exogenous expectations, constant returns to scale, and simple functional forms) necessary to obtain closed form solutions.

Adoption of such models for descriptive purposes requires verification of the underlying assumptions that given available information producers will behave in such a way that places them on the corresponding efficient path for the current period. Juxtaposing the early approaches with that of recent work leads to a questioning of the appropriateness of use of detailed rational choice hypotheses as the basis for specification of dynamic choice models. What are the characteristics of the dynamic choice problem faced by farmers? What is their decision process? More importantly, do answers to these questions justify adoption of a specific detailed rational choice hypothesis from which a consistent model can be derived?

#### *Characteristics of Dynamic Choice and the Role of a Behavioral Theory*

Weaver (1983) enumerated the following as important characteristics of short-run agricultural production decisions: 1) multiple outputs are produced by multiple inputs, 2) some input flows are quasi-fixed, 3) some input flows are stochastic and beyond the decision-maker's control, e.g. climatic factors and pest effects, 4) output prices are uncertain when production plans are made, 5) government programs affect choices, and 6) a variety of inputs and outputs can be adjusted to achieve short-run constrained objectives. The model presented can be interpreted as one of provisional choice (Weaver 1977) where these choices can be adapted both intra- and inter-seasonally as new information occurs. However, where and in what form do dynamics affect such provisional choice?

Without lengthy rationalization it would appear that the following additional characteristics are elemental to the dynamic agricultural production problem.

1. Resource application is not instantaneous. Intra-seasonal timing of application as well as inter-seasonal choices are dependent on the occurrence of stochastic climatic and environmental events which are beyond the producer's control.
2. Past allocation decisions may affect the cost of current actions. For example, the past sequence of cropping and cultivation methods affect current production possibilities.
3. Inter-seasonal adjustment of quasi-fixed factors of production may be possible

through long-term rental agreements or direct purchase. However, in some cases, these possibilities may be affected by institutional, social, and market distribution constraints.

4. Returns-to-size may be decreasing in the short-run (intra-seasonally) though possibly increasing in the long-run (inter-seasonally).
5. Limited management labor and time resources may be required for adjustment of quasi-fixed factors or adoption of new technology.
6. Outputs may play intermediary roles in producing other outputs.

If these characteristics are added to observed characteristics of the static production choice problem identified above, the necessary complexity of any descriptive dynamic rational choice hypothesis would seem clear. However, before adopting such a consistent modeling approach a closer look at the dynamic decision environment would seem appropriate.

In stepping from a static to a dynamic case, the problem of describing the decision process is complicated by human response to the decision environment. An important general difference between the static and dynamic decision environments is the fixity of the decision environment. In the static case, a fixed environment exists. In the dynamic case, two possibilities exist for how the decision environment changes. In the simplest case, the decision environment might change in a completely predictable manner. For example, the structural characteristics of the environment might be repeating with the levels of information parameters changing in a predictable way. At the other extreme, the decision environment might be non-repeating in its structure, or even if its structure is repeating, future levels of information parameters may not be predictable. Consideration of the dynamic agricultural decision environment would seem to suggest that 1) the horizon over which uncertain market prices and government incentives are predictable may be quite short and variable. Not only have dramatic changes in the structure of government supply control programs been observed (Morzuch, et al.), but input and output markets have been dramatically affected by unpredictable events during the post-war period. Secondly, non-market events affecting productivity of inputs and price levels may be generated by mechanisms

that leave structural prediction of their occurrence infeasible. These observations suggest that a variety of elements of the decision environment faced by agricultural producers may be non-repeating and where the structural characteristics of that decision environment are repeating, the measures of its characteristics may be difficult (i.e., costly) to predict. An important implication of this non-repeating nature of the inter-seasonal decision environment is that the efficiency of achieving rational or optimal decisions may not improve as a result of learning and adaptation to past errors in decisions.

Given this type of decision environment, it is important to question the descriptive usefulness of rational choice models. To proceed, it is appropriate to consider the evidence emerging from a literature which focuses on the human behavioral aspects of observed decision-making rather than on a prescriptive ideal as the appropriate basis for a descriptive theory of behavior. Thus, the approaches based on, or motivated from this literature might justly be labelled behavioral approaches. Several recent reviews of literature serve as an adequate basis for establishing the key points which have emerged over the past thirty years of behavioral literature, see e.g., March, Posner, Simon (1978), or Sage. Of primary interest is literature which has focused on the suggestions of cognitive psychology concerning decision processes in complex environments. Simon (1955, 1956, 1957) initially responded to empirical observations of decision behavior by generalizing the purely rational decision model through introduction of human decision-making technology as a constraint. The implication of this approach was the concept of bounded rationality. Constraints were introduced to acknowledge limits in computational capability, extent of organization and use of memory, and uncertain preferences as well as consequences of actions. Although this tone has been maintained in the literature, lessons from empirical observation have led to an acknowledgement that decision processes may not be accurately described by such simple extensions of rational models. In particular, several lessons from this literature seem important to note for decisions made in non-repeating environments.

