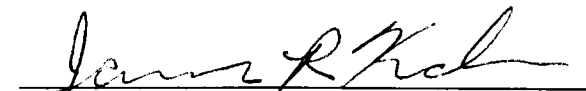


To the Graduate Council:

I am submitting herewith a dissertation written by Thomas Neil Yoder entitled "The Effects of Uncertainty on Producer Response to Environmental Policies: The Case of Integrated Pest Management by Lawn Care Firms." I have examined the final copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Economics.

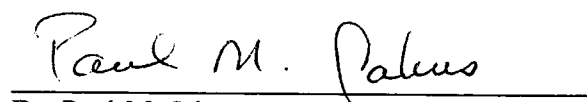

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THE EFFECTS OF UNCERTAINTY ON PRODUCER
RESPONSE TO ENVIRONMENTAL POLICIES:
THE CASE OF INTEGRATED PEST MANAGEMENT BY
LAWN CARE FIRMS

A Dissertation
Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Thomas Neil Yoder

August 1995

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ABSTRACT

Producers in many markets face uncertainty about production costs at the beginning of the production process. In this study, a model of producer behavior is developed which explicitly incorporates expected penalty functions for over and under-predicting the future state of nature. If these expected penalty functions are asymmetric, producers in this model shift planned resource levels away from the levels associated with the predicted state of nature to maximize expected profits.

The conditions under which this shifting of resource levels may occur are set forth and empirically tested using data collected from a sample of professional lawn care firms. Endogenous switching regression models are specified and estimated using random effects maximum likelihood methods and estimated generalized least squares techniques. The results lend support to the theoretical concept that firms, in response to asymmetric penalties, plan input and output levels that deviate from the levels associated with the predicted state of nature.

The estimated technology measures allow for comparative static analysis of the effects on pesticide use of potential environmental regulations or taxes in this market. The results suggest that policymakers can use economic incentives, such as a tax on preventive pesticides, to alter the relative penalties between over and under-predicting pest damage and thereby reduce the intensity of pesticide use. The results also indicate that policymakers should jointly consider nitrate and pesticide pollution when devising a policy portfolio, since taxing fertilizer use with the aim of reducing nitrate pollution will, *ceteris paribus*, increase the intensity of pesticide use.

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1. INTRODUCTION

1.1 OBJECTIVES AND APPROACHES

Uncertainty about the occurrence of future events influences the behavior of producers and consumers in many markets. Needless to say, this behavior has not gone unnoticed by economic theorists and empirical researchers. In broad terms, much of the research has been concerned with developing a theoretical framework that explains the optimal allocation of resources under uncertainty (including the optimal insurance policy), and then applying the framework to specific markets. A general conclusion is that the violation of certain market conditions (e.g., symmetric information) affects the allocation of resources by individual agents. In this study, I investigate the role of a specific market condition--producers facing asymmetric penalty functions¹--in determining the allocation of resources by individual firms.

The objectives of this study are to: (i) develop a general behavioral model for producers who face uncertainty about the future occurrence of an event which affects productivity, (ii) identify the implications for resource allocation as suggested by the model, (iii) empirically test these theoretical concepts and measure the resource allocation effects in the case of lawn pesticide use, and (iv) illustrate methods for obtaining important policy measures from the model. In general, uncertainty about an event that affects productivity may result in asymmetric penalty functions between over and under-predicting the occurrence of that event. Consequently, input and output levels chosen by individual producers may differ from those levels chosen under either certain or symmetry uncertain conditions. The model developed in this study allows for the

¹Penalty functions are asymmetric when the penalty for marginally over-predicting the level of some uncertain variable that affects productivity is not equal to the penalty for marginally under-predicting the level of the uncertain variable.

measurement of these asymmetry effects on resource allocation.

1.2 OVERVIEW OF THEORETICAL ISSUES

There are two distinct types of risk-taking activities: invented games of risk in which the actors enter voluntarily, and uncertain events where the risk can be shifted from actor to actor within the system, but can never be removed from the system. This study deals only with the latter type, where events are exogenous to each economic actor within the system. Hurricanes, pest infestations, and disease are examples of these events about which the occurrence is uncertain at the beginning of economic processes.

Alternative theories about agent behavior under uncertainty have been hypothesized and tested, including expected utility-maximizing, expected profit-maximizing, safety-first, and minimax models.² While these theories differ with respect to the underlying behavioral assumptions, often the implications for resource allocation under uncertainty versus certainty are very similar.³ This comparison of resource allocation between certainty and uncertainty does not imply, however, that uncertainty imposes a deadweight loss on society, except for the loss that occurs due to the cost of providing insurance (Raviv 1979). Indeed, recognizing that uncertainty can never be removed from the system but only shifted implies that such a comparison is meaningless in terms of deadweight loss. Of importance is the comparison of resource allocation as the uncertainty is shifted to the different actors within the system.

Economic agents often decide to shift all or part of the uncertainty to other agents through

²See Hirshleifer and Riley (1979) for a survey of expected-utility theory, Roy (1952) for an example of safety-first models, Wald (1950) for an example of minimax models, and Pannell (1990) for a recent application of expected profit-maximization theory.

³For example, Arzac (1976) concluded that firm output levels under price uncertainty are lower than under certainty for all four different models of behavior which were analyzed.

the purchase of insurance. Much of the research conducted on behavior under uncertainty has focused on the importance of market conditions in determining how the uncertainty is shifted and shared (the optimal insurance policy), and the resulting consequences for resource allocation. This research agenda is shown in Figure 1.1. Examples of market conditions include risk aversion or neutrality among the actors, competitive or monopolistic markets, and asymmetric versus symmetric information between the actors. Certain market conditions may lead to resource allocation levels which are independent of how the risk is shifted among consumers, producers, or third parties. However, violation of these conditions, *ceteris paribus*, leads to different market resource allocation levels dependent upon which actor ends up assuming the uncertainty. My hypothesis is that in some markets, insurance can be produced jointly with the product that mitigates the effect of the insured event, thus allowing for a cost savings if the producer instead of a third party or the consumer bears the uncertainty. In these markets a deadweight loss in addition to the cost of insurance occurs if the producer does not bear the uncertainty.

Jointly-produced insurance⁴, by allowing for the use of preventive technology, may lead to asymmetric expected penalty functions which give the producer incentives to act as if she or he was over or under-predicting the insured event. This asymmetry condition may also result from regulations, as in the case of marketable pollution permits. In both instances, the producer is uncertain about current period production costs due to the possible but uncertain occurrence of events which affect productivity. The producer must predict the likelihood that an event will occur, and then plan output and input levels for the current period. This planned allocation of resources depends upon the expected penalties for both over and under-predicting the event. If

⁴Insurance is jointly-produced when a producer can provide both insurance and the product that mitigates the effects of the insured event using less resources than it would take to produce the two products separately.

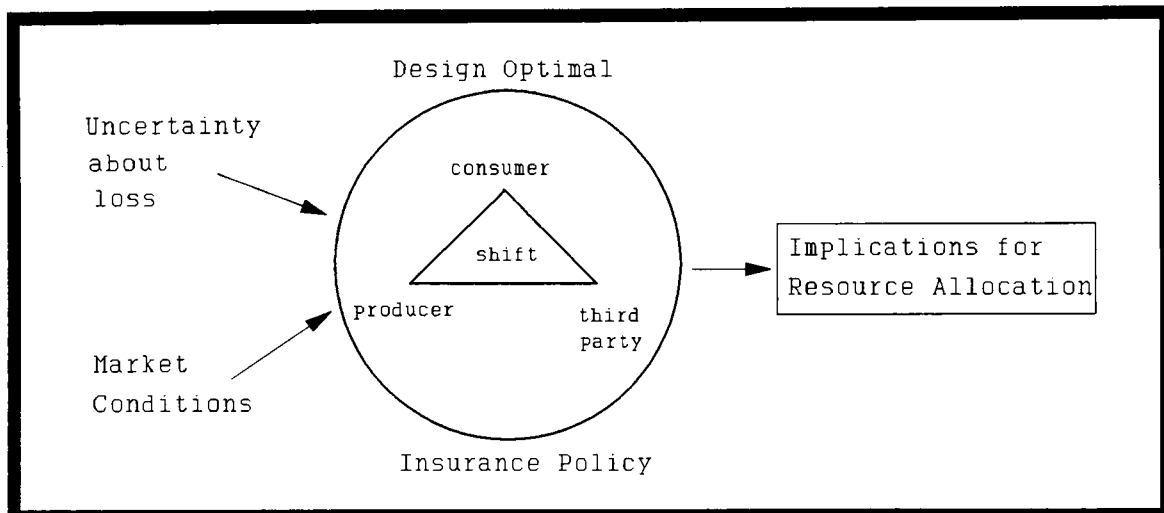


Figure 1.1: The implications for resource allocation of behavior under uncertainty

these penalties are asymmetric, then planned input and output levels will deviate from the levels associated with the predicted event. In the case of marketable pollution permits, this implies that planned pollution levels by individual producers may deviate from the targeted emission levels.

1.3 SKETCH OF METHODOLOGY

Throughout this study, I assume that the objective of producers is to maximize expected profits and that all producers are risk neutral. For ease in presentation, an attempt is made to use terminology and notation that is consistent with the existing literature on profit functions and behavior under uncertainty. However, since I depart from the traditional specification by explicitly incorporating asymmetric expected penalty functions into the profit function, some new and, therefore, unfamiliar notations and terminology are required. When these new terms are introduced, care is taken to provide precise definitions.

A general approach is taken to modeling the behavior of a producer when the producer faces uncertain costs due to an exogenous, uncertain variable. As noted above, the expected penalty functions for over and under-predicting the level of the uncertain variable are explicitly incorporated into the profit function, rather than the more traditional approach of distinguishing

between expected profits for levels which fall at or below some predicted level of the variable and levels that are higher than predicted. This approach is advantageous for both theoretical and applied policy analysis. On theoretical grounds, this approach reveals a third, distinct effect of a change in input price on input and output levels. In addition to the familiar output and substitution effects, a change in input price can alter the relative penalties between over and under-predicting the level of the uncertain variable. This relative change in penalties leads to a strategy bias effect, which is the change in planned input and output levels resulting from a change in relative penalties. From a policy perspective, this approach provides for a better understanding of how producers will change their behavior in response to policy incentives.

As a result of the general approach taken in this study, several different markets provide potential empirical testing grounds for this model. Producer behavior in markets that allow for the trading of pollution permits provides an application of this model which is currently of interest to many regulators and firms. However, these systems are just being implemented and, as a result, data for testing are unavailable. The health maintenance organization (HMO) provides another potential test for this model. While data for HMO's may be available, the structure of health service provision is very complex, making it difficult to isolate and test for the resource allocation implications of asymmetric penalties. Agriculture markets, because of the influence of uncertain natural events such as pest infestations and drought, provide potential applications of this model. Fortunately, there is an agricultural market which is small and well-defined, and therefore provides a good empirical test for this model. The market is lawn pest control, and the application of the model is to the lawn care operator (LCO).

The literature on agricultural pest control and integrated pest management provides the framework for applying the model to the LCO. An empirical model is developed that allows for the use of ex post data observations to test the behavioral propositions of the model. Endogenous

switching regression models are specified and estimated using random effects maximum likelihood methods and estimated generalized least squares techniques. The estimated parameters provide measures of technology that are then used to identify the effects of asymmetric penalties on resource allocation. These technology measures also allow for comparative static analysis of the effects on pesticide use of potential environmental regulations or taxes. Of particular interest is the effect the alteration of relative penalties has on pesticide use.

1.4 OVERVIEW OF POLICY ISSUES

In its conception, the lawn care industry was regulated by the same set of policies that applied to agricultural pesticide use. The policy story today, however, is much different. As lawn pesticide use in urban areas increased, so did citizens' concerns about the potential health risk of applying pesticides in densely populated areas. As a result, most states have now adopted new regulations aimed specifically at reducing exposure to lawn pesticides.

This initial emphasis on reducing exposure parallels the development of agricultural pesticide policy. Pesticide use in agriculture became widespread after World War II. With the continued use of pesticides came evidence that chemicals posed a health risk to workers and consumers. The initial response was to enact regulations that controlled exposure to pesticides, such as setting standards for pesticide residues on food and stiffening the label requirements. This emphasis on controlling exposure to pesticides has slowly switched during the past twenty years to an emphasis on reducing pesticide use. The agricultural community has developed and implemented nonchemical integrated pest management methods on many different crops, sometimes at very little additional cost over the use of pesticides. This specific policy progression in agriculture and, more generally, the increasing concern about ecosystem as well as human exposure to pollutants, leads naturally to the following question explored in this study;

if the policy emphasis switches to reducing lawn pesticide use rather than exposure to pesticides, which regulations provide the proper incentives to achieve this objective? Since the behavioral decision model that applies to the lawn care firm is quite different than most agricultural production models, providing the right incentives to reduce lawn pesticide use may require a different set of policies than those implemented in agriculture.

1.5 OUTLINE OF THESIS

This thesis is laid out as follows. In Chapter 2, a general model of producer behavior under cost uncertainty is developed and the implications for resource allocation as suggested by the model are identified. After providing some background information on the lawn care industry and integrated pest management, the model is applied to the lawn care operator in Chapter 3. Data collection methods, including survey design and implementation, and estimation techniques and results are discussed in Chapter 4. The effects of asymmetric penalties on pesticide use are discussed in Chapter 5, as are the effects of potential taxes and regulations, including policies which change the relative penalties. Finally, the implications of this research for analyzing resource allocation issues in other markets is discussed in Chapter 6.

1.6 OMITTED TOPICS AND LIMITS

The aim of this study is not to provide an exhaustive account of producer behavior under uncertainty. Rather, the focus is on a specific type of uncertainty--the possible but uncertain occurrence of an exogenous event which affects the costs of production. This is the insurance problem, not a warranty problem in which the failure rate of a product is an endogenous decision variable for the producer. The analysis is also limited to risk neutral behavior under one behavioral objective--expected profit maximization. Behavior under expected utility of profit,

safety-first, or game theoretic criterion are not analyzed. Finally, the model developed in this study is descriptive of individual, not aggregate, producer behavior. Thus, depending on conditions prevailing in the market, the implications for resource allocation at the individual producer level may be different than for the system as a whole. The implications of this distinction will be examined in the final chapter.

