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Production Decision Making in an Adaptive Mode

Philip I. Szmedra

Michael E. Wetzstein

Ronald W. McClendon*

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*U.S. Department of Agriculture/ERS/RTD, Washington, D.C. 20005; Departments of Agricultural Economics and Agricultural Engineering, respectively, University of Georgia, Athens, GA. 30602.

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Abstract

This paper presents a general theory which reconciles agent maximizing behavior with alternative assumptions and provides a theoretical basis for X-Efficiency behavior by indicating conditions where maximization may not result in an optimal solution. An empirical application substantiates the significance of considering X-Efficiency behavior and illustrates its usefulness in policy analysis.

Production Decision Making in an Adaptive Mode

The agent maximizing behavioral assumption (MBA) is a foundation of neoclassical economics. The underlying paradigm is that agents always exhaust opportunities for net gain (Rozen). However literature in other disciplines has established that agents do not always maximize (Akerlof and Dickens).

Neoclassical theory postulates that agents make full use of all information regarding a change in resolving the optimization model and decisions are made in terms of marginal considerations only (Gilad et al.). The essence of maximization focuses neoclassical theory on allocative efficiency to the exclusion of other efficiencies that may be more significant in many instances. Dissatisfaction with this paradigm has led economists to investigate a variety of alternative ad hoc assumptions regarding agents behavior (Day, 1978; De Alessi). The alternatives, termed economies of irrational behavior or X-efficiencies, are based on an assumption that agents reach a defined standard judged to be within their capabilities (Leibenstein, Müller, Rozen).

The objective of this paper is to present a general theory which reconciles the MBA with alternative assumptions. MBA is shown to be a particular case in the general theory of agent behavior. The model provides a theoretical basis for agents not employing the MBA and indicates conditions where the MBA will not result in an optimal solution. An empirical application substantiates the significance of considering X-efficiency behavior and illustrates its usefulness in policy analysis.

Theoretical Model

Dissatisfaction with the neoclassical framework generally began in the late 1950's when various constraints to maximization were proposed (De Alessi). However it was not until the 1960's that alternatives to the MBA including satisficing, multiple goals, organizational slack, and resistance to change were suggested. Various attempts toward reconciling these behavioral alternatives have occurred over the past three decades including the works of Williamson and Rozen. A theoretical model supported with an empirical application may be a more efficient procedure however in developing an understanding among behavioral alternatives than unmetrical prose.

Following the work of Gilad et al., Heiner, Hey, and Shipley, a theory of agent behavior may be structured to include complexity, D, of a process and an agent's competence or perceptive skills, A. Perceptive skills characterize an agent's competence in deciphering relations among agent behavior and various states of the environment, X. A set U of agent's controls is determined by a control relation δ: $D \cdot A \rightarrow U$. The consequences arising from agent's controls are denoted as a set C and are determined by γ: $U \cdot X \rightarrow C$. Denoting P for agent's preference and τ for the probability distribution of X, then an agent's behavior may be characterized by the quadruple $\{U, (X,\tau), C, P\}$. Assuming continuity of preferences and the equivalence relation, an expected utility function $E\{\sigma[\gamma[\delta(D,A),X)]\}$ may be employed, where E is the expectation operator. A positive relation between competence, A, and expected utility is assumed, whereas increased complexity, D, is expected to reduce utility. Competence and complexity will also influence higher moments of expected utility. Greater competence in a process is hypothesized to stimulate correct control actions, and thus dampen any variation. As complexity increases, directives for controlling stochastic processes become increasingly difficult to achieve, resulting in larger variation.

The MBA, based on marginal analysis, assumes an agent can distinguish all actions available. Thus a partition relation, Ω: $U \rightarrow Z$, results in a one-to-one correspondence between U and partitions Z, denoted Z^*. This extreme case of perfect perception is assumed under the MBA. Alternatively, null perception is represented by partition Z^o containing the whole set of controls where an agent is unable to perceive different consequences resulting from alternative controls. A general representation containing both perfect and null perceptions may be denoted by a class of partitions $\theta = \{Z_\alpha | \alpha \varepsilon a\}$, where a is a class of sets. An agent may not be able to distinguish all actions that are available, and thus U is partitioned into perceptually equivalent actions (Marschak, Shipley).