- 1) Individuals have vastly different computational capabilities.
- 2) Decisions must often be made in unexpected decision environments in which

- preferences are not fully specified and where all relevant alternatives and possible consequences cannot be identified.
- 3) Decisions often involve a high degree of subjective evaluation of possible alternative actions *and* their consequences.
  - 4) Controlled experiments which might allow iterative development of rational decisions are often not feasible due to the extent to which decision environments change.
  - 5) Preferences or objectives of choice are often ambiguous and, more importantly, interactive with past actions and their consequences.
  - 6) A variety of decision processes and cognitive styles have been observed of which rational processes (in which preferences and the characteristics of opportunities are fully known prior to decision-making) are a subset.
  - 7) A variety of biases have been consistently observed in the processing of information by decision-makers. This suggests that information is both selected and processed in a highly subjective, personal manner which is conditional upon characteristics of the decision environment, e.g. time pressure, availability of information, and extent of change from past experience. Furthermore, individuals are not consistent in their subjective selection and processing of information. Instead, their methods or styles vary over time as personal environments and experiences change, as risk preferences change, and as the current decision problem changes.

While limited space prevents a discussion of examples of observed behavior by agricultural producers which are consistent with these lessons, in each case many come to mind. What are the implications of this literature for empirical study of dynamic production decisions in agriculture? Three general conclusions emerge which serve as caveats and directives for model specification as well as for choice of an appropriate method of empirical learning. First, this literature suggests that there does not exist a single, widely applicable behavioral theory of choice, particularly in non-repeating environments. Sage enumerates and reviews empirical support for a wide array of models of decision processes. These alternatives can be organized into three general types: 1) holistic evaluation in which preferences (possibly sub-

jective) and all opportunities are fully known and all alternatives are evaluated according to their contribution to the implicit goal of constrained preference optimization, 2) heuristic evaluation in which full knowledge of preferences and opportunities are not known, precluding explicit consideration of all alternatives and requiring use of more simplified decision rules, e.g. lexicographic or elimination by ranked aspects, and 3) holistic evaluation in which current alternatives are considered within the context of past experience which has led to experience-based decision rules (e.g., safety first rules of Day et al.), and intuition is relied upon to assess a complete characterization of alternative actions and their possible consequences. A second general conclusion of this literature is that while major aspects of a variety of decision processes have been identified, specific models of these alternative processes are at a nascent stage of development. A final conclusion is that deviations between observed behavior and the predictions of rational holistic choice models do not provide an acceptable basis for the inference that such deviations are simply stochastic errors. Instead, observed deviations appear to be persistent in occurrence, magnitude and direction.

The implication of these conclusions for modelling decision-making is apparent. Where the decision environment is complex, neither fully observable nor accessible to the decision maker, and possibly non-repeating, holistic models seem of questionable usefulness for description of observed behavior. The characteristics of dynamic production decisions enumerated above suggest a need for an approach to empirical study of such decision behavior which is 1) free of restrictive priors of a particular purely rational decision model, and 2) sensitive to the weakness of our current understanding of how decisions are made.

The remainder of this paper will consider two possible approaches which are motivated by these two implications. First the assumption of the existence of a specific form of a rational choice model will be relaxed by focusing on reduced form dynamic choice functions using cross-sectional data which may be consistent with a variety of alternative choice problems. Secondly, an analog to the classical decision theoretic concept of the value of information is proposed for the descriptive model in this section. Finally a dramatically different approach to time series modelling of

dynamic production decisions will be presented which is motivated by the researcher's admission that little is known about which decision model is appropriate and maximum learning from the data is desired.

### Information Processing at the Firm Level

#### *Alternative Approaches to Modelling Information Processing*

This modelling approach relies on cross-sectional data to identify the role of information concerning the physical environment within an intra-seasonal production process. Information has value to the extent that it can influence timing and application decisions for an input. Information is not a direct physical input such as labor, land or fertilizer, but rather information influences the output level when it is used in conjunction with a direct input. An information processing theory of decision making is based on the assumption that individuals have an input mechanism for the acquisition of information, a filtering mechanism for interpretation and an output mechanism for making choices. Information processing theories can be broadly classified as either classical decision theory approaches or behavioral approaches which are based upon observed behavior.

The classical approach to determining the impact and the value of information relies on Bayesian updating and has two basic requirements (Raiffa). This approach requires the problem to be highly structured. That is, the decision maker must be aware of all of the possible options for gathering information, all of the events that may possibly occur, the measure of the payoff associated with each realization, and the chances that a given event will occur. In this sense, the classical approach represents an example of holistic decision making (Sage). Second, the decision maker's choice subsequent to receiving information should be predictable given the structure of the problem. In principle, theorists can set up this problem as a dynamic programming problem under uncertainty in which the conditional distributions of future exogenous variables are estimated using all available information up to the current period. In practice these problems are difficult to solve both analytically and computationally, with the exception of a few special cases. In many cases, approx-

imate, suboptimal procedures may be required. The classical approach necessarily assumes that managers can be represented as, at least, "as if" mathematical statisticians capable of solving specific optimization problems that are often beyond the analytic capabilities of expert analysts with significant computing power at their disposal. On the one hand, this approach takes an important step towards realism by allowing incomplete (or imperfect) information to influence the actions of the manager. On the other hand, the classical approach moves away from reality by assuming that the manager follows optimizing rules of behavior for situations in which the optimization assumption has minimal empirical support. In contrast, the behavioral approach attempts to rationalize observed behavior by allowing for the biases and heuristics that managers use in making judgements under uncertainty. These approaches typically assume the existence of feedback mechanisms that direct managers onto behavioral paths through the use of historical successes and failures (Cross).