2. PRODUCER BEHAVIOR UNDER COST UNCERTAINTY

Profit maximization is the objective of producers in the standard microeconomic model. When all elements of the system are known with certainty at the beginning of the production process, the producer's choice of action uniquely determines the level of profits. However, when technology or productivity is uncertain at the commencement of the production process, the ex ante decisions determine a set of potential profit levels. According to Arrow (1971), there are two components of the choice function relevant to explaining choice under uncertainty: the valuation of consequences and the relative strength of belief in the occurrence of different outcomes. Traditionally, when only two outcomes are possible, the choice function has incorporated these two components by specifying the level of profits (consequence) times the probability (strength of belief) that an event will occur plus the expected consequence if the event does not occur.

A simple modification of this specification permits the modeling of choice when the set of possible outcomes contains many elements. Using a probability density function and integrating the consequences over the level of some uncertain variable, the choice function distinguishes between the expected profits for levels which fall at or below some predicted level of the variable and the expected consequence if the actual level is higher than the predicted level. This specification, however, obscures the role that penalties play in altering the choices under uncertainty. When the penalties for under-predicting and over-predicting the outcome are asymmetric, the producer, rather than choosing input and output levels by looking at the profit associated with the expected level of the state, will instead choose input and output levels that equalize the expected over- and under-prediction penalties.

In this chapter, the role that asymmetric penalties play in determining resource allocation

is explained for producers who operate under cost uncertainty. The conceptual framework developed below is general and could be applied to address many different uncertainty conditions faced by a producer. But, to simplify matters and facilitate understanding, the discussion in this chapter is limited to one specific set of uncertainty conditions. Further, a concrete example--producer behavior for a lawn service firm--is used to explain the theoretical concepts, rather than general language.

At the time that production plans are made, lawn service firms are uncertain about pest infestations which occur later in the season. This uncertainty affects productivity which affects costs which, in turn, affects profit. Thus, the starting point in this discussion is an explanation of the effect that uncertainty has on productivity; the ending point is an explanation of how asymmetric penalties affect resource allocation. Since this path from start to finish is not well-trodden, a few preliminary comments seem appropriate.

- (1) Uncertainty affects profit because there exist constraints on ex post decision-making. These constraints, termed flexibility conditions, along with technology conditions provide the basis for understanding the significance of differentiating between ex ante and ex post input and output levels.
- (2) Typically, two producer actions are of interest when studying behavior under uncertainty: the optimal ex ante action and the optimal ex post action. Introducing the concept of penalties into the analysis requires study of a third action: the optimal action ex post if all inputs and outputs can fully adjust to any desired level. These three actions and their associated cost, revenue, and profit levels are termed respectively, "planned", "realized", "optimal potential".
- (3) Pest infestations are denoted by θ throughout. The pest infestation that actually occurs is termed realized pest infestation. The term "planned pest infestation" is also frequently

used and, since the phrase lacks an intuitive meaning, some explanation is required. As will be discussed in the next section, inputs are required to control pest infestations, with the relationship between inputs and pest control represented by a kill function. The direct relationship between inputs and pest control means that planned input levels are adequate to control a specific level of pests, and no more. This specific pest level which is controlled by the planned level of inputs is termed the planned pest infestation (θ^P).

- (4) To facilitate understanding of unfamiliar and, perhaps, unconventional concepts, the story of producer behavior under cost uncertainty is told using familiar microeconomic diagrams and exposition. The diagrams are illustrative of the concepts and in many cases, for ease in illustration, are drawn using simple linear functions. The risk in doing so is that, even when done with extreme care, all of the underlying technological conditions which are so crucial to deriving a solution to the producer problem may not be fully embodied in the functions as drawn. The hope is that the illustrations, being suggestive of the conditions that must hold for a solution, will provide the necessary insight required to formulate the model mathematically, duly noting all conditions required for a solution to the producer problem.

2.1 FLEXIBILITY AND TECHNOLOGY CONDITIONS

Flexibility and technology conditions are constraints that prevent firms from achieving the optimal level of profits for the pest level that actually occurs. Flexibility is defined in the literature in terms of ex post adjustments to ex ante input and output levels, with the extremes being zero flexibility when no adjustments can be made ex post, to total flexibility in the case where all outputs and inputs can be adjusted ex post (Hey 1979). In the case of the lawn service

firm, outputs⁵ can not adjust from their ex ante levels while inputs can adjust, but only in an upward direction.⁶ Table 2.1 shows the possible combinations of input and output flexibility conditions, and where this specific case fits in with other possible combinations.

Table 2.1: Flexibility conditions for a lawn service firm.

Outputs	Inputs		
	Full Adjustment	Limited Adjustment- Upward Only	Limited Adjustment- Downward Only
Full Adjustment	No	No	No
Limited Adjustment- Downward Only	No	No	No
Limited Adjustment- Upward Only	No	No	No
Zero Adjustment	No	Yes	No

Zero output flexibility means that the optimal levels of outputs for the realized pest infestation can not be achieved, resulting in less than optimal realized profits. Zero output flexibility, in the case of lawn service firms, is due to the contractual arrangement made at the beginning of the growing season. Limited (to only one direction) input flexibility does not necessarily result in less than optimal input levels but, as discussed below, technology conditions constrain ex post producer actions such that the optimal input levels might not be obtained.

Technology conditions define the feasible production possibility set ex ante, and along with the flexibility conditions, the feasible set ex post. Lawn service firms guarantee pest control

⁵The measure of outputs for lawn service firms is quantity of lawn area serviced standardized by quality. Throughout this study, output is measured in 1000 square foot units. See Chapter 3, Section 3 for definitions of lawn service firm outputs.

⁶These specific conditions are discussed in detail in Chapter 3.

(zero output flexibility), so if the ex ante level of inputs are inadequate for controlling the realized pest infestation, input levels must adjust ex post, subject to the feasible ex post production possibilities set. For a lawn service firm, both the ex ante and ex post input possibilities sets are defined, in part, by the kill function. The kill function is a structural relationship which identifies the link between pest infestation levels and productivity. As pest infestations increase, more inputs are required to produce a given output level, and thus productivity decreases.

These technology conditions are illustrated in Figure 2.1, which is derived from the familiar isocost/isoquant diagram commonly used to depict feasible production possibilities at different levels of output. Figure 2.1 is an isocost/*isopest* diagram, with each isopest curve representing the feasible combination of inputs to control a given *pest infestation*. The family of isopest curves fill the inputs Z_1Z_2 space, with output being held constant everywhere in this plane. The isocost line has the standard microeconomic interpretation of being a "locus of input combinations that may be purchased for a specified total cost" (Henderson and Quandt 1980, p.74). Thus, a tangent point between an isocost and isopest curve is the minimum cost of producing the given output level for the pest infestation of that particular isopest curve. As pest infestations increase (expand), the minimum costs for producing the output level also increase. This relationship between different pest infestations and minimum costs depends upon technology, and is represented in Figure 2.1 as an expansion path. Note that this path tracks expansion in pest infestations (for a given output level) rather than the familiar textbook example of an output expansion path. The path takes on different shapes depending upon the assumptions about technology, an important point to remember throughout the discussion in this chapter since costs, revenues, and therefore profits are derived from this understanding of how productivity decreases as pest infestations increase. For ease in illustration, the expansion path is drawn as homothetic but nonhomothetic paths are plausible as well.

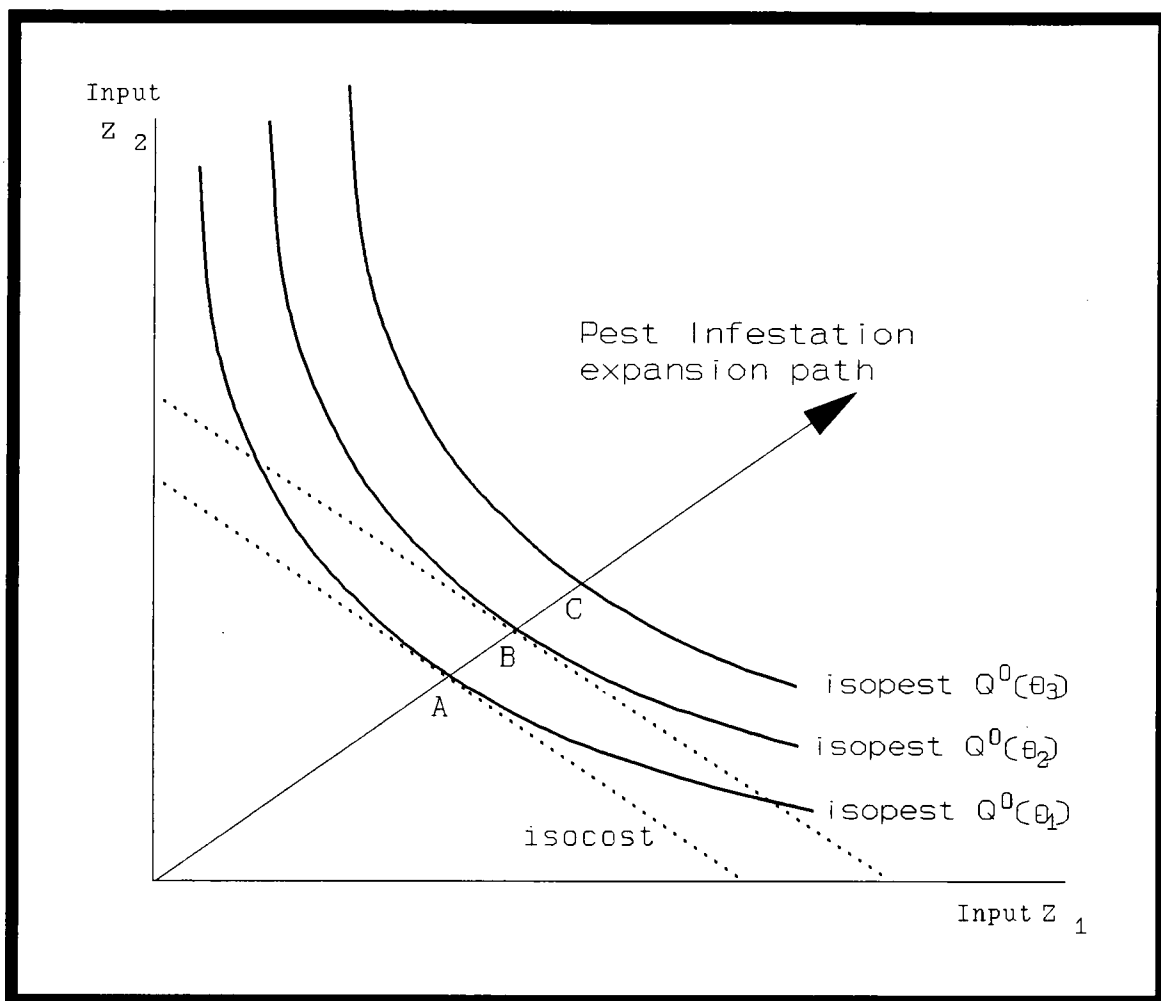


Figure 2.1: Production technology and the pest infestation expansion path for fixed output level.

The next step in deriving a profit function is to represent both ex ante and ex post technologies using this isocost/isopest framework. These technologies may be distinctly different, and thus two families of isopest curves must be drawn in inputs $Z_1 Z_2$ space. In Figure 2.2, the shaded area is the ex post production possibilities set given that ex ante input levels are hired at Point B. The *ex post* isopest curve for pest infestation θ_3 is denoted as θ'_3 . The ex ante and ex post isopest curves belong to different families since ex post technology is structurally different from ex ante technology. Different combinations of inputs are required ex post to treat any level of pest infestation. The ex post isopest curves are conditional on the ex ante decisions,

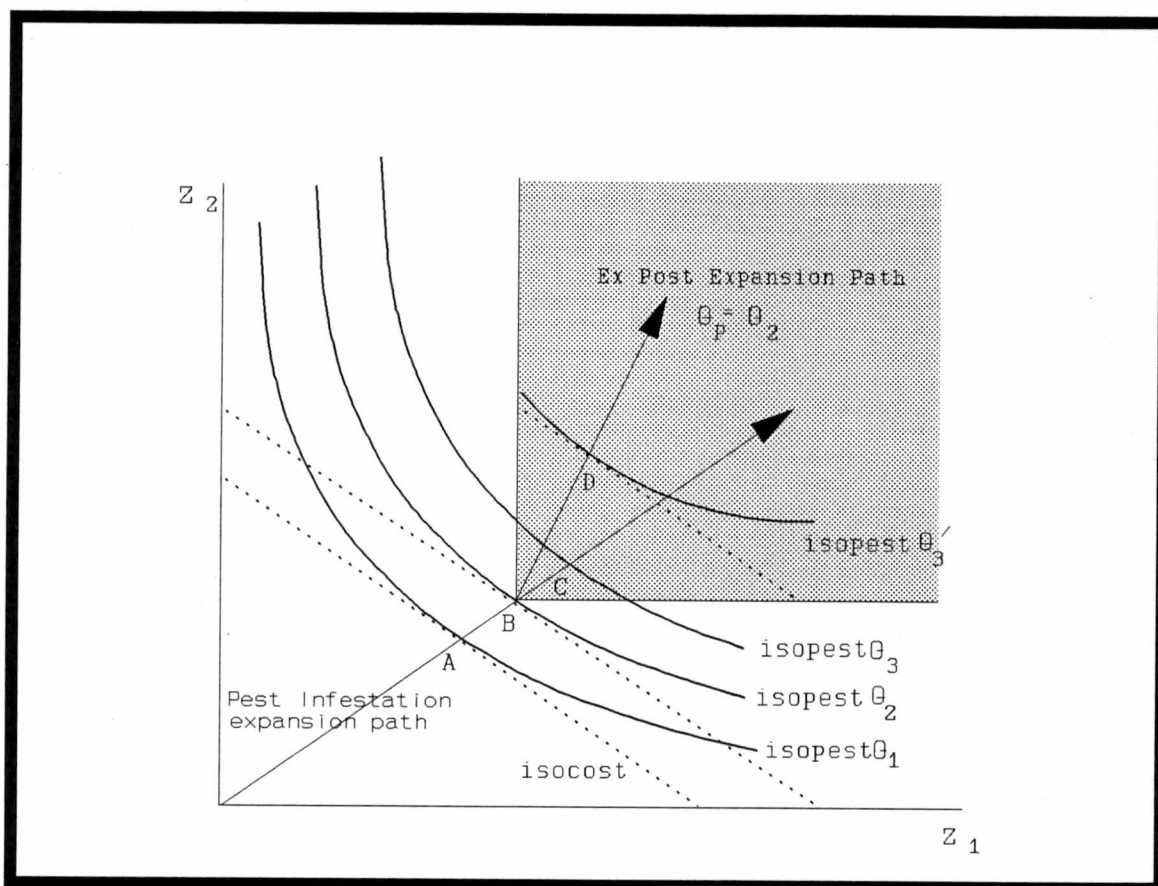


Figure 2.2: Ex post production technology.

accounting for the limited flexibility condition that inputs cannot adjust downward ex post. Thus, the expansion path for each family of ex post curves originates at the ex ante levels of inputs and are bounded in the $Z_1 Z_2$ plane by the ex ante input levels. This is a graphic illustration of the condition that, if the ex ante levels of inputs are inadequate to control the realized pest infestation, then one or more inputs must be hired ex post to produce the ex ante output level.