Analogously an agent may only be aware of a certain class N of environments, $\phi = \{N_\alpha | \alpha \varepsilon a\}$ where ϕ denotes a measurable partition of X. The two extreme cases, perfect and null information, are denoted by N^* and N^o respectively. Deterministic MBA models assume perfect information N^* as well as perfect perception Z^*. Stochastic MBA models relax the assumption of perfect information and allow for alternative partitioning of X associated with Z^*. MBA models incorporating risk aversion with unknown preferences further relax the assumptions on perceptions. A set of risk efficient outcomes may be identified indicating the lack of agent's ability to perceive significant differences among outcomes within the set. However lack of agent perceptions may be associated with behavior other than risk aversion (Musser et al.). X-efficiency provides a foundation for investigating these alternative behaviors which result in the partition of Z_α. Thus the structure of the perceived information available to an agent is the pair of partitions (Z_α, N_α), $\alpha \varepsilon a$.

Definition: A partition Z_α is defined to be finer than an alternative partition Z_β, if and only if for every $\Omega_\alpha \varepsilon Z_\alpha$ there exists $\Omega_\beta \varepsilon Z_\beta$ such that $\Omega_\alpha \subseteq \Omega_\beta$ (Shipley).

An analogous definition may be stated for partition N_α. Increased fineness conveys the intuitive idea of being more perceptive or having more information. Thus improved perception and increased information of a process results in a finer partition of Z_α and N_α, respectively. The decision problem is a situation in which an agent's knowledge is limited to inadequate partitions, Z_α and N_α, a payoff relation μ: $Z_\alpha \cdot N_\alpha \rightarrow R$, and belief about τ. All possible lack of knowledge is considered in this model: imperfect perception and information; the inability to determine the relation among actions, states and outcome; and limited determination of environmental occurrence. Such a formulation is termed bounded rationality by Simon (Shipley), and characterized by a lack of computational capacity resulting in inadequate information. Lack of knowledge concerning the relevant outcome partitions of Z_α and N_α limits an agent's ability to behave rationally. This break among actions, states, and outcomes may lead to a fundamentally different model of behavior than that of the MBA. If Z_α and N_α are coarse or if assumptions concerning the domain of N_α are wrong, employing the MBA may not maximize behavior.

Fineness of Z_α and N_α

In a temporal context, denote R_t^* as the maximizing behavioral payoff in time t, the discrepancy between R_t^* and realized payoff in time t, R_t, is $S_t = R_t^* - R_t$. The MBA suggests that some type of updating procedure will be employed which increases the fineness of partition Z_α and N_α, and thus reduces this discrepancy. However, the partition Z_α or N_α may not become finer if the discrepancy is below a certain threshold level K. Akerlof and Yellen attribute this behavior to small differences in utility related to S_t whereas Gilad et al. cite cognitive dissonance as a possible explanation. Any discrepancy, S_t, will arouse cognitive dissonance $D_t = f(S_t)$, where $f'>0$ for $S_t>K$. Cognitive dissonance activates an information filter

$$I = \begin{cases} 0 \text{ if } 0 < S_t \leq K \\ 1 \text{ if } S_t > K. \end{cases}$$

If the dissonance is smaller than K , the filter blocks the dissonant information from influencing the partitions of Z_α and N_α. An agent avoids or discounts unsupportive information regarding current partitions. The partitions Z_α and N_α are a function of K. Agents balance the cost of continuing to block dissonant information with expected benefits of self-image or reduced mental costs. Thus cognitive dissonance blocks out information that economists may consider relevant and distorts perceptions of information that is allowed. This results in coarser partitions of Z_α and N_α leading to bounded rationality.

Domain of N_α

The MBA may not be followed even if cognitive dissonance or other forms of bounded rationality do not block perfect perception. As stated by Hey, if the assumptions an agent makes concerning the domain of a partitioned environment N_α, do not contain the actual state of the environment, e, then the MBA will not lead to a true maximum. In a stochastic setting, an agent typically will not know e, nor the dimensionality of X. For the MBA an agent must specify a N_α which does in fact contain e. The MBA requires that agents know $e \varepsilon N_\alpha$. This requires that N_α have sufficient domain to guarantee that $e \varepsilon N_\alpha$ is true. Noting the unknown nature of e and X, this may result in N_α possessing a much larger domain than necessary and having a dimensionality considerably greater than X. In this case the MBA may be inefficient in terms of the large information requirements for modeling agent behavior.

Alternatively, agents may choose a simpler method which Hey terms sub-optimal behavior. An agent does not consider a large domain for N_α, but instead specifies N_α sufficiently small to be able to maximize behavior with the MBA if $e \varepsilon N_\alpha$. This behavior is analogous to dynamic optimization problems where N_α is based on a vector of state variables constrained to consider only the major environmental states of the process (Burt). However, in the presence of computational cost, the optimal degree of N_a is an open question.