The way that information is used to deal with the hazards of the operating environment presents a formidable modelling problem and given the great number of possible decision models suggested by the behavioral literature, an approach which is consistent with a wide set of models may be in order. A large number of studies in cognitive psychology indicate that a variety of biases and heuristics in decision making evolve which affect information acquisition and formulation (Tversky and Kahneman). Despite these conclusions, the manager's attitude toward risk remains the economist's standard excuse for explaining the deviation between observed behavior and expected profit maximizing behavior. Recognizing that managers operate within a hazardous, non-repeating economic and physical environment and that they develop biases and heuristics which affect their use of information, part of this deviation between observed and predicted behavior may be explained by how information is processed by the manager. Therefore, it is of interest to establish a modelling approach which explicitly allows for such biases and heuristics in information processing.

#### *A Model of Multi-stage Input Decisions*

This model focuses on the production process within an uncertain physical environment

where inputs are applied during the season and result in the final product which is realized at the end of the season; i.e., a multistage production process. The season can be considered to be composed of a series of stages where various inputs are applied at each stage. At the beginning of the  $n$ th stage a two part decision must be made: whether information should be acquired regarding the environment, and the choice of input levels. The input choice decision is influenced by the information acquisition decision.

Consider a two stage production process. Final production depends on the application of inputs at two stages where these inputs are denoted by  $x_j^{(k)}$  where  $j$  indicates the input applied,  $j = 1, 2, \dots, J$ , and  $k$  indicates the stage,  $k = 1, 2$ . For notational convenience an  $_-$  is used to indicate the sequence of factor demands for a given stage; i.e.,  $\underline{x}^{(k)} = (x_1^{(k)}, x_2^{(k)}, \dots, x_J^{(k)})$ . Some inputs may be applied in both periods (e.g., pesticides, irrigated water) while other inputs may be applied in only one of the periods (e.g., fertilizer). Bellman's principle of optimality (Bertsekas) establishes that the manager's optimal input application decisions can be achieved recursively. That is, the final decision to be made is the choice of the level of  $\underline{x}^{(2)}$  given past decisions (the levels of inputs applied during the first stage and the results of the information collection decisions in both stages) and the state of the crop's performance in the second stage. At the beginning of the second stage the manager's information decision is made given the levels of inputs applied in the first stage,  $\underline{x}^{(1)}$ , and the results of the first stage information collection decision and the crop performance in the first stage. This decision is preceded in the time ordered sequence of events by the first stage information collection decision. The characterization of the decision process within a recursive structure is consistent with the behavioral literature. Without being more specific about the optimization problem, this recursion process suggests the existence of the following generally specified sequence of demand equations for information and productive inputs

$$(1) \quad \begin{aligned} I^{(1)} &= f_1(\underline{w}^{(1)}, \underline{w}^{(2)}, c) \\ x_j^{(1)} &= g_1(\underline{w}^{(1)}, \underline{w}^{(2)}, c, z^{(1)}) \\ I^{(2)} &= f_2(\underline{w}^{(1)}, \underline{w}^{(2)}, c, \underline{x}^{(1)}, I^{(1)}) \\ x_j^{(2)} &= g_2(\underline{w}^{(2)}, c, \underline{x}^{(1)}, z^{(2)}), \end{aligned}$$

and output is denoted

$$(2) \quad Q = h(\underline{x}^{(1)}, \underline{x}^{(2)}, U)$$

where

- $\underline{w}^{(k)}$  = vector of input prices associated with the vector of inputs  $\underline{x}^{(k)}$  which are normalized by the output price;
- $c_i$  = normalized cost of obtaining information (assumed constant throughout the season for the  $i$ th observation);
- $I^{(k)}$  = the information collection decision in the  $k$ th stage;
- $z^{(k)}$  = an index reflecting the state of the crops during the  $k$ th stage;
- $Q$  = final output level;
- $U$  = random disturbance;

for  $k = 1, 2$ .

The system in (1) generally differs from dynamic factor demand formulations (McLaren and Cooper; Epstein) by treating the information acquisition decision as a factor demanded. In theory, management decisions are conditioned on the results of an information collection procedure as well as the accuracy of the information set. In practice, the data typically measure whether a manager participated in an information collection procedure. In the development of this model the information decision is measured as a dichotomous variable: collect information or do not collect information. Information influences the production process by providing a more accurate view of the state of the crop development (or the physical factors influencing crop development). The state of the crop development may include knowledge of the pest population level, the stage of the plant development, or the crop moisture requirements. However, this crop development index (CDI) is not observed with accuracy during the production process and must be considered an unobservable variable. Let the first stage CDI for the  $i$ th observation be described by

$$(3) \quad z_i^{(1)} = \eta_0 + \phi_1(I_i^{(1)})\epsilon_i$$

where  $\epsilon_i$  is normally distributed with mean zero and variance  $\sigma^2$ . In the second stage the CDI for the  $i$ th observation depends on a term which is a function of past productive input decisions and the second stage information collection decisions, and is described by

$$(4) \quad z_i^{(2)} = \eta_1 + \sum_{j=1}^J \eta_{2j} \psi(x_{ij}^{(1)}) + \phi_2(I_i^{(2)})\epsilon_i$$

Equations (3) and (4) imply that the conditional variance of  $z^{(k)}$  changes as the manager

acquires information. The formulation is in keeping with the spirit of Just and Pope (1978) and has been applied in the static setting by Just and Pope (1979) and Griffiths and Anderson.