Figure 2.2 also contains cost information for the firm. The points at which the isocost lines are tangent to the ex ante and ex post isopest curves are the minimum cost levels for treating pests using ex ante and ex post technology, holding output constant. Upward shifts in the isocost lines represent increased costs to the firm. As shown in Figure 2.2, costs are increasing as the pest level increases, holding output (Q) constant. This cost condition for the firm is written as

$$C_{EX ANTE}(\theta_i, Q) < C_{EX ANTE}(\theta_k, Q) \quad \text{for } \theta_i < \theta_k \quad (2.1)$$

Further note that the cost of treating any pest level using ex post technology is comparatively higher than the cost of treating that same pest level using ex ante technology. This cost condition is written as

$$C_{EX ANTE}(\theta_i, Q) < C_{EX POST}(\theta_i, Q) \quad (2.2)$$

Thus, the ex ante cost of treating pest level θ_3 is represented by an isocost line tangent to isopest θ_3 at Point C, which as drawn is considerably less than the ex post cost of treating this same pest level (Point D). It should be noted that if the ex ante and ex post costs of treating all pest levels are exactly equal, then a firm would never employ ex ante technology. Instead, the firm would wait until the actual pest infestation levels are known, and then apply ex post pest control technology.

Thus far the discussion has focused on what a producer *can* do, given the technology and flexibility conditions. This information is now used to identify what a producer *will* do, assuming the objective of maximizing expected profits.

2.2 COSTS, REVENUES, AND PROFITS

Under uncertainty, planning input and output levels to maximize expected profits depends upon a set of potential realized profit levels. In this case of zero output flexibility, realized profit is defined as planned revenues minus realized costs, since zero output flexibility equates planned and realized revenues. Thus, the discussion in this section begins by identifying the set of potential realized costs (ex post input levels) that could occur for each potential planned revenue (outputs) level. This step will produce families of potential profit functions and a potential profit envelope function. Then, with an assumption about the probabilities of realizing these different potential profits, the expected profit function can be derived. Expected profit-maximization, the

solution to the problem, is defined as planning input and output levels that maximize this expected profit function.

Figure 2.2 contains the necessary information to derive potential realized costs for the firm, given the zero output flexibility condition. Holding output constant, several of the minimum cost points, where the isopest and isocost lines are tangent, are plotted against pest infestations in Figure 2.3. The points on the minimum cost line correspond to the points on the pest infestation expansion path in Figure 2.2. Point D is the realized cost to treat pest infestation level θ_3 , given the ex ante decision to hire inputs at Point B on isopest curve θ_2 . The extra cost for under-predicting θ_3 by $\theta_3 - \theta_2$ is the amount U, and is written as $[C_{\text{EX POST}}(\theta_3; Q, \theta_2) - C_{\text{EX ANTE}}(\theta_3, Q)]$. Point B, the minimum cost to treat pest infestation level θ_2 , is also the realized cost for treating θ_1 , given that inputs were hired ex ante at Point B and the condition that inputs can not adjust downward ex post. The extra cost for over-predicting θ_1 is the amount O, and is written as $[C_{\text{EX ANTE}}(\theta_2, Q) - C_{\text{EX ANTE}}(\theta_1, Q)]$. Mapping the costs in this manner clearly highlights the fact that ex ante decisions result not in a unique point, but instead in a unique *set* of points. The higher costs for over- and under-predicting pest infestations result from the fact that under uncertainty, the unique minimum cost point for treating the realized level of pest infestation will not be obtainable, except in the special case when planned pest levels actually occur.

The above analysis treated output as constant. Next consider the output decision. For a lawn service firm, the output level is the total area of lawn serviced. Revenues depend on this output level which depends on marginal costs. The relevant cost information is obtained from the set of minimum cost points that lie on the ex ante expansion path. Also, as will be explained in more detail in Chapter 3, marginal costs for lawn service firms are increasing as output (lawn area) increases, holding prices and pest infestation constant. Figure 2.4 shows a few members of the family of marginal cost curves. Output (Q) is measured on the horizontal axis. Larger

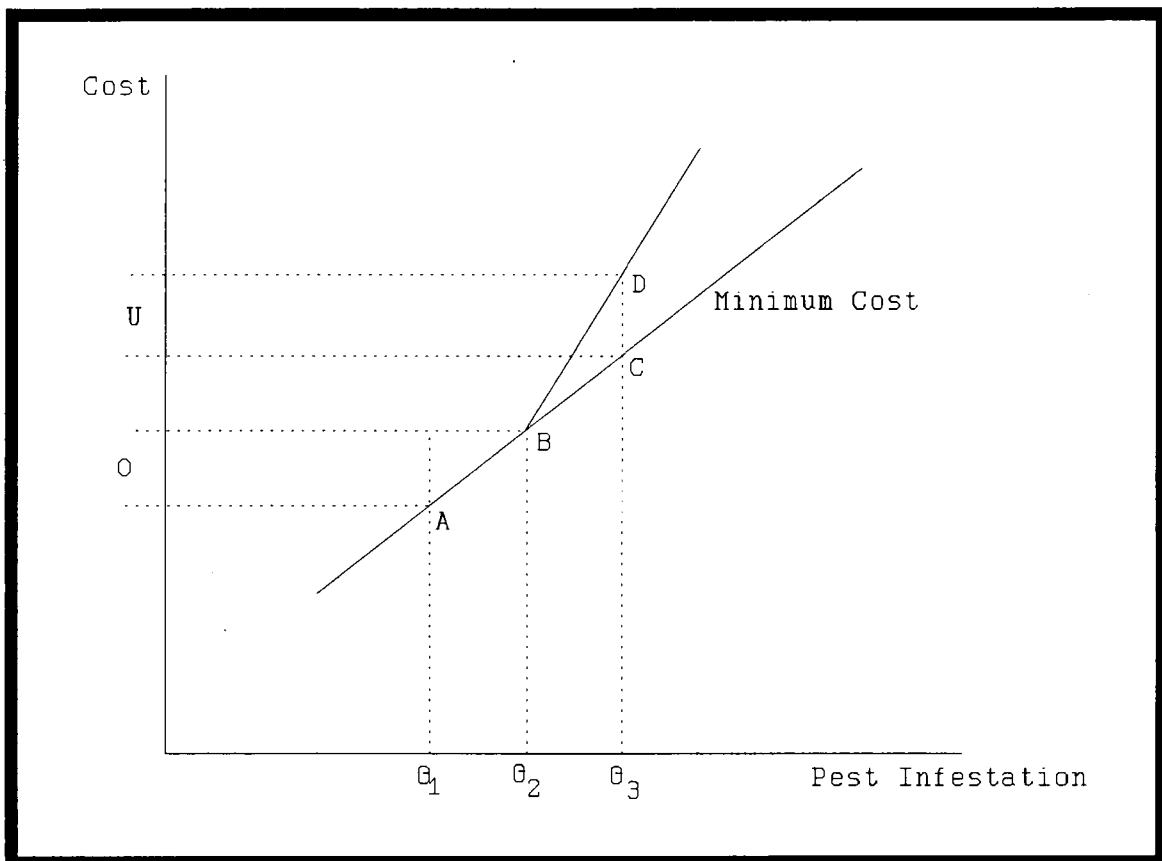


Figure 2.3: Ex ante and ex post costs as a function of pest infestation level.

pest infestations shift the marginal cost curves up and, therefore, lower planned output levels are associated with higher planned pest infestations since there is no matching increase in marginal revenue for the firm at higher pest infestation levels. Thus, given exogenous output prices, revenues decrease as planned pest infestations increase.

With the technology, flexibility, increasing marginal costs, and exogenous price assumptions and following a profit-maximization rule of marginal revenue equals marginal cost, potential (ex ante) profits decrease as pest infestation levels increase. Marginal cost shifts upward with increased pest infestation levels, but marginal revenue stays constant, since output price is exogenous and not a function of producer costs. In other words, as pest infestation levels increase it costs more to produce each unit of output (lawn area) but the price received for each unit stays the same, resulting in decreasing potential profit levels as pest infestations increase.

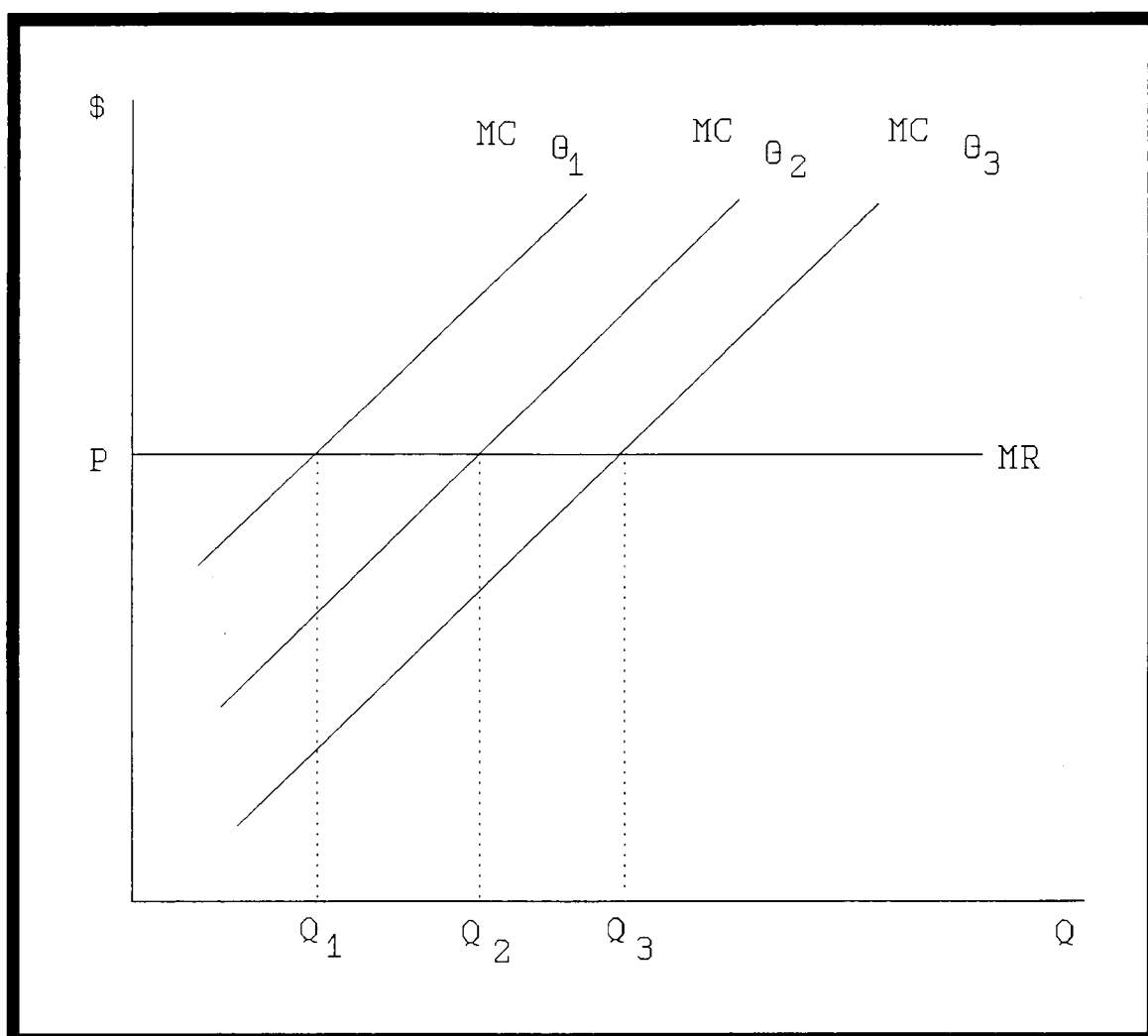


Figure 2.4: Marginal costs shift upward as pest levels increase.

Notice that *potential* profits are not *expected* profits, as the effects of uncertainty on producer behavior have not yet been incorporated into the analysis.

Writing total revenues as TR , potential profits for any output level (Q) are written as

$$\text{Potential } \pi_Q = TR(Q) - C_{EX ANTE}(\theta_i, Q) \quad \text{if } \theta_i \geq \text{actual pest level} \quad (2.3a)$$

else

$$\text{Potential } \pi_Q = TR(Q) - C_{EX POST}(\theta_{i+a}; Q, \theta_i) \quad \text{where } a > 0 \quad (2.3b)$$

As stated above in conditions (2.1) and (2.2), the cost of producing any output level increases

as the pest level increases. Using this condition, we can state that potential profits are a decreasing function of pest infestation levels, as shown in Figure 2.5. Just as there is one family of *isopest curves* for each level of output, there is a family of *potential profit functions* for each level of output. Although only a few family members for three families are shown in Figure 2.5, each isopest curve in all families of isopest curves can be mapped as a potential profit function. Figure 2.5 also contains the envelope of potential profit functions which correspond to the points where marginal revenue equals marginal cost for each potential output level. Thus, every point on the envelope of potential profit functions is a member of a different isopest family.