An alternative to the MBA is to assume agents behave reasonably (Hey). Agent behavior in many cases is rule governed by intuition, heuristics, or other adaptive mechanisms (Day, 1975). As suggested by Hey, adaptive mechanism behavior may be preferable because the scope for learning is limited, particularly in the presence of computational cost. As a process proceeds, agents will expand their information base which reduces uncertainty, and thus, the probability of a mistaken response. However, agents' behavior will not converge towards MBA behavior as the information base increases through time. Instead adaptive mechanism behavior is generated in which an agent must ignore actions which are appropriate for only rare or unusual situations, excluding actions which may enhance performance under certain conditions. This is generally in conflict with assumptions in economic theory where it may be expected that as agents' information base increase they move toward MBA behavior (Pingali and Carlson, Crawford, Huffman).

Application

Previous pest management research has focused on determining the economic threshold; that level of pest density which warrants a specific control action (Headley). Analytical models of the pest-crop system introduced MBA techniques into threshold determination (Hall and Norgaard, Shoemaker). These complex techniques were designed to replace simpler decision rules developed by biological scientists commonly referred to as action thresholds (Moffitt et al.). Action thresholds may generally be defined as the minimum pest density where it is profitable to apply a fixed recommended dosage rate. In practice, the coarseness of Z_α and N_α have prevented complex decision techniques from replacing simpler decision rules. Empirical evidence supporting this conclusion is presented by Hall and Moffitt, who determined that relative to a MBA solution little net revenue is lost by employing a simpler decision rule.

Thus for agents concerned with managing pests as well as for policy considerations, the issue is determining the robustness of action thresholds and how they compare with alternative decision rules. Specifically, a rule developed through an adaptive mechanism in which a pre-specified control action is implemented notwithstanding the contemporaneous state of N. Additionally, due possibly to cognitive dissonance, agents may not strictly follow action thresholds but modify threshold recommendations to include their personal perceptions of the production system.

Modeling these three alternative hypotheses concerning agent pest management behavior: strict action threshold compliance, inertial behavior, and adaptive mechanism behavior, requires detailed information on the environmental state X. Process models for crop production systems have in the last two decades provided expanded information on the environmental state of the crop, X. Although these simulation models have generally increased the fineness of N_α, limited effort has been directed at modeling agent perceptions concerning the fineness of Z_α.

The Soybean Integrated Crop Management (SICM) simulator (Wilkerson et al.) is employed to model the three alternative hypotheses concerning agent pest management behavior. Four major components comprise the SICM model. These include a soybean crop growth model with a soil water balance routine; insect population growth and crop damage models including the velvetbean caterpillar, a defoliating pest potentially damaging to soybeans in the Southeast during August and September; the southern green stinkbug, a late season pod and seed feeder; and the corn earworm, a pod or seed feeder depending on timing of adult influx; a pesticide tactics component; and an economic component which provides for net returns above variable costs as a measure of success of agent behavior.

Three pest control strategies were modeled, corresponding to an adaptive mechanism, strict action threshold compliance, and deviation from strict compliance, the three behavioral hypotheses. The adaptive mechanism behavior relies on an application of permethrin on August 15th regardless of pest populations in the field. In addition, a later season control of methyl parathion to combat stinkbugs, is applied on September 10th. Strict compliance behavior represents an insecticide application on the day following an extension recommendation to treat. A control action is initiated when daily updated insect populations and/or defoliation levels reach action threshold levels and are observed during the course of a once weekly scouting interval. Deviation from strict compliance, inertial behavior, is modeled after the results of a study by Hatcher et al., which found that soybean producers tend to follow pest management extension recommendations only sporadically through a season and may delay a chemical control up to a week after a recommendation to treat. Specifically, producers adhered to extension guidelines 69 percent of the time an action threshold was reached. When a recommendation was followed, a treatment was applied within a three day window of economic advantage 41 percent of the time. In the remaining instances, a control was applied after this period, up to seven days post threshold. When extension guidelines were ignored, producers applied an insecticide according to adaptive mechanism behavior, the pre-specified calendar date control.

The SICM model was modified to incorporate Georgia Coastal Plain soil conditions and simulated yields were validated (Hood et al.). Fifteen insect infestation and influx timing patterns as well as probability of occurrence were identified from data collected at the Coastal Plains Experiment Station, Tifton, Georgia for the years 1972 through 1984. The model was run for each of nine weather years (1975-1983) under every insect influx and timing scenario for both the strict compliance and adaptive mechanism strategies. Thirty iterations of each insect scenario for all weather years were run to model inertial behavior, incorporating a random number generator to initially model compliance and then timeliness of threshold adherence. The 15 influx patterns for each type of behavior were aggregated into three infestation levels, light, moderate, and heavy, based on their probability of occurrence.

Finally, the three aggregated infestation levels were combined, again based on probability of occurrence, to derive overall results for the different behaviors.