For illustrative purposes we will focus on the special case where the information collection decision is made on a seasonal basis; i.e.,  $I_1^{(1)} = I_1^{(2)} = I_1$ . This is not a particularly restrictive assumption since many field monitoring services contract their services at the beginning of each season. Let the final output be expressed as

$$(5) \quad Q_1 = A \prod_{k=1}^2 \prod_{j=1}^J [x_{ij}^{(k)}] \xi_j^{(k)}.$$

Maintaining an expected profit maximizing framework and following the backward recursion process the information demand equation is written as

$$(6) \quad I = H_1^{(1)} \alpha + w$$

where  $I$  is a dichotomous variable and  $w$  is independently distributed normal with mean zero and variance  $\omega^2$ . The logarithm of the  $j$ th productive factor demand equations in stages 1 and 2 are written as

$$(7) \quad \begin{aligned} \tilde{x}_j^{(1)} &= H^{(1)} \beta_j^{(1)} + u_j^{(1)} \\ \tilde{x}_j^{(2)} &= H^{(2)} \beta_j^{(2)} + u_j^{(2)} \end{aligned}$$

where  $H^{(1)} = [H_1^{(1)} H_2^{(1)}]$  with  $H_1^{(1)} = [\tilde{w}^{(1)} c]$ , and  $H_2^{(1)} = [z^{(1)}]$ ;  $H^{(2)} = [H_1^{(2)} H_2^{(2)} H_3^{(2)}]$  with  $H_1^{(2)} = [\tilde{w}^{(2)} c]$ ,  $H_2^{(2)} = [\tilde{x}^{(1)}]$ , and  $H_3^{(2)} = [z^{(2)}]$ ; and  $\tilde{\cdot}$  denotes the natural logarithm. Notice that the CDI for each stage is included in an *ad hoc* manner. The  $u_j^{(k)}$  are normally distributed error vectors with the properties

$$(8) \quad \begin{aligned} E\{u_j^{(k)}\} &= 0 \text{ for all } j = 1, 2, \dots, J; \\ E\{u_j^{(k)} u_j^{(m)}\} &= \sigma_{jk}^2 I_N \quad \text{for } k = m \\ &= 0 \quad \text{for } k \neq m. \end{aligned}$$

Since the CDI is unobservable to the econometrician in both stages, using  $\psi(x_{ij}^{(1)}) \tilde{x}_j^{(1)}$  and substituting (3) and (4) into (7)

$$(9) \quad \begin{aligned} \tilde{x}_j^{(1)} &= H_1^{(1)} \beta_{j,1}^{(1)} + v_j^{(1)} \\ \tilde{x}_j^{(2)} &= H_1^{(2)} \beta_{j,1}^{(2)} \\ &\quad + H_2^{(2)} (\beta_{j,2}^{(2)} + \eta_2) = v_j^{(2)} \end{aligned}$$

where

$$(10) \quad v_{i,j}^{(k)} = \phi_k(I_i) \epsilon_i \beta_{j,m} + u_{i,j}^{(k)}$$

and  $\beta_{j,m}^{(k)}$  are the coefficients associated with  $H_m^{(k)}$  for the  $j$ th equation. The system equations is written as

$$(11) \quad \begin{aligned} \tilde{x}^{(1)} &= [I_j \otimes H_1^{(1)}] \beta_1^{(1)} + v^{(1)} \\ \tilde{x}^{(2)} &= [I_j \otimes H_*^{(2)}] \gamma + v^{(2)} \end{aligned}$$

where  $H_*^{(2)} = [H_1^{(2)} H_2^{(2)}]$  and  $\gamma_j = [\beta_{j,1}^{(2)} (\beta_{j,2}^{(2)} + \eta_2)]'$ .

Assuming that  $E \epsilon u_j^{(k)} = 0$  for all  $j$  and  $k$ , the error vectors  $v_j^{(k)}$  are heteroscedastic within each equation and stage and correlated across stages (see Stefanou for details). Information influences the estimation of the productive factor demands by the recognition of the heteroscedastic error structure of (9). When information acquisition is not an option (or is ignored), for a given stage, the error vector  $v_j^{(k)}$  is homoscedastic for all  $j$ . The system of input demands requires probit estimation of (6) and system estimation of (11). The estimation of such a system depends on the functional form specified for  $\phi_k(I)$  and relies on generalized least squares (GLS) procedures that are discussed in the existing literature. The two prime considerations focus on the heteroscedastic error variance estimation (Hildreth and Houck; Rao (1970, 1972); Amemiya) and the system estimation (Zellner; Goldberger; Oberhofer and Kmenta; Magnus).