Figure 2.5 can also be interpreted as illustrating the set of potential realized profit levels associated with each potential output level. Each member of this family of potential realized profit functions emanates from a point on the potential profit envelope, and is associated with one point on the pest infestation expansion path and its related ex post expansion path of the corresponding output isopest family. The important point to remember is that the shape of the potential profit functions is determined by technology and flexibility conditions. Different assumptions about technology lead to different-shaped potential profit functions. Changing the shape of the ex post expansion paths changes the shape of the potential profit functions.

The set of potential realized profit levels as represented by the potential profit functions, along with the probabilities of realizing each pest infestation, determine expected profits. The expected profit evaluated at any point on the potential profit envelope is written as

$$E\pi(\theta_i, Q) = TR(Q) - C_{EX\ ANTE}(\theta_i, Q) - \int_{\theta_i}^{MAX} C_{EX\ POST}(\theta; Q, \theta_i) \cdot f(\theta) d(\theta) \quad (2.4)$$

where $f(\theta)$ is the probability density function of pest infestations.

The derivation of expected profits is illustrated in Figure 2.6 by overlaying a probability distribution for pest infestations over top of the potential profit function diagram. For instance,

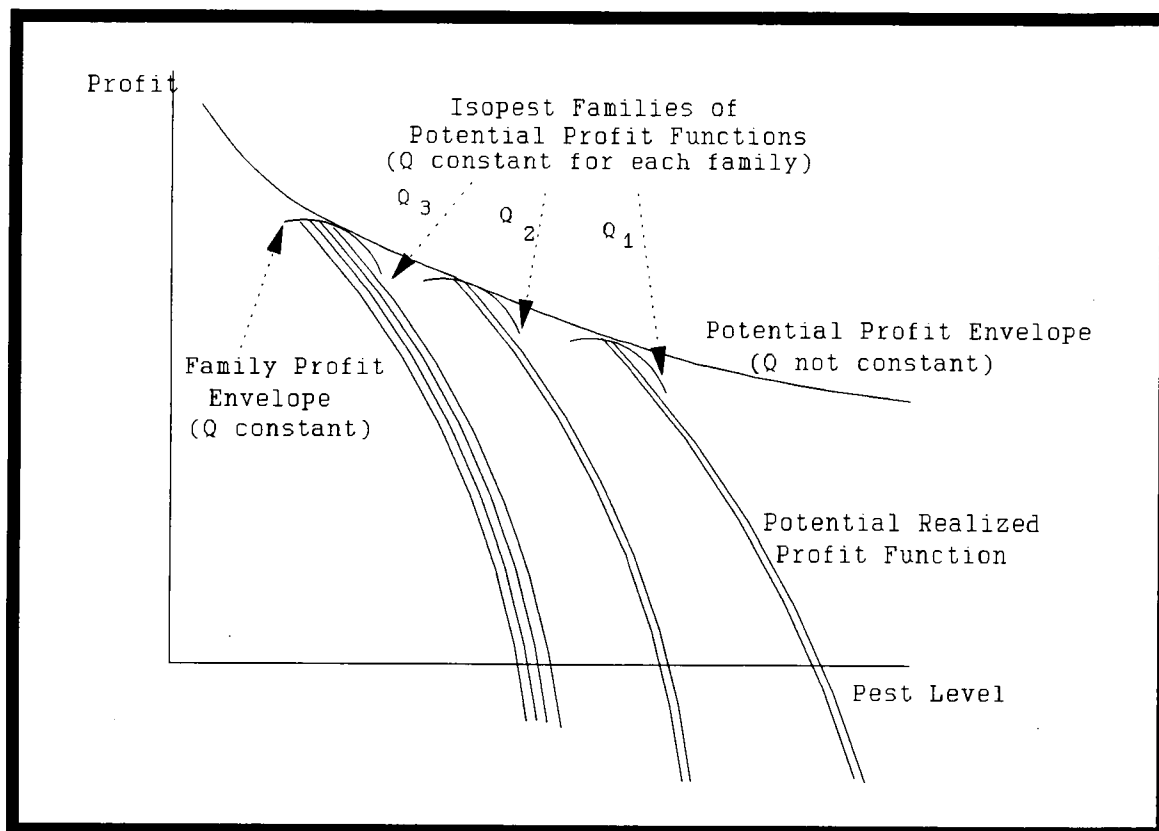


Figure 2.5: Envelope of potential profit is derived from families of isopest curves.

at point B in Figure 2.6 expected profits are equal to (1) profits at Point B (Profit_B) written as $[\text{TR}(Q) - C_{\text{EX ANTE}}(\theta_b, Q)]$ minus (2) the expected cost of under-predicting the pest level, written

$$\text{as } \int_{\theta_B}^{\text{MAX}} C_{\text{EX POST}}(\theta; Q, \theta_B) \cdot f(\theta) d\theta.$$

The bottom diagram in Figure 2.6 illustrates the *expected* profit function, which unlike the *potential* profit function, is not everywhere decreasing when plotted against pest levels. The solution for the producer problem of maximizing expected profit lies at the maximum of this function.

This diagrammatic exposition of the solution to the producer problem can now be used to illustrate asymmetric penalties and their effects on the optimal solution and, further, to show

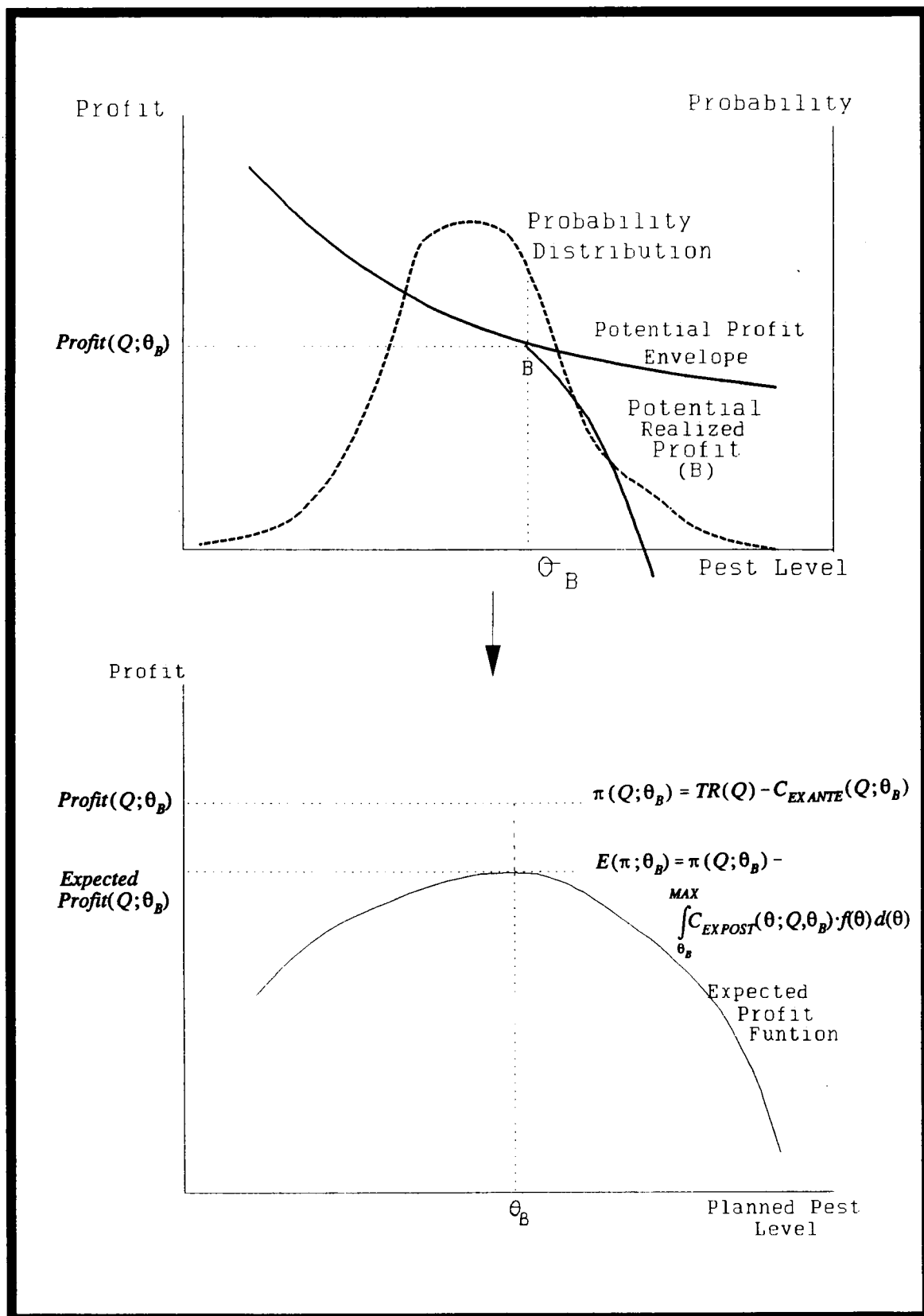


Figure 2.6: Derivation of expected profits.

that shifting uncertainty to the producer from the consumer can both decrease costs and increase the use of polluting inputs at the individual producer level.

2.3 ASYMMETRIC PENALTIES

Throughout the above discussion, over- and under-prediction penalties are mentioned incidentally, but obtaining the solution to the producer problem under uncertainty did not require an explicit acknowledgment of their role in determining the optimal action of the producer. This is not to say that penalties did not influence the optimal outcome; instead, as shown in this section, the relative penalties (along with the subjective probability distribution) determine the planned producer action. It is these penalties which link the flexibility and technology conditions with the effects on resource allocation which these conditions foster.

A penalty is the difference between realized profit and the maximum potential profit associated with the pest infestation that occurs. These penalties can be shown using the potential profit diagram which is reproduced below as Figure 2.7. The over-prediction penalty if $\theta^P - a$ occurs is represented by the distance A, and the distance B represents the under-prediction penalty if $\theta^P + a$ occurs. The over-prediction cost penalty is written as

$$C_{EX ANTE}(\theta^P, Q) - C_{EX ANTE}(\theta^P - a, Q) \quad (2.5)$$

and the under-prediction cost penalty is written as

$$C_{EX POST}(\theta^P + a, Q; \theta^P) - C_{EX ANTE}(\theta^P + a, Q) \quad (2.6)$$

The two cost penalties are symmetric if, and only if

$$C_{EX ANTE}(\theta^P, Q) - C_{EX ANTE}(\theta^P - a, Q) = C_{EX POST}(\theta^P + a, Q; \theta^P) - C_{EX ANTE}(\theta^P + a, Q) \quad (2.7)$$

As drawn, the under-prediction penalty is greater than the over-prediction penalty and the penalties are said to be asymmetric. Depending upon the structure of technology, the penalties

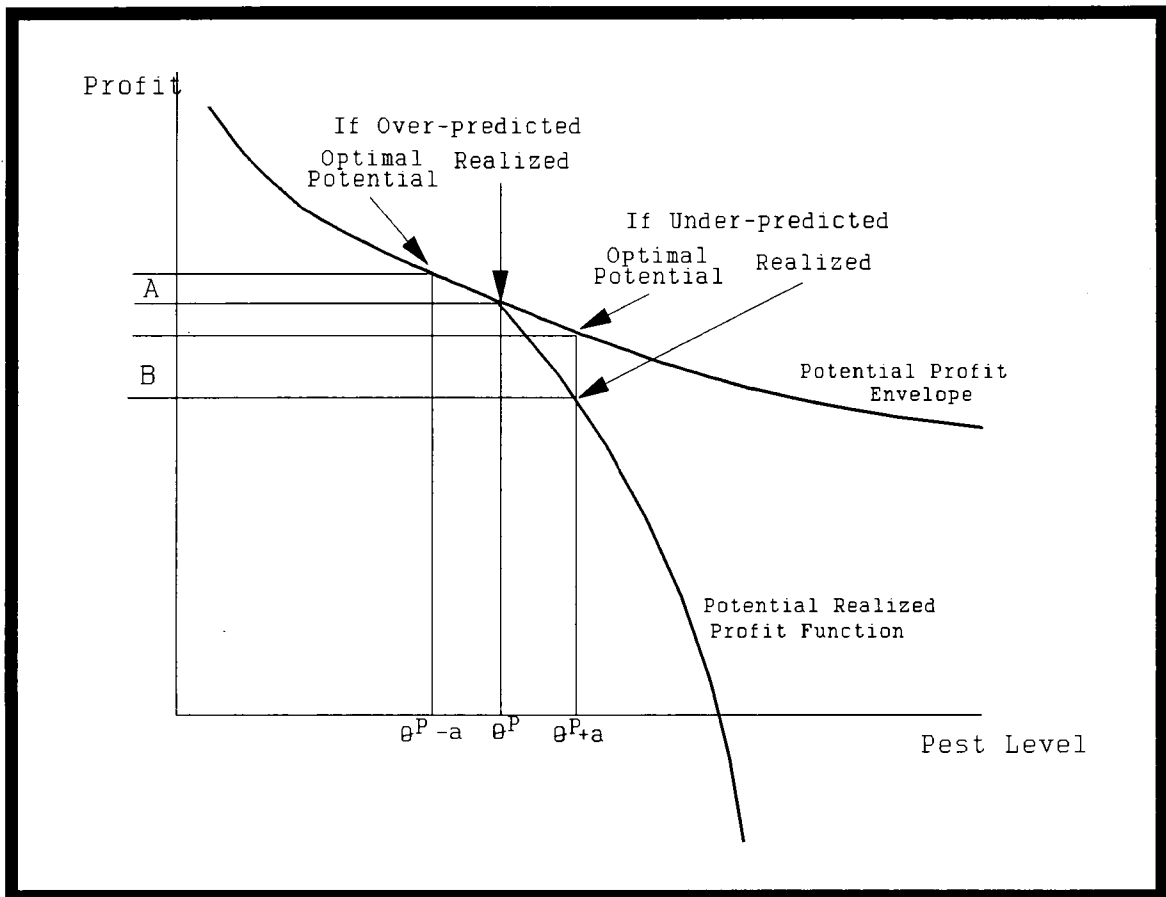


Figure 2.7: Asymmetric penalties.

may also be symmetric or asymmetric in the other direction. The over-prediction penalty is measured from two points on the potential profit envelope which is derived solely from ex ante technology; the under-prediction penalty is the difference between a point on the potential profit envelope and a point on the associated potential realized profit function. The potential realized profit function, unlike the envelope function, is derived from ex post technology. This insight suggests that asymmetric penalties occur because of differences between the two technologies. It need not be the case that penalties are everywhere symmetric or asymmetric. The ex ante and ex post technologies of the firm could be such that the two penalties are symmetric within a certain range of pest levels, and asymmetric elsewhere. The point of emphasis is that the penalty structure under cost uncertainty is technology driven.