Results

Expected net returns per acre, variance, and stochastic dominance results for the three alternative behaviors under light, moderate, heavy, and overall infestation levels are provided in table 1. Adaptive mechanism behavior provides for higher expected returns under both light and moderate infestations. However, strict compliance behavior under heavy infestations is both expected value and EV dominant. These results underscore the virtue of extension guideline recommendations under heavy pest infestations. A relatively early season heavy influx of insects initiates an early control, which, given the residual action of the pesticide used in this study, provides protection for generally the remainder of the crop's period of susceptibility. Modifying guidelines (inertial behavior) under conditions in which extension recommendations were developed to provide optimal outcomes, results in diminished returns. Inertial behavior only dominates strict compliance behavior, in terms of expected value, for a light infestation. This reflects more the success of following adaptive mechanism behavior in those instances when guidelines were completely disregarded, than the desirability of a delayed compliance regime under light infestations. Based upon these results, delaying a control, if in fact a producer has decided to follow an extension control call, is a poor producer decision.

Similar results are apparent when stochastic dominance criteria are employed. Adaptive mechanism is either first or second degree stochastic

Table 1. Expected Annual Net Returns Per Acre and Stochastic Dominance Results

Infestation Level	Behavior: Strict Compliance	Inertial	Adaptive Mechanism
Light	$37.90 (7445.44)[a]	$61.39 (8639.84)	$72.02 (8391.95)
Moderate	45.07 (7329.26)	35.85 (7271.31)	56.85 (8215.34)
Heavy	48.55 (7276.83)	27.15 (8205.15)	45.37 (9065.50)
Over-All	44.91 (8300.11)	41.72 (8715.28)	59.43 (9333.48)

Light			
Strict Compliance		1	1
Inertial		–	1
Moderate			
Strict Compliance		−1	2
Inertial		–	1
Heavy			
Strict Compliance		−1	−2
Inertial		–	2
Over-All			
Strict Compliance		0	2
Inertial		–	2

[a] Variance in the parentheses.
1 Indicates column dominates row behavior by FSD.
2 Indicates column dominates row behavior by SSD.
−1 Indicates row dominates column behavior by FSD.
−2 Indicates row dominates column behavior by SSD.
0 Indicates neither behavior dominates by SSD.

dominant (FSD or SSD) over the other two behaviors except for strict compliance under heavy infestation.

These results support the hypothesized relationships developed by Hey and Heiner. Specifically, strict compliance would enhance returns under a heavy infestation which would, however, necessitate a direct departure from rule-governed behavior. Considering the overall probabilities for specific insect infestations, adaptive mechanism dominates both strict compliance and inertial behavior by SSD. The relatively high variance associated with adaptive mechanism behavior indicates its failure to mitigate effects of pest densities on returns in high pest density years. However this failure is completely compensated by higher returns in other years. The relatively low probability, less than ten percent, of heavy simultaneous infestation of all three pests in any year results in the overall dominance of adaptive mechanism behavior. This result is consistent with Hey's hypothesis. The inferiority of the overall result for strict compliance indicates that N_α employed in the development of these extension recommendations may not have contained e. In fact, this is consistent with the general philosophy of extension in providing conservative action thresholds (Adams). Thus these recommendations are not considering the full domain of N_α. An implication substantiated by the relatively poor performance of strict compliance under light infestations.

Implications

X-efficiencies suggest alternative policy recommendations in contrast to the MBA, and may in comparison be relatively easy to adopt by agents. Instead of continuing to develop complex techniques for determining the economic threshold based on the MBA, a more promising avenue of research may be to investigate modifications in adaptive mechanism behavior. Thus, rather than suggesting a complete switch from current practices, an alternative is to recommend possible changes to existing adaptive behavior. This approach is consistent with evidence by Byerlee and de Polanco that agents will generally not adopt a complete package of new technologies but instead adopt in a sequential manner.

For pest management, MBA would require increased effort in expanding N_{α} employed in determining strict compliance for light and moderate infestations, followed by a recommendation to agents that requires a complete switch from the adaptive mechanism to strict compliance. Alternatively, X-efficiency techniques would investigate possible modifications of appropriate adaptive mechanisms. Generally, the mechanism of pre-determined pesticide applications would be recommended. However, when heavy regional infestation occurs, a recommendation to closely monitor a crop would be suggested. Then if conditions warrant, a modification suggesting a possible change in application material and timing in the adaptive mechanism could be recommended. This approach does not require a complete switch in technologies as suggested by MBA. Agent's resistance to changing behavior is not as formidable compared to the MBA, allowing this X-efficiency recommendation a greater probability of adoption.

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