### Measurement of the Value of Information

A measure of the value of information can be obtained within this framework. The concept of the value of information becomes more complex when one considers a dynamic decision process. One can distinguish between two types of value of information measures: an addition to the information set (i.e., whether to collect information in the next production stage), and the development of an entire information set (i.e., whether to collect information in the next production stage). For the model developed here, the latter type of information value measure is of interest.

The final output relationship in this case is specified

$$(12) \quad \tilde{Q}_1 = \tilde{A} + \sum_{k=1}^2 \sum_{j=1}^J \xi_j^{(k)} \tilde{x}_{ij}^{(k)} + U_1$$

where  $U$  is a normally distributed error vector with mean zero and variance  $\sigma_U^2 I_N$ , which is not correlated with  $u_j^{(1)}$ ,  $u_j^{(2)}$ , or  $\epsilon$  for  $j = 1, 2, \dots, J$ . Let  $*$  denote the ordinary least squares (OLS) estimate, and

$$\hat{\tilde{x}}_j^{(k)} \Big|_{\text{GLS}} \quad \text{and} \quad \hat{\tilde{x}}_j^{(k)} \Big|_{\text{OLS}}$$



denote the predicted values of the  $j$ th equation for the  $k$ th stage using the heteroscedastic error structure (i.e., accounting for information acquisition) and the homoscedastic error structure (i.e., ignoring information acquisition), respectively, for the estimation of (11) with the cost of information set equal to zero. With the point expectation of  $U = 0$ , a measure of the value of information (VOI) is

$$(13) \quad \text{VOI} = N^{-1} \sum_{i=1}^N \left[ \hat{Q}_i \Big|_{\text{GLS}} - \hat{Q}_i \Big|_{\text{OLS}} \right]$$

where

$$(14) \quad \hat{Q}_i \Big|_{\text{GLS}} = \exp \left\{ \tilde{A}^* + \sum_{k=1}^2 \sum_{j=1}^J \xi_j^{(k)*} \left[ \hat{x}_{ij}^{(k)} \Big|_{\text{GLS}} \right] \right\}$$

$$\hat{Q}_i \Big|_{\text{OLS}} = \exp \left\{ \tilde{A}^* + \sum_{k=1}^2 \sum_{j=1}^J \xi_j^{(k)*} \left[ \hat{x}_{ij}^{(k)} \Big|_{\text{OLS}} \right] \right\}.$$

While a large VOI suggests a considerable impact of information on managers' production decisions, a small VOI may suggest that information acquisition has little value or the description of the information variable is too diffuse and does not adequately reflect the impact of information acquisition as an input in the production process. This measure of the value of information is not guaranteed to be non-negative with a zero cost of monitoring as is the case with the classical decision theoretic model.

If information acquisition decisions can be made throughout the season then the system of equations characterized by (1) needs to be specified and estimated. This system involves dummy endogenous variables and requires a mixture of conventional and limited dependent variable estimation techniques. Heckman and Maddala and Lee have provided theoretical and empirical examples of this type of model estimation.

Where static production models suggest that the level of output is not sensitive to the timing of input applications, the approach taken in this section allows for dynamic input application decisions during the season using cross-sectional data. While this model maintains the maximization paradigm, it includes behavioral restrictions on how information influences production decisions. Namely, information provides a more accurate view of the state of the crop development and influences the demand for productive inputs via the error struc-

ture. Like the classical decision theory approach imperfect information can influence production decisions, but the mechanism for information processing is specified in a way that is consistent with the data that are typically available and with a wide set of behavioral models.

### Estimation of Dynamic Production Choice Functions with Minimal Priors

#### Approaches to Specification

The traditional functions of a theory of choice for specification of consistent empirical models are to 1) identify relevant variables, 2) establish a causal ordering of these variables, i.e., partition them into two subsets: endogenous and pre-determined or exogenous, and 3) suggest a limited set of characteristics of the functional relationship between these variables (e.g. monotonicity, symmetry, convexity, linear or zero-degree homogeneity). For example, following Weaver (1982) a general static theory of choice might establish the vector ( $Z \Omega$ ) as the set of relevant variables and hypothesize that the elements of  $\Omega$  are exogenous information and quasi-fixed factor flows and  $Z$  are endogenous choice variables solving

$$(15) \quad \max G(Z; \Omega).$$

To ensure the existence of continuous choice functions  $Z = g(\Omega)$ , it would be required that  $G(\cdot)$  satisfy a further set of properties outlined in Weaver (1982). Specific properties of  $g(\cdot)$  such as predictions of the signs of own-price comparative-statics and symmetry of substitution effects would follow only from further assumptions concerning the properties of  $G(\cdot)$ . For example, as Weaver (1982) noted, twice continuous differentiability of  $G$  in  $Z$  and  $G_{Z\Omega} = I$  would be required for symmetry, a more general result than that of Pope. Similarly, knowledge of the form of  $G_{Z\Omega}$  would be required to establish monotonicity and the signs of own price effects. In general, monotonicity and neo-classically sloped choice functions would not be expected. In the static case, the further restrictions of  $G(\cdot)$  required to ensure existence of continuous choice functions satisfying this type of properties are often motivated by the prior belief or assumption that the decision environment is repeating and iterative learning leads decision-makers to behavior which is "as if" rational. However,

as Weaver (1982) noted, even when based on a specific behavioral hypothesis, these priors leave a wide variety of model specification issues unresolved.