At this point, the distinction between asymmetric penalties and asymmetric *expected* penalties must be made. Asymmetric penalties are solely a function of technology. Asymmetric *expected* penalties, on the other hand, can occur because of asymmetric probabilities as well as asymmetric penalties. For instance, if both over- and under-prediction result in the same penalty, but over-prediction is more likely to occur than under-prediction, then the *expected* penalty for over-predicting pest damage is greater than for under-predicting. One could also imagine a situation in which both penalties and probabilities are asymmetric and offset each other, with the resulting expected penalties being equal. This situation, in fact, is the solution to the problem of maximizing expected profits.

Producers, through their planned actions, affect the probabilities of incurring the two penalties. As planned levels of inputs are increased and outputs decreased, the probability of over-predicting the pest infestation level increases and the probability of under-predicting decreases. It is the probability of incurring a penalty, not the probability of realized pest levels, which is changed by the producer action. The pest level that actually occurs is independent of any action taken by the producer. The producer can affect, however, the probability of incurring a penalty through her or his *ex ante* input and output decisions. The solution to the expected profit-maximization problem occurs where the expected penalties are minimized. Given the output level, the choice of planned pest level does not affect total revenue and, therefore, maximizing expected profits is only a matter of minimizing costs. Planned profits in the lower diagram of Figure 2.6 is the solution to the expected profit-maximization problem, and represents the point where any further marginal change in planned input and output levels, in either direction will have the same impact on expected profits.

For the purpose of highlighting the effect that asymmetric penalties have on planned resource levels, consider the case where probabilities of pest damage are symmetrically

distributed about the mean value. When penalties are asymmetric in this case, producers shift their planned actions away from the action associated with the expected level of pest infestations. This shifting of resource levels in response to asymmetric penalties will be termed strategy bias. If penalties are symmetric, on the other hand, then maximizing expected profit reduces to the problem of maximizing profit for the expected level of pest infestations.

The effects of asymmetric penalties on planned and realized resource levels for this special case are summarized in Table 2.2. The rows indicate the three categories of penalty structures that could occur; the columns indicate the three categories of realized pest infestation compared with the expected value of pest infestation. Of special interest are the cases in which asymmetry unambiguously causes unnecessary use of pesticides, a polluting input.⁷ If the under-prediction penalty is greater than the over-prediction penalty, and if the realized pest level is less than or equal to the expected pest level, then the actual pesticide use will exceed the level of pesticides necessary to control the expected pest infestation level. The implication is that certain penalty structures will always provide an incentive for expected profit maximizing firms to use pesticides more intensively than is required to control the expected pest infestation level. On the other hand, notice that if the under-prediction penalty is less than the over-prediction penalty, then firms may never have an incentive to use pesticide in amounts that exceed the amount required to control the realized pest infestation.

2.4 THE CASE OF CHEAPER PREVENTIVE TECHNOLOGY

An interesting application to examine is the case where shifting the uncertainty to the firm from the consumer allows the firm to use cheaper, more efficient preventive technology. This

⁷Unnecessary pesticide use, defined in technological terms, occurs when the realized level of pesticide use is higher than the optimal minimum cost level of pesticide use for the realized pest infestation.

Table 2.2: Effects of penalty structure on pesticide use

Penalty Structure	Realized Pesticide Use Compared With Optimal Pesticide Use for Mean Level of Pest Infestation		
	If realized pest level is less than mean value	If realized pest level equals mean value	If realized pest level is greater than mean value
Symmetric	greater than	equal to	ambiguous ²
Under-prediction less than over-prediction	ambiguous ^{1,2}	ambiguous ²	ambiguous ²
Under-prediction greater than over-prediction	greater than	greater than	ambiguous ^{1,2}

¹Depends on the degree of asymmetry and the realized level of pest infestation.

²Depends on the structures of ex ante and ex post technology.

condition of ex ante technology being more efficient than technology applied ex post is thought to exist in the provision of lawn care. Health care provision is another example of where this technology condition may exist. Shifting uncertainty to the firm can be thought of as a change in the flexibility and technology conditions. For instance, in the lawn care market the cost of maintaining a healthy lawn at the beginning of the season is uncertain due to the uncertainty about pest infestations throughout the year. The consumer can bear this cost uncertainty, waiting until pest infestations occur and then hiring a lawn care firm to control the pests. In this case, the firm knows its cost of production but is restricted to using only ex post technology. The alternative to the consumer is to purchase insurance against pest infestations at the beginning of the season, thereby shifting the uncertainty to the firm. Bearing the uncertainty through the insurance contract imposes flexibility conditions on outputs, but the firm does have the opportunity to use both ex ante and ex post technologies. Operating under certainty, the expected penalties are zero,

but the total cost of treating the realized pest level for a given output level may be higher than the realized costs for a firm operating under uncertainty, due to the opportunity that a firm has under uncertainty to employ the more efficient ex ante technology.

If this technology condition holds for a lawn service firm, then it may be to the firm's advantage to assume the uncertainty by offering insurance against pest damage in addition to its pest control product. This bundling of insurance with pest control has happened in the lawn service industry, and the health maintenance organization (HMO) provides another example of this, by bundling health insurance with health care. The effects on resource allocation are driven by the asymmetric penalty structure imposed by the differences in efficiency between ex ante and ex post technologies. While ex ante technology is more efficient in the sense that costs are lower than if solely ex post technology is used, overall economic efficiency may actually decrease if the externality costs from increased pesticide use more than offset any internal cost savings to the firm from using the cheaper ex ante technology.

The theoretical framework developed in this chapter provides the basis for the empirical work that follows. The remaining chapters will provide both an increased understanding of these theoretical concepts through more specific, detailed analysis and an illustration of how these concepts can be implemented in empirical studies.

3. APPLICATION TO THE LAWN CARE OPERATOR

In this chapter the theoretical model is applied to the lawn care operator. Background information on the development and organization of the industry, the demand for lawn care services, and the service production process is provided in the first section. Next, models of agricultural pest control and production are reviewed, with a special emphasis placed on understanding how integrated pest management inputs are involved in the pest--pest control--crop relationship. Based on this agricultural literature, the effects of lawn care production inputs on pests are specified in a turfgrass pest damage function. The physical input requirements are then translated into the employment of economic inputs by applying the model of producer behavior developed in Chapter 2 to the lawn care operator. The theoretical application is discussed in Section 3, followed by the specification of the empirical model and hypothesis tests in Section 4.

3.1 THE LAWN CARE INDUSTRY

Industry Development and Organization

Dick Duke founded Chemlawn Corporation in 1968 and thereby established the chemical lawn care industry. During their first full year in 1969, 4000 customers were serviced which generated \$226,000 in net revenues (Hall, 1992a). Twenty years later, the industry had grown to an estimated \$1.95 billion in annual revenues, with 9.5 million residential customers accounting for 1.6 million acres being treated with chemicals (Lawn Care Industry, 1990). Based on a sampling of states, the estimated number of establishments licensed to apply pesticides on

residential lawns in the contiguous U.S. is 17,000.⁸ As expected, these establishments are concentrated in the heavily populated areas of the country--the North Central and Northeast regions and in Florida, Texas, and California. The top twelve states, shown in black on the map in Figure 3.1, account for approximately two-thirds of the total number of lawn service establishments in the contiguous United States.

Despite the tremendous growth in the industry, most companies remain small. The "State of the Industry" survey conducted by Lawn Care Industry magazine in 1990 found that 96% of firms had sales of less than \$1 million. However, the largest companies have been getting larger through a recent merger trend in the industry. Most of the mergers have been between large and small firms, but Chemlawn and TruGreen, the two largest companies in the industry during the 1980's, have both been purchased by ServiceMaster. As a result of this consolidation, market share for the top company in the industry is probably close to 25 percent, with the second largest company having approximately a 4 percent market share.

The maturing of the industry and the saturation of markets has led to a very competitive pricing policy among firms. Bob Andrews, president of the Professional Lawn Care Association of America and owner of The Greenskeeper lawn service company, believes that product pricing often "is based on what they think their competition is charging rather than any actual cost factor involved in running their business" (Hall 1992b, p.26). Pat Norton, president of the second-largest company in the industry, adds that "a good reputation" used to command a higher price, but now homeowners "have ten bids and the low bid gets it" (Hall 1992b, p.30). These comments suggest that firms in the lawn service industry are perceived as selling a homogenous

⁸The chemical lawn care industry is classified as part of SIC 0782. *County Business Patterns*, the best government source on establishments, reports data for the lawn care industry at the industry group (0780) level only and, therefore, does not provide establishment totals which are comparable to my estimate. However, I did rely on 1989 *County Business Patterns* data to determine the distribution of establishments by state.

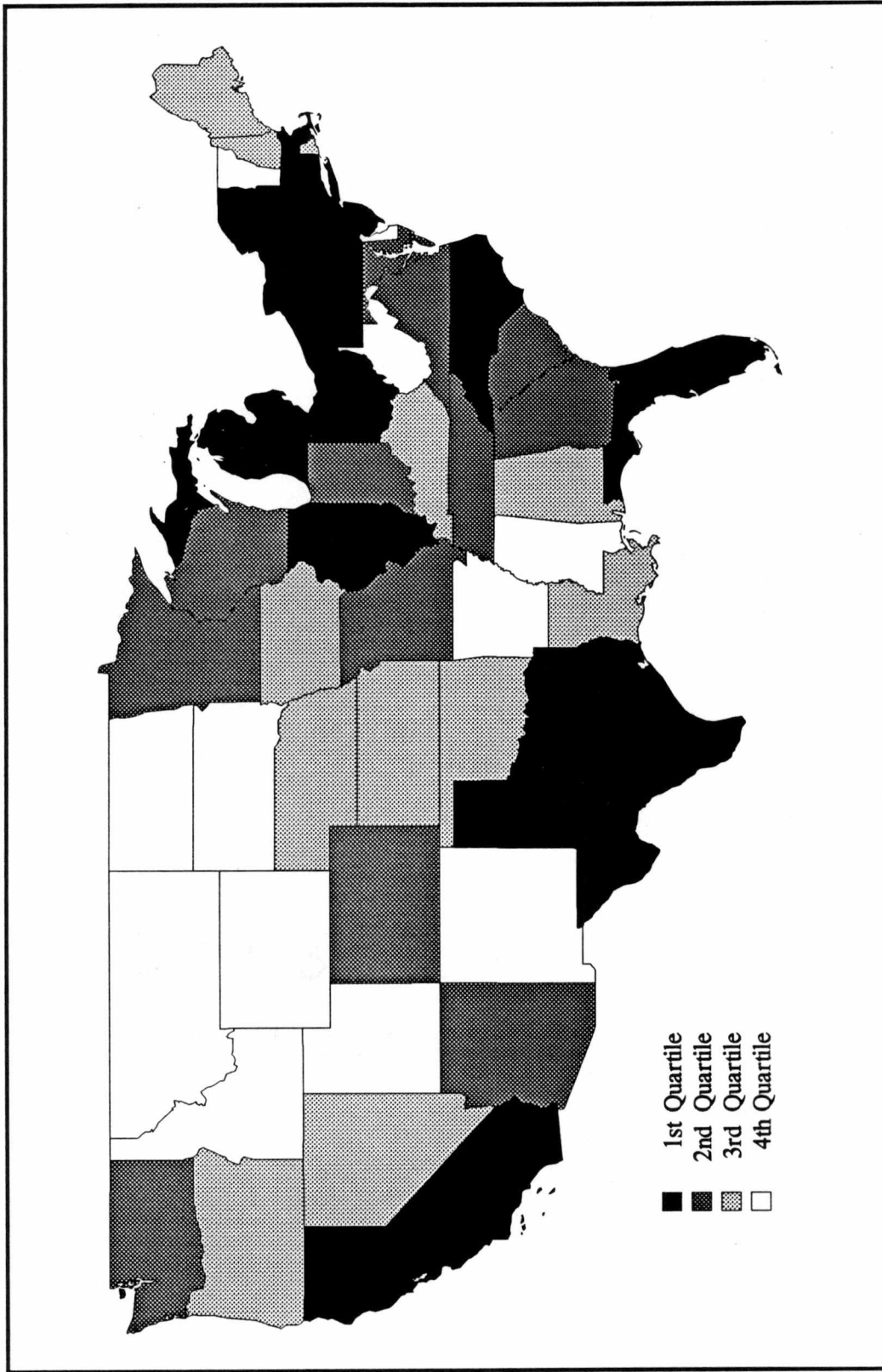


Figure 3.1: States ranked by number of Landscape and Horticulture Service Establishments (SIC 780)

service at a competitive (similar) price, and thus are assumed to be price-takers in both output and input markets in this study.

Demand for Lawn Pest Control

A recent survey of homeowners in the Minneapolis metropolitan area (Schmitt, 1991) provides some interesting insights into the demand for lawn pest control. The survey results suggest that professional lawn care services and do-it-yourself products are substitutes, with the demand for lawn care services being more elastic than the demand for the basket of DIY products at current prices. The pertinent findings of the survey are summarized in the following four points:

- (1) Approximately 18% of homeowners hired professional lawn services, 54% applied lawn care products themselves, and 28% did not use any fertilizer or weed killer during the year.
- (2) Professional lawn services provide more intensive maintenance. On average, a lawn care operator provided over four treatments of fertilizer and pest control per year. Do-it-yourself (DIY) homeowners, in contrast, fertilized an average of three times per year and used weed killer an average of twice per year.
- (3) Over half (55%) of the homeowners hiring professional lawn services said they would have done the lawn themselves or cut back in other ways if the price was between 10-50% higher per year.
- (4) Less than half (45%) of DIY homeowners, if faced with 30-200% higher prices annually, would reduce the number of applications or otherwise cut back lawn care maintenance.

Service and the Production Process

A lawn service firm (hereafter referred to as an LCO) provides both fertilization and pest control services for residential lawns and insurance against pest damage, along with possibly

other related turfgrass and landscape maintenance services, such as mowing. Most customers hire a lawn service at the beginning of the growing season and enter into a contract that specifies the services to be provided and the annual cost. Services (outputs) are measured in units of lawn area serviced at a standard quality level. Some states require written contracts that must be renewed annually, while other states permit oral contracts that are ongoing from season to season. With an "ongoing" contract, prices are fixed during the current season but may be changed from one season to the next, with the company notifying the customer of the new price prior to applying the first treatment of the season. Regardless of whether the contract is written or oral, most states require that the LCO provide to the consumer at the beginning of the season the proposed dates of application, the pesticides to be used during these applications, and any relevant pesticide label instructions. Thus, the LCO is required to set the output level and planned input levels simultaneously at the beginning of the production process.

Depending upon the climate and the length of the growing season, LCO's typically apply between four and six treatments per season, with each treatment timed six to eight weeks apart. Fertilizer is normally included in each treatment, while weed, insect, and disease controls may be applied depending upon the time of season and the condition of the lawn. For example, due to the importance of timing in controlling insects, many firms will apply preventative applications of insecticides if a certain insect problem is expected to occur before the next scheduled treatment. Since the LCO provides insurance against pest damage, this preventative application saves the firm the added expense of returning to the lawn at the actual time of the insect infestation, should the insect infestation occur.

Firms are often classified as either dry or liquid, depending upon whether they use a granular or liquid formulation of fertilizer. Since liquid fertilizers can be tank-mixed with pesticides, liquid companies have to make only one pass over the lawn to apply all of the

necessary materials. On the other hand, dry companies must apply fertilizer using a spreader, and then make another trip over the lawn spraying a liquid weed control.⁹ However, since pesticide formulators offer granular fertilizer in combination with many insect controls, a separate trip across the lawn to apply insect controls is often not necessary.

These combination products and the ability to tank-mix insect controls and liquid fertilizer have greatly contributed to keeping costs and prices low and, therefore, to the rapid expansion of the market. But another important factor is the development of application equipment which has made the production process analogous to an assembly line. The manager can mix the product, calibrate the equipment, and then teach the technician a few simple skills on how to operate the spreader or the spray gun. The treatment process is routine and, after a short learning process, becomes very fast for even unskilled labor to perform. The treatment of an average-sized lawn takes approximately 8-10 minutes using lower-skilled, lower-paid workers. The disadvantage of uniform treatment is that some products may be wasted since the appropriate fertilizer and pesticide requirements are not the same for every lawn.

3.2 THE TURFGRASS PEST DAMAGE FUNCTION

Knowledge of the pest--pest control--crop relationship is necessary to understand the production technology of the LCO. The use of pesticides and integrated pest management methods to control pests in agriculture has received much attention during the past twenty years. While the specific economic problem faced by a LCO is different than the farmer problem, this research does provide the basic framework for modeling the relationship between pests and inputs.

⁹Granular fertilizer and weed control combinations are available, but the weed control is not effective unless the grass blades are wet at the time of the application.

Review of Agricultural Pest Models

The pest--pesticide--crop relationship has been modeled using a damage function and a kill function (e.g., Feder and Regev 1975, Lichtenberg and Zilberman 1986). The damage function explains the pest damage to a crop as a function of the number of pests and the damage per pest, where the damage per pest is a function of environmental variables such as temperature and humidity. Both the number of pests and the damage per pest are unknown for the treatment period and, since pests are often mobile, the number of pests is assumed independent of temporary pest control methods taken in previous periods.¹⁰ This assumption allows for a static framework to be utilized to analyze a farmer's pest control decisions.

Pesticide applications reduce crop damage by reducing the pest population. This relationship between the amount of pest controls applied and the proportion of pests killed is typically modeled using a kill function that exhibits decreasing returns to scale. Pest damage can also be controlled through factors that affect the damage per pest. These factors include planting pest-resistant species and the timing and quantity of irrigation and fertilization applications. Implementing these factors requires information (presumably from consultants) for which "the cost is of a fixed nature and is not related to the amount of information" (Feder 1979 p.98). With this fixed-cost assumption along with assuming all agricultural inputs other than pesticides are applied in an optimal manner, the decision facing the farmer is to maximize profits by weighing the benefits of increased crop output against the costs of pesticides.

This modeling framework has led to the development of population thresholds, which are

¹⁰However, as Hueth and Rejev (1974) explain, previous pesticide applications may reduce the efficacy of future treatments due to increased pesticide resistance. In this case, pest damage during the current period is related to the pest control methods used in previous periods.

rules of thumb allowing for easier implementation of pest control advice. The action threshold¹¹ is "interpreted...as the minimum population level for which it is profitable to apply a pre-specified, fixed amount of pesticide, ordinarily a recommended or label dosage rate" (Moffitt 1986 p.70). The determination of the appropriate label dosage rate is a separate economic problem which presumably depends upon the risks and benefits to society. An alternative rule of thumb is the economic threshold, defined by Headley (1972) as "the population that produces incremental damage equal to the cost of preventing that damage". Using the economic threshold as a guide, farmers decide not only on the number of treatments, but also on the dosage rate of each treatment. The economic threshold is the solution to the farmer's problem.

The pest--pest control--lawn maintenance relationship differs in one important aspect from the farmer's problem as constructed above: the lawn service firm contracts at the beginning of the season for a fixed level of output that includes insurance against pest damage and, therefore, once pest damage occurs the lawn service firm *must* apply a pest control and cannot use either the economic or action thresholds as their guides for profit maximization. However, the agricultural framework does provide a good base model for the turf maintenance problem. In particular, the damage and kill function concepts are used in an expected profit maximization framework to model the pest control decisions facing the lawn service firm.

Turfgrass Pest--Pest Control--Maintenance Relationship

Many different turfgrass pests can infest and damage a lawn during any one season. These pests may include many different species of annual and perennial grasses, broadleaf weeds, surface and subsurface insects, and diseases. Fortunately for the LCO, most of the different species within each pest category can be controlled with the same pest control program and, thus,

¹¹This threshold, based on economic tradeoffs, was defined in the entomology literature and, therefore, is sometimes referred to as the economic threshold by entomologists.

only five different pests are considered when developing a model of lawn pest control: crabgrass and other annual grassy (monocot) weeds; broadleaf (dicot) weeds; surface insects; subsurface insects; and diseases.

The damage to turfgrass (θ) as a result of pest infestations is a function of the number of each turfgrass pest (B) and the damage each pest causes (D), $\theta(B, D(F))$, where F is a vector of environmental growing conditions. This vector contains both structural and maintenance conditions. Examples of structural conditions include the amount of sunlight and air movement the plant receives, the variety and species of turfgrass plant, and the soil type. Except in the extraordinary case, structural conditions are usually treated as fixed by homeowners and lawn service firms. Maintenance conditions include the amount of water and fertilizer the plant receives, the mowing height and frequency, the soil Ph level, and the amount of soil compaction and thatch buildup. All maintenance conditions are controllable by the homeowner, but an LCO may only receive or supply a contract for a subset of these maintenance services. For example, many homeowners water and mow their lawns, but contract for fertilization and pest control services.

An **integrated pest management input**, defined as any input that mitigates pest damage by affecting either B or D , may be hired by a lawn service firm to control pest damage. These inputs include chemical, biological, and genetic pest controls which reduce damage to turfgrass by killing the pest population (B), and cultural practices which improve the environmental growing conditions (F) to reduce the damage per pest (D). The relationship between the amount of pest controls applied (Z) and the proportion of pests killed (K) is explained by the kill function:

$$K = K(Z); \quad K' > 0, K'' < 0 \quad (3.2)$$

Throughout this study, I assume that firms apply pest controls in a manner consistent with their label¹² and, furthermore, that this rate and method of application will control pests as claimed on the label. I also assume that substitute pesticides are available if pests develop a resistance to a particular chemical¹³. The kill function for cultural IPM inputs is analogous to the pest control kill function, except that cultural inputs usually affect the damage per pest rather than the number of pests.

By the definition of an LCO, fertilization and pest control are always within the domain of controllable inputs. To the extent that other cultural practices are within the control of the LCO, IPM theory suggests that the use of pesticides can decrease without affecting turf quality if these cultural practices are implemented correctly. But since the correct practices vary by species, climate, and environmental growing conditions, the ability to reduce pesticide use depends upon the knowledge of the worker. Examples of this include: (1) Tall fescue varieties have a very low susceptibility to damage from grubs, but a bluegrass lawn could be easily destroyed by grubs; (2) the deeply shaded areas of a lawn will not suffer from crabgrass infestation but may require a control for aphids while the sunny areas of the lawn have just the opposite requirements; (3) leaf spot disease may cause no damage to a correctly mowed lawn, but may cause severe damage to a lawn mowed too short. The point is that since lawns are not homogeneously established or maintained, the optimal levels of IPM inputs, especially fertilizer and chemical pest control applications, will vary for each particular lawn. To properly carry out these IPM practices, an LCO must employ a trained labor force that can correctly identify the turfgrass species and environmental growing conditions on each lawn.

¹²It is a Federal offense to apply a pesticide in a manner inconsistent with its label.

¹³The substitution of Dylox® for Oftanol® for the control of subsurface insects provides an example of where a substitute pesticide was available (at a similar price) when grubs developed a resistance to Oftanol® insecticide.

A trained labor force is capable of reducing pesticide usage in two ways. First, by applying the correct amount of fertilizer to each lawn, the grass plant is more competitive and can tolerate a higher pest population. Second, pesticides can be *selectively* applied to susceptible areas to prevent damage or, with the use of frequent inspections, pesticides may only be applied on a curative basis. With a seasonal, untrained labor force, many LCO's choose to apply the same rate of fertilizer and preventive pesticide applications to each lawn. Only if a worker is educated and capable of correctly identifying species and environmental growing conditions, can pesticide use be reduced with correct cultural practices. Obviously, if more of the cultural practices are within the control of the LCO, the opportunity to reduce pesticide use is greater.

Agronomic theory implies that lawn service firms will employ in varying amounts several or all of these IPM inputs in the maintenance of turfgrass. Economic theory, however, suggests that employment of IPM inputs is based on the *economic decisions* facing firms. In the next section, this information on the relationships between pest damage and inputs is used to apply the theoretical model developed in Chapter 2 to the LCO.

3.3 APPLICATION OF THEORETICAL MODEL

Based on the discussion in Sections 3.1 and 3.2, assume that the following characteristics apply to the production of lawn care services:

- (1) The producer knows the technological possibilities of providing multiple outputs with multiple inputs.
- (2) The level of management knowledge, in terms of agronomic education and experience in dealing with pest infestations, is fixed for the production period of one season, but is variable over the longer run.
- (3) Naturally-occurring pest damage for the production period is uncertain and unknown to

management at the time the output levels are contracted (fixed) and production plans are made.

- (4) Output and input prices are exogenous and known to the producer, with the producer free to buy inputs and sell outputs at the given prices.
- (5) Marginal costs of production are rising as output increases for any branch location due to the increasing distance traveled to service the additional homeowner.
- (6) The producer's primary objective is to maximize expected variable profits by forming an expectation about the level of naturally-occurring pest damage and planning input and output levels accordingly.
- (7) Integrated pest management inputs must be hired to mitigate naturally-occurring pest damage, should such damage occur. This is the provision of insurance.

Three outputs are produced by the lawn care operator: lawn care service, mowing service, and insurance against pest damage.¹⁴ Outputs are measured in units of lawn area serviced at a standard quality level. The definition of each product is given below. Note that products are assumed to be homogenous within each category.

- (1) **Lawn care service** includes all fertilization, pesticide, biological, and cultivation integrated pest management services provided to maintain a healthy lawn. Quantity is measured in 1000 square foot units of lawn area maintained at the competitive health standard;¹⁵ price is the average annual price per 1000 ft².
- (2) **Insurance against pest damage** is the contractual obligation to mitigate the effects of

¹⁴Other products, (e.g., snow plowing), are assumed nonjoint or homothetically separable in production, and thus need not be considered when estimating the production technology for these three products.

¹⁵It is assumed that all firms produce the same quality level of thick, green, healthy turf (a homogenous product). Any firm that fails to meet this standard would lose customers to its competitors and therefore, this quality level is termed the competitive health standard.

lawn pest damage for the current season, should such damage occur. Quantity is measured in 1000 square foot units of lawn area insured; price is the average annual price per 1000 ft².

- (3) **Mowing service** includes all lawn mowing and landscape maintenance services, such as trimming, edging, and pruning. Landscape design and installation services are not included as part of this product. Quantity is measured in 1000 square foot units of lawn area maintained; price is the average annual price per 1000 ft².

Being able to define three, distinct products does not imply, however, that all three prices and quantities are observed. The standard practice is to produce lawn care service and insurance in a one-to-one fixed proportion. As a result, combined, not individual, prices and quantities for these two products are observed. Problems in specifying the model do not arise as a result of this bundling of insurance with lawn care service as long as the fixed proportion always holds. The two products can be treated as a single product with $kY_1 + Y_2$ quantity produced and a price of $kP_1 + P_2$, where k is the fixed proportion of Y_1 to Y_2 (Henderson and Quandt 1980). This approach is used, with lawn care service and insurance treated as a compound product, where $k=1$.

The LCO uses six variable inputs in producing its products: skilled labor; unskilled labor; fertilizer; preventive pesticides; corrective pesticides; and application and maintenance equipment. Inputs are assumed to be homogenous within each category, with the costs of these six inputs representing the total cost of the LCO in producing its output. Definitions of each input are listed below.

- (1) **Skilled labor** are workers which have passed the state pesticide examination and are licensed applicators. The price of skilled labor is the average hourly wage rate; the quantity is the number of hours employed annually.