Although it is clear from McLaren and Cooper, and Epstein that specific dynamic choice problems can also serve these specification functions, the approach presented here rejects the usefulness of this methodological approach for construction of descriptive dynamic models. The behavioral literature, in combination with observed dynamic characteristics of the production technology and the decision environment faced by agricultural producers, suggests that in the case of the dynamic production choice problem a theory of choice may be more elusive than in the static case. This literature suggests that even adoption of a general rational choice hypothesis (e.g. a dynamic generalization of (15)) may not be appropriate. A further complication, to be discussed below, follows from the fact that a dynamic theory of choice requires adoption of a theory of information acquisition and processing as a basis for specification of the mechanism generating  $\Omega$ . In the static case, information is assumed instantaneously available to the decision-maker, allowing this problem to be ignored. Empirical evidence found in the behaviorist literature of subjectivity and biases in information processing as well as of instability of objectives and infeasibility of iterative learning which might converge to efficient behavior when the decision environment is non-repeating suggests that the assumption of "as if" purely rational choice is inappropriate for descriptive purposes in the dynamic case.

In statistical terms, this literature suggests that 1) the compositions of sets of conditioning pre-determined variables and endogenous variables, as well as 2) the form of the conditioned likelihood of the endogenous variables may not be stable over time for an individual decision maker. In the aggregate, however, it may be more reasonable to assume that the composition of behavioral styles or modes is stable for a sufficiently large group of decision-makers. This suggests that the behaviorist literature combined with empirical observation might be relied on in a very general way as a source of suggestions for the identification of relevant variables, while the exogeneity partition, and possible characteristics of functional relations would be left open to be resolved by empirical evidence.

In the face of such weak priors, what lessons or results can be expected from empirical observation? Perhaps the most appropriate issues to resolve would be 1) verification of relevance of variables, 2) verification of the causal ordering of variables, and 3) identification of lag structures relating variables. It is precisely these issues which modern time series analysis is designed to resolve (see Grenander and Rosenblatt; Sargent and Sims; Geweke; Zellner and Palm), and for which traditional econometric approaches must rely upon resolution prior to estimation. Although priors may be sufficiently strong for the static case to resolve these specification issues, in the dynamic case it seems clear that insufficient priors exist and a data based time series approach to learning would be preferred. If specific theories of choice or of information processes are to play any role in model specification, the weakness of our priors in the dynamic case suggests these theories should serve as *guides* for post-estimation hypothesis testing rather than for restriction of models prior to estimation.

In the remainder of this section the usefulness of multivariate time series methods for empirical study of dynamic choices will be assessed. Time series methods have in the past been thought to produce purely data dependent estimates which 1) preclude identification of structural relationships having some theoretical interpretation and 2) often require *ad hoc* restrictions on the form of estimated relationships. However, in what follows a method will be introduced which allows data dependent estimation of a time series model which may be consistent with specific structural hypotheses. This property allows the validity of structural hypotheses to be assessed post-estimation. This possibility allows the consistency of specific theories with empirical evidence to be tested rather than assumed prior to estimation.

### A Time Series Approach Allowing Minimal Priors and Structural Analysis

Stepping toward model specification, direct observation can be relied upon for identification of multiple outputs and inputs involved in the dynamic production process. However, the causal ordering among different outputs, or among different inputs may be complex. For example, outputs may directly serve as

intermediate inputs for still other outputs, or an indirect effect may result when their production alters quasi-fixed input characteristics leaving some outputs infeasible. At a minimum these observations suggest 1) the existence of a vector autoregressive relationship among outputs. On the input side, time intensity and actual resource costs of adjustment of production practices, and intertemporal relationships among production possibilities suggests 2) inputs committed in one period may affect the outcome of inputs in a future period. Finally, 3) lags may exist in the direct productivity of inputs. These observations can be summarized by generalizing the traditional multiple output, multiple input short-run production transformation function (PTF). For example, according to these observations the PTF used in Weaver (1983):

$$F(Y_t, X_t) = 0$$

would be written in Markovian (or autoregressive) form:

$$(16) \quad F(Y_t, X_t | Y_T, X_T) = 0$$

where

$Y_t, X_t$  are vectors of 1) current output and 2) intra-seasonally variable input and quasi-fixed (variable only interseasonally) inputs, respectively, and

$Y_T, X_T$  are vectors of relevant past values of  $Y_t, X_t$ ,  
e.g.  $X_{iT} = [X_{i,T-1} \dots X_{i,T-T_i}]$