- (2) **Unskilled labor** are workers who are not state licensed pesticide applicators. The price of seasonal labor is the average hourly wage rate; the quantity is the number of hours employed annually.
- (3) **Fertilizer** is any nutrient material applied to turf. All liquid and granular formulations are included in this category. The fertilizer is assumed to be homogenous, i.e., no distinction is made between the use of slow-release versus fast-release, or complete versus incomplete fertilizers. The price of fertilizer is the average price per pound of nitrogen; the quantity is the total number of pounds of nitrogen applied annually.
- (4) **Preventive pesticides** are all chemical control substances applied ex ante to suppress weed, insect, or disease pest populations. All formulations are included in this category. Also included are the pesticide portions of granular fertilizer and pesticide combinations (e.g. fertilizer + preemergent weed control + insect control). I assume that all firms in a region face the same pest populations and therefore select from the same set of pesticides. The choice of formulation depends on the set of prices faced by the firm, but the total amount of active ingredient (AI) applied is independent of the formulation chosen. These assumptions are necessary for the definition of homogenous pesticides. The price of pesticides is equal to the average cost per 1000 ft²; the quantity of pesticides is equal to the number of square feet treated annually, measured in 1000 ft² units.
- (5) **Corrective pesticides** are all chemical control substances applied ex post to suppress weed, insect, or disease pest populations. The price and quantity are measured in the same manner as preventive pesticides.
- (6) **Application and maintenance equipment** is defined as vehicles, spray equipment, and mowing and cultivation equipment. The price of equipment is equal to the average annual depreciation or lease costs of this equipment, replacement parts, and maintenance

and truck fuel costs per unit; the quantity of equipment is equal to the number of units.

Two inputs--branch offices and management knowledge--are fixed for the current production period, although variable over multiple production periods. The definitions of these fixed inputs are given below.

- (1) **Management knowledge** is the technical ability, gained through either experience or education, to estimate the occurrence of and mitigate the effects of naturally-occurring pest damage. Quantity is the total number of years of experience and agronomic education; the market price is assumed equivalent to the shadow price.
- (2) A **branch office** consists of buildings and land at one location from which the production of services originates. Quantity is the number of branch offices; price is the lease/rental cost of the property.

The states of naturally-occurring pest damage are defined as the percent of the total lawn area damaged by each of the five types of pests during the current production period, holding all structural environmental variables fixed and allowing for no human intervention.

Having defined all of the exogenous and endogenous variables, the model is specified as:

$$\max_{\vec{X}} E\pi = TR(\vec{P}, \vec{M}) - Cost_{EX ANTE}(\vec{P}, \vec{M}) - \int_{\theta^P}^{\theta^{MAX}} Cost_{EX POST}(\vec{P}, \vec{M}; \theta^P) f(\theta) d\theta \quad (3.3)$$

where $E\pi$ is expected variable profits.

X is a (8x1) vector of outputs and inputs.

M is a (2x1) vector of the fixed inputs:

$M = M_1$ the level of management knowledge

M_2 number of branch offices

θ is the state of naturally-occurring pest damage.

P is a (8x1) vector of netput prices:

$P = P_1$ unit price of lawn care service + insurance

P_2 unit price of mowing service

P_3 unit price of skilled labor

P_4 unit price of seasonal labor

P_5 unit price of fertilizer

P_6 (5x1) subvector containing unit prices of preventive pesticides

P_7 (5x1) subvector containing unit prices of corrective pesticides

P_8 unit price of equipment

Differentiating (3.3) with respect to the netput prices yields the optimal planned action, with the output supply functions written as

$$\frac{\partial \pi}{\partial S} = Y^P(P, M) \quad \text{where } S = (P_1, P_2) \quad (3.3a)$$

and the input demand functions written as

$$\frac{\partial \pi}{\partial W} = -Z^P(P, M) \quad \text{where } W = (P_3, \dots, P_8) \quad (3.3b)$$

The equations (3.3a) and (3.3b) represent the planned action of a producer, given the subjective probabilities of different states and the values of the exogenous variables. The standard approach in the literature for estimating the technological parameters of the model is to assume a functional form for (3.3), collect data for the exogenous and endogenous variables, and then estimate the parameters using the profit and netput functions in a system of equations. By calculating elasticities, technological change biases, and other technological measures from the estimated parameters, researchers are able to test the hypotheses of interest and make recommendations for policy.

The standard approach will not be followed in this study, however, for several reasons.

First, the data requirements for identifying the asymmetric penalty effects are too demanding and the data cannot be collected. Using the standard approach, the shifting of resource levels in response to asymmetric penalties (strategy bias) and other theoretical concepts developed in this study could be tested if both ex ante and ex post technology are estimated. If the same firm uses both technologies, however, only an aggregate technology can be estimated unless the amount of labor, equipment, and other inputs used in each of the technologies is known. This division of the data is difficult to collect because producers' cost accounting methods typically do not distinguish, for example, how many of a worker's hours or what percent of equipment use is spent on ex ante versus ex post technology. Only the aggregate of ex ante and ex post inputs is recorded. With aggregate actions, only an average of the two technologies can be identified from the profit function and, thus, the theoretical concepts important to this study can only be tested in an ad hoc manner with the standard empirical approach.¹⁶

Methods are available, however, to identify the effects of asymmetric penalties on producer behavior. The most important theoretical behavior that I wish to empirically test is the existence of strategy bias when producers face asymmetric penalties for over and under-predicting the level of pest damage. Fortunately, this theoretical behavior also explains the use of IPM methods by a LCO, which is the behavior most important from a policy perspective. In particular, the characteristics that are important in determining whether or not a firm implements IPM practices are also those that identify strategy bias, and most importantly, can be identified

¹⁶Using concepts and terms developed in Chapter 2, the data problem is that not all of the observed hiring decisions lie on the optimal state expansion path. For example, assume that a firm over-predicts damage for two pests and under-predicts damage for the other three pests. For the over-predicted pests, the input combination lies on the optimal state expansion path. However, for the under-predicted pests, the actual input combinations will lie not on the state expansion path, but at some other point on the isopest curve. Thus, technology follows two different structures, and two separate models must be specified and estimated corresponding to tradeoffs along the optimal state expansion path and along the isopest curve.

from the data. Given the decision by the firm on whether or not to use IPM, the level of pesticide demand can then be estimated. Identifying these relationships provides both information on the implications for resource allocation of asymmetric penalties and information on how policies can be implemented to increase IPM practices and reduce pesticide demand by lawn care firms. Thus, I will not be concerned with empirically estimating all of the technological parameters, but only those important for testing the theoretical concepts developed in Chapter 2.

3.4 EMPIRICAL MODEL AND TESTS

The decision on whether or not to use IPM methods to control a pest is based on the theoretical model developed above, and is synonymous with the strategy bias decision¹⁷. A producer employs integrated pest management methods if she or he plans to use scouting and other IPM inputs in addition to pesticides to control the predicted level of pest damage. A firm will not use IPM methods if the expected profit from using solely pesticides is greater than the expected profit from using IPM. Thus, the IPM decision is a function of the exogenous variables in the expected profit function, along with possible specific pest effects.¹⁸ Also, the five IPM decisions--monocot and dicot weeds, surface and subsurface insects, and diseases--may be made jointly. Therefore, when modeling the five IPM decisions facing each firm, this correlation between pests must be taken into account.

Note that this decision to use IPM captures the strategy bias decision. For example, if a LCO predicts that 25% of the total area serviced will be damaged by grubs and then uses preventive pesticides on 50% of the total area, the LCO has decided to follow a preventive

¹⁷This is true only if corrective technology is nonhomothetic with preventive technology.

¹⁸For example, annual grassy weeds may be more difficult to control using IPM practices than diseases.

strategy bias. On the other hand, if only 10% of the area is treated with preventive pesticides, the LCO has decided to use a corrective strategy bias to maximize expected profits. By definition, IPM methods are not used if the level of preventive pesticides exceeds the predicted level of pest damage. Thus, the absence of IPM corresponds to the existence of preventive strategy bias. And in this case, preventive strategy bias may increase the demand for polluting inputs. Modeling the IPM decision, therefore, provides an empirical test for the existence of strategy bias and the consequences for the hiring of polluting inputs; both the theoretical and policy interest are attended to by modeling the IPM decision and the resulting pesticide intensity.¹⁹

The decision on whether or not to use IPM for any pest is written as:

$$No\ IPM = \begin{cases} 1 & \text{if } \pi_{No\ IPM} \geq \pi_{IPM} \\ 0 & \text{otherwise} \end{cases} \quad (3.4)$$

and thus

$$No\ IPM = f(P, M, \theta, T) \quad (3.5)$$

where P is the netput price vector, M is the vector of fixed inputs, θ is the vector of the states of nature, and T is a vector representing fixed pest effects. Writing $X_{it} = [P'_{it} \ M'_i \ \theta'_{it} \ T'_{it}]$, the empirical model to be estimated for firm i and pest t is

$$No\ IPM_{it} = X_{it} B_0 + \delta_{it} \quad (3.6)$$

¹⁹Pesticide intensity rather than pesticide input demand is modeled in this study. Pesticide demand measures the absolute amount of pesticides applied to turfgrass; pesticide intensity, on the other hand, measures pesticide use relative to the total area of turfgrass serviced. The intensity measure is used to maintain consistency with IPM theory, which emphasizes substituting other inputs for pesticides in treating a pest population on a given area of turf.

where δ_{it} is an unobserved disturbance that captures errors in expected profit-maximizing behavior by the firm and measurement errors by the researcher. I assume that $E[\delta_{it}|X_{it}] = 0$ and $E[\delta_{it}|X_i] = 0$, implying that δ_{it} is uncorrelated with the explanatory variables for all five pests. In other words, the explanatory variables are strictly exogenous (Avery, Hansen, and Hotz 1983). With the assumption of the interdependence of the five IPM decisions for each firm, the $E[\delta_{it}, \delta_{iw}] \neq 0 \forall t \neq w$. Also, the δ_i are assumed independently distributed.

Given the decision on whether or not to use IPM methods, the actual observed pesticide intensity depends upon netput prices, management knowledge, and the actual state of nature. Pesticide intensity is the percent of output (total lawn area) treated with corrective and preventive chemical pest controls,²⁰ and thus provides a direct measure of the use of IPM methods to control a given pest population. As mentioned above, the theory of firm behavior suggests that the structural relationship between the explanatory variables and pesticide intensity may be different when a pest is treated with IPM methods versus solely with pesticides. This difference represents any differences between the ex post and ex ante state expansion paths. The pesticide intensity (PI) decision is written as

$$\begin{aligned} PI_{it} &= X'_{it} B_1 + u_{it} \quad \text{if No IPM} = 1 \\ PI_{it} &= X'_{it} B_2 + v_{it} \quad \text{if No IPM} = 0 \end{aligned} \quad (3.7)$$

where u_{it} and v_{it} are unobserved disturbances with $E(u_{it}) = E(v_{it}) = 0$, and $E(u_{it}, u_{iw})$, $E(v_{it}, v_{iw})$, $E(u_{it}, v_{iw})$ may not equal zero for all $t \neq w$. That is, the $E[PI_{it}|X_{it}] = X'_{it} B$, and the pesticide intensity decision for each of the five pests within a firm may not be independent. The disturbance vectors u_i and v_i are assumed to be independently distributed but may be

²⁰As stated above in Section 3.2, it is assumed that pesticides are applied at the rate specified on the label.

heteroscedastic. Note that if the slope parameters $\beta_1 = \beta_2$, then ex ante and ex post technology are homothetic in θ and the condition for asymmetric input penalty functions is not satisfied.

Another decision of interest is the level of strategy bias. Depending upon the shape of the penalty functions, the level of bias may be lower the higher the level of management knowledge. That is, the effects of netput prices on the strategy bias outcome should be diminishing as management knowledge increases. To test this hypothesis, formulate the strategy bias outcome for both corrective and preventive regimes as

$$Bias_{it} = \prod_{k=1}^8 P_{kit}^{\alpha_k + \beta_k M_i} \quad (3.8)$$

where P_k denotes the price for netput k and M_i is the level of management knowledge. If the parameters β_k and α_k have opposite signs, then management knowledge diminishes the effect of netput prices on the level of bias. Taking the natural logarithm of (3.8) allows for estimating this model using linear methods.

This model which consists of both the IPM decision and the resulting pesticide intensity and strategy bias outcomes is a variant on the standard endogenous switching regression model. While this may be the first application to IPM research,²¹ switching regressions have a long history in the econometric literature. In Chapter 4, I review the econometric methods for switching regression models, and then apply a variant of these methods to the model laid out above. A distinct advantage of a switching regression model is that the two outcomes from the different regimes can be compared for each LCO. In other words, the results will indicate the pesticide intensity level had a LCO chosen an IPM strategy rather than solely relying on pesticides. This comparison and other model results lead to the analysis of some interesting

²¹Burrows (1983) uses a similar approach to estimate cotton pesticide demand. The IPM decision is modeled first and then the result is used as an instrumental variable in the estimation of pesticide demand.

policy questions, which I discuss in Chapter 5.

4. ESTIMATION OF THE MODEL

Data collection methods and definitions and descriptive statistics for the variables in the model are presented in the first section. Next, the standard endogenous switching regression model and several applications that appear in the economic and sociology literature are discussed. The model developed for this study is very similar to the traditional switching regression model, with the exception that, since the data consists of multiple observations per firm, the model involves random effects within regimes and correlation across regimes. This interdependence poses problems when identifying the model and, consequently, two-step estimation rather than the standard full-information maximum likelihood estimation method is proposed. In the final section, estimation results are presented and discussed.

4.1 DATA

Sampling Design

Data for this study are not available from industry or government sources. Because of this lack of secondary data, information on producer actions was collected directly from a sample of lawn care establishments. As shown previously in Figure 3.1, lawn care establishments are concentrated in the North Central and Northeast states, and Texas, California, and Florida. The northern producers operate in cool-season turfgrass zones with shorter growing seasons than their counterparts in the southern, warm-season turfgrass zones. These differences in growing conditions suggest that northern and southern production technology require two separate analyses. Limited research funds, however, restrict the scope of this study to one analysis. Since eight of the top twelve states reside in cool-season turfgrass zones, the decision was made to estimate cool-season production technology, with the sample to be selected from one of the

North Central states.

In most states, producers must obtain an annual applicator business license for each branch location. A list of state-licensed branches was obtained from six North Central states: Indiana, Michigan, Ohio, Pennsylvania, New Jersey, and New York. There are a total of 5,051 registered establishments in these states, with 91 % of these branches located in metro areas. The map in Figure 4.1 shows the zip code locations of state-licensed branches in these six states.

Pesticide regulations are similar in all the states, with the exception of Michigan. Michigan requires all workers to pass a state pesticide application exam, while the other five states permit workers to apply pesticides "under the supervision" of a responsible certified applicator. Since the Michigan regulations do not permit the estimation of the technological relationship between pesticides and unskilled labor, the sample was chosen from one of the other five states.