In summary, our observations suggest that 1)  $\partial^2 F / \partial Y_{it} \partial Y_{jt-\tau} \neq 0$  for some outputs  $Y_i, Y_j$ ; 2)  $\partial^2 F / \partial X_{ht} \partial X_{kt-\tau} \neq 0$  for some inputs  $X_h, X_k$ ; and 3)  $\partial F / \partial X_{ht} = 0$  although  $\partial F / \partial X_{ht-\tau} \neq 0$  for some inputs  $X_h$ . It is clear that while in the static case the researcher need only specify the elements of  $Y_t$  and  $X_t$ , in the dynamic case the elements of  $Y_T$  and  $X_T$  (i.e. the lag structure of production) must also be specified. While traditional priors concerning the form of production relations might be useful in specification of the functional form of  $F(\cdot)$ , the composition of  $Y_T$  and  $X_T$  is an empirical issue for which few priors exist. In addition, it should be noted that the vectors  $Y_t, X_t$  have not been partitioned by their exogeneity. Again, such specification could only follow from adoption of a particular behavioral hypothesis which recognized the fixity of certain inputs during the period in which choices are implemented. As noted by Weaver (1982, 1983), fixity could follow from the absence of

rental markets or zero salvage value on input stocks, or both. It would seem appropriate to acknowledge that such fixity is an empirical issue for which only the weakest priors exist.

Having identified possible inputs and outputs involved in the production technology, specification of a model of production choices requires at least a general consideration of the determinants of choice. Suppose  $\Omega_t$ , a vector of current, and possible characteristics of future stochastic levels of relevant information variables, and  $\Omega_T$ , a similar vector of past relevant information, can be identified from past empirical observation and consideration of possible behavioral hypotheses. As already noted the vector  $\Omega_t$  may include information which is endogenous as well as that which is exogenous to choice. Thus, values of elements of  $\Omega_t$  which measure characteristics of future stochastic levels of relevant information may be at least partially determined by elements of  $\Omega_T$ , or by exogenous elements of  $\Omega_t$ .

An important implication of this observation is that dynamic model specification requires a consideration not only of theories of choice, but also of a theory of the measurement and processing of information. Rational expectations hypotheses (REH) represent an example of such an information theory. However, as in the case of selection of a theory of choice, evidence in the cognitive psychology literature suggests that no theory of information acquisition may be universally appropriate. Two alternative approaches may be useful. Weaver (1977) suggests specification of a generally acceptable, minimum information set (GAMI) which would describe exogenous information that could be hypothesized to be freely available, and generally relevant to decision makers. Weaver (1978) outlined a specific measurement model in which such a GAMI set could be stochastically related to price expectations to allow for errors in measurement and specification.

In summary, neither a theory of choice nor a theory of information acquisition and processing has been adopted. Instead it is suggested that direct observation, and a variety of behavioral hypotheses be relied upon to motivate only the set of possibly relevant variables. Though this strategy would fail to present a detailed model which is consistent with a particular behavioral hypothesis and a specific information measurement model, it would present the basis for specification and estimation of a model which is consistent with the

weakness of our priors. In addition, through the choice of the proper estimation strategy a variety of structural specification issues might be resolved through data dependent learning (Weaver (1982), Leamer).

This possibility is offered by adoption of multivariate ARMA methods. These methods, as do any econometric time series modelling methods, require the existence of adequate time series observations. It would seem reasonable to proceed by assuming the availability of such data, otherwise the empirical consideration of any intertemporal dynamic models would be infeasible. Specifically, we assume the availability of time series for the vectors  $(Y_t, X_t, \Omega_t)$ , allowing observation of  $(Y_T, X_T, \Omega_T)$ . For convenience, redefine notation by defining  $z_t$  as a vector of monotonic transforms of the elements of  $(Y_t, X_t, \Omega_t)$  which allow  $z_t$  to be represented by the following general linear ARMA model:

$$(17) \quad A(L)z_t = B(L)U_t$$

where

$A(L)$  and  $B(L)$  are full rank matrices of polynomials in the lag operator  $L$ , e.g.

$$A(L) = A_0 + A_1L + A_2L^2 + \dots,$$

$A(L)$  and  $B(L)$  contain only convergent polynomials,

$U_t$  is a zero mean vector error process with a contemporaneous covariance matrix equal to the identity matrix and zero serial correlation.

As stated, (17) represents an unrestricted ARMA form, the existence of which is guaranteed for any vector  $z_t$  for which there exists an invertible MA representation  $z_t = \phi(L)U_t$  where  $|\phi(L)q_t| \neq 0$  for all  $q_t$  such that  $|q_t| < 1$ ,  $\sum_{s=0}^{\infty} \|A_s\|^2 < \infty$ , and  $U_t$  is serially uncorrelated. (Conditions for the existence of the MA representation can be found in Doob).

The usefulness of this general ARMA form for structural analysis has been established by Zellner and Palm; Wallis; and Geweke. This approach requires estimates of  $A(L)$  and  $B(L)$  obtained in the absence of any prior exogeneity hypothesis. Given such estimates, a specific exogeneity hypothesis would have testable implications. Suppose such a hypothesis proposes that a vector  $x_{1t}$  of elements of  $z_t$  are exogenous to the determination of a vector  $z_{2t}$  of elements of  $z_t$ . Re-ordering the elements of  $z_t$  according to this exogeneity partition, we could define  $z_t^0 = [z_{1t} z_{2t}]$  and rewrite (17) as:

$$(18) \quad \begin{bmatrix} a(L) & b(L) \\ c(L) & d(L) \end{bmatrix} \begin{bmatrix} z_{1t} \\ z_{2t} \end{bmatrix} = \begin{bmatrix} e(L) & 0 \\ 0 & f(L) \end{bmatrix} \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix}$$

Geweke has established that  $z_{1t}$  is exogenous to  $z_{2t}$  if and only if 1)  $b(L) = 0$ , and 2)  $c(L)$  and  $d(L)$  involve only positive powers of  $L$ . In this case, the second row of (18) has a structural interpretation as a complete, dynamic simultaneous equation model (CDSEM) of the determination of  $z_{2t}$  conditional on the current value of  $z_{1t}$  as well as the past histories of  $z_{1t}$  and  $z_{2t}$ . The first row of (18) represents a structural model of the determination of  $z_{1t}$  if indeed it is exogenous. In this case,  $z_{1t}$  could only be explained by its own past history or the stochastic noise  $\epsilon_{1t}$ , or both.

These results allow the important conclusion that (18) represents an attractive basis for empirical study of dynamic structural forms when minimal priors exist concerning an appropriate theory of choice or of information acquisition and processing. Given a specific joint null hypothesis based on any particular theory, (18) represents an alternative hypothesis whose existence is ensured by the stochastic properties of  $z_t$ . Most importantly, (18) *cannot* be interpreted as *ad hoc* in specification since it can be consistent with structural interpretation. This is not the case for 1) reduced or final forms or 2) autoregressive or moving-average representations of (18).

These points can be appreciated more completely within the context of a consideration of estimation of the unrestricted ARMA model (17). Estimation of an ARMA form such as (17) or (18) requires estimation of 1) the orders and 2) the parameters of the polynomials involved in  $A(L)$  and  $B(L)$ . Until recently, consistent estimators of the orders of these polynomials were not available. Although a combination of various fit criteria and attention to parsimony could be used to establish order (see, e.g. Box and Jenkins), a unique choice of order could not be defended empirically. Without consistent estimates of order, a unique ARMA representation cannot be identified and structural interpretation cannot be made. An alternative is to estimate either the AR or MA form of an ARMA model since the order of either of these forms is theoretically infinite. Geweke showed that spectral methods could be used to consistently estimate the parameters of a finite approximation of the AR form, see Weaver and Banerjee. Because the spectral regressors are orthogonal the order of the AR approximation can be established

through standard sequential hypothesis tests. As still another alternative, Geweke has also shown that the orders of polynomials involved in the final form of a CDSEM can be estimated by the same method, allowing the final form to be used to test various exogeneity hypotheses. However, the resulting model fails to provide structural information since any final form is consistent with an infinity of different CDSEMs.

Fortunately, recent contributions by Akaike (1974, 1977), Pham-Dinh-Tuan, and Hannan provide means of obtaining consistent estimators of both order and parameters of ARMA forms. This possibility suggests the following methodology as attractive for study of dynamic behavior.

1. Identify the set of products involved in production.
2. Identify a set of possible behavioral models which appear consistent with observed behavior.
3. Extract from this set of models a set of possibly relevant variables.
4. Without imposing further priors, estimate the ARMA representation of the multivariate stochastic process generating the data.
5. Employ this unrestricted ARMA representation as a basis for testing restrictions consistent with particular behavioral hypotheses.

The difference in methods of learning upon which this proposed method is based and that of the conventional econometric approach to study of behavior is subtle. In the proposed approach, minimal priors are admitted and a model is initially estimated which is consistent with a wide range of theories of choice and information processing. The existence of this initial model is motivated by statistical properties of the data rather than a specific behavioral hypothesis which conditions the resulting model. Instead, specialization of the unrestricted model to investigate the validity of particular hypotheses is conducted post-estimation using a restricted model. In contrast, the conventional econometric approach relies on a specific theory of choice and a variety of *ad hoc* specification decisions to motivate a specific econometric model prior to estimation. The resulting estimated model is conditioned upon a variety of both theoretic and *ad hoc* priors. This approach not only clouds potential inference, but also masks empirical evidence which could be useful in construction of a descriptive theory of choice.

## Summary

This paper suggests that dynamic production choice modelling should evolve from observed behavior and should not be constrained by currently available theoretical models that may be inappropriate for more general problems than those encountered by agricultural decision makers. Furthermore, these models assume rational optimization behavior by decision makers operating in fixed decision environments in which information is instantaneously available and rationally processed. It was argued that these assumptions are not acceptable descriptions of observed dynamic behavior. Although such assumptions allow specification of theoretical models which might serve as bases for construction of consistent empirical models, such an approach was argued to provide limited opportunities for empirical learning since the interpretation of results of such models requires prior acceptance of the validity of underlying assumptions. In this context, the alternative of estimating an empirical model which may be consistent with a wide range of behavioral theories is a more attractive approach where priors are weak concerning the mechanism generating observed choices. This approach allows estimation of a model which can be interpreted independently of the validity of a particular theory of choice or set of assumptions needed to derive a consistent model of choice. However, if a particular theory of choice is of interest, this approach allows post-estimation investigation of its validity by proposing the implied consistent model as a testable null hypothesis. In this way, the approach allows consideration of specific behavioral hypotheses, but does not maintain restrictions which would restrict the researcher's ability to discover empirical relationships that were unexpected prior to estimation.

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