A decision was made to sample just one area to avoid problems with the measurement of states of nature. Sampling just one area limits the analysis with respect to the state variable, but not with respect to asymmetric penalties or other technology measures. On the other hand, sampling one area may not provide a sufficient number of observations for estimation. Therefore, an important criterion when selecting the sample from these five North Central states is to find a large sample size in a small geographic area. Such a sample provides many observations of actions for producers who face the same states of nature. The Nassau-Suffolk, New York metropolitan area meets this criterion. This area contains 556 branches, accounting for 11 % of the North Central universe. Another reason for selecting these Long Island counties is the potential for human pesticide exposure and groundwater pesticide contamination. The area is densely populated, with sandy soils which increase the risk of nitrates and pesticides leaching into the groundwater (USDA Soil Conservation Service 1975).

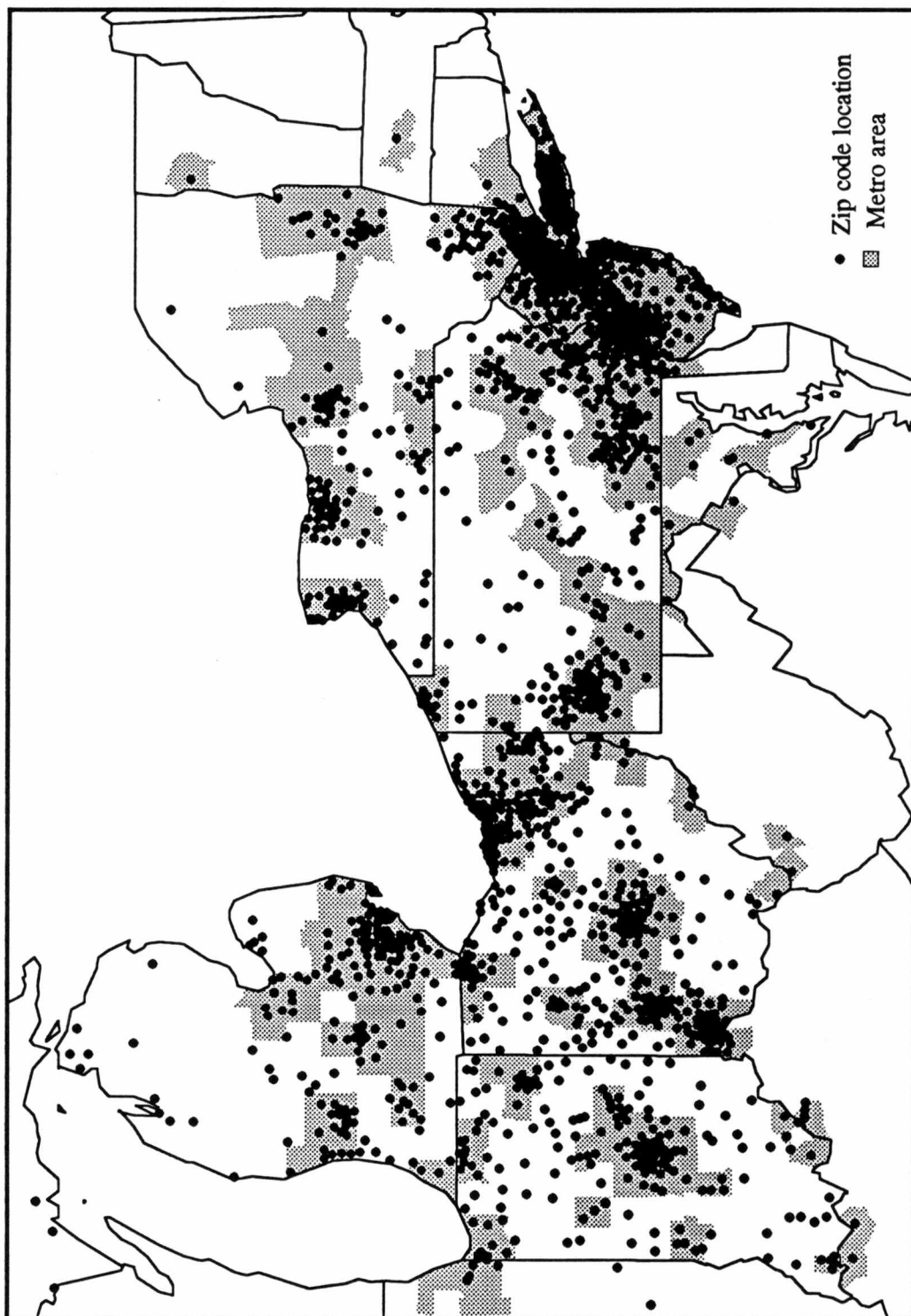


Figure 4.1: Distribution of state-registered lawn service establishments in the North Central region

Survey Design

An important consideration in survey design is the willingness and ability of producers to participate. Through testing, I discovered the key issue in meeting these two criteria; the question must be formulated in a manner that coincides with the way a producer organizes the requested information. For example, testing of the questionnaire revealed that producers had difficulty providing the total number of square feet serviced. This question was replaced by asking for the average lawn size and the number of lawns serviced to obtain the output quantity.²² Asking questions in this manner shifts the burden of interpolation to the researcher and away from the respondent, thereby increasing both the ability and willingness of producers to participate.

In an additional effort to boost participation rates, I sought and obtained the endorsement of the state industry organization. The New York State Turfgrass Association, in an accompanying cover letter, encouraged producers to participate in the survey. A copy of this cover letter and the questionnaire are found in Appendix A.

Survey Implementation

Questionnaires were sent to all Long Island branch locations registered with the New York Department of Environmental Conservation to apply pesticides to turfgrass.²³ The questionnaire was addressed to the branch manager/owner at each location. Initial mailings were timed to coincide with the beginning of the off-season, in hopes that the increase in available management time would correspond to increased participation rates. Responses were tracked by

²²Producers may confuse the median with the mean lawn size. This possible confusion will lead to measurement error only to the extent that lawn sizes are not distributed normally about the mean.

²³Tree services, landscape design firms, parks, schools, and municipalities were not included in the sample.

identification numbers on the return envelope. The mailing list was updated using this ID number and the questionnaire information was entered into a separate unlinked computer data file. This procedure insured that the respondent remained anonymous. A total of 39 producers responded to the first mailing. Nonrespondents were remailed, which increased the overall participation rate to 9.7% for a total of 54 observations. Of these 54 observations, five were from branches that did not provide pest control services during 1993 and four were incomplete,²⁴ which left a total of 45 responses available for analysis. As shown in Figure 4.2, the response rates are fairly uniform geographically across the sample space.

This sample size is sufficient for the purpose of testing the behavioral model, particularly with respect to the resource allocation effects of asymmetric penalties. The 45 firms, each with five pest observations, provide for a total of 225 IPM and pest intensity decisions. If the empirical model and methods proposed in this study are validated by this sample, more resources could then be employed to expand the sample to the point where the research results could be used to inform policy makers with a higher level of confidence.²⁵

With a low response rate, sample bias for those variables that are important in testing the dictates of theory is a concern. In this study, the potential sample bias that poses the biggest concern is for the management knowledge variable. As suggested by the model, firms with higher levels of management knowledge may engage in smaller amounts of strategy bias. An upward bias in a small sample, therefore, may result in the explanatory power of the model being rejected, when in fact a larger, unbiased sample may prove otherwise. With respect to

²⁴Several incomplete questionnaires were completed after contacting the respondent. However, four respondents removed their identification number and thus could not be contacted for completion of the questionnaire.

²⁵In Chapter 5, methods for obtaining important policy measures from the model are illustrated.

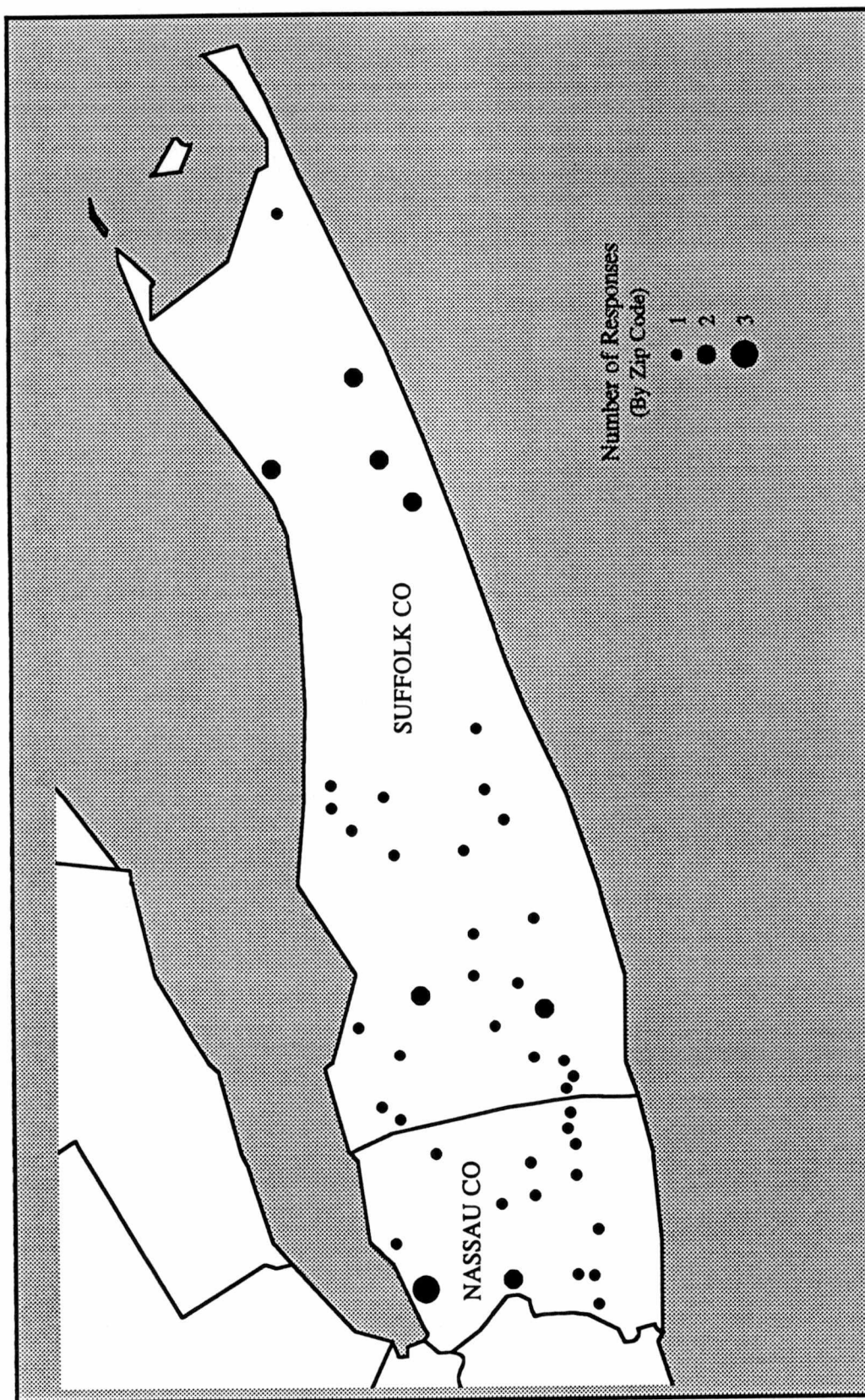


Figure 4.2: Geographic distribution of survey responses

management knowledge and the other variables, the extent of the bias caused by nonresponses is unknown.

Data Analysis

Data were transferred from the questionnaire to a computer file, where the data were systematically checked for data entry errors. The summary results for each survey question are given in Appendix B. The variables in the empirical model were then constructed from these survey results. The methods used to construct the data variables are explained in Appendix C.

Descriptive statistics for the firm-level variables are found in Table 4.1. Definitions for these variables are listed in Section 3.3 above. The mean pest control/insurance and mowing/maintenance outputs are given in 1000 ft² units. There is quite a wide variation in output levels in the sample. Of the 45 respondents, 14 (31 percent) provided only pest control/insurance services and no mowing/maintenance or other services. Mean prices for inputs and outputs are given in dollar units. The average fertilizer intensity for respondents is 3.8 pounds per 1000 ft². With respect to the management knowledge variable, branch managers who responded to the survey have, on average, 20 years of turfgrass experience and agronomic schooling. This relatively high level of knowledge in the sample suggests that if nonresponse bias exist, it most likely is in the upward direction. Thus, the bias in the sample, if it does exist, works against providing support for the behavioral model.

Table 4.2 contains the means and standard deviations for the pest-level variables. The predicted states of nature and the pesticide intensities are measured as a percent of total output treated with pesticides. There is wide variation in predictions and intensities across firms in the sample. Mean prices are measured in dollars per 1000 ft². For three of the five pests, firms practiced a preventive strategy bias on average. The greatest preventive bias is for crabgrass, while broadleaf weeds have the largest corrective bias. A total of three firms decided on a

Table 4.1: Descriptive statistics for firm-level variables

Variable	Mean	Std. Dev.
Pest Control/Insurance Output	1772.0	2473.8
Mowing/Maintenance Output	601.42	719.66
Management Knowledge	20.244	11.004
Nitrogen Intensity	3.7954	0.8455
Price of Pest Control/Insurance Output	52.202	24.164
Price of Mowing/Maintenance Output	184.08	93.858
Price of Skilled Labor Input	14.008	5.9722
Price of Unskilled Labor Input	8.0513	1.8023
Price Ratio of Skilled to Unskilled Labor	1.8054	0.8669
Price of Fertilizer Input	0.9449	0.3260
Price of Equipment Input	2374.3	1749.9

preventive bias for all five pests, while nine firms had a corrective bias for all five pests. The number of firms deciding on a preventive or corrective strategy bias for each pest is given in Table 4.3. The significant level of strategy bias in the sample suggests that asymmetric penalties exist between over and under-predicting the state of nature.

4.2 ESTIMATION METHODS

In classical scientific experiments, subjects are randomly assigned to either a control or a treatment group. Treatment effects are then determined by comparing the outcomes of the two groups. Since the selection into groups is random and therefore exogenous to the subjects, the results are applicable to the entire population. Social science experiments, however, often do not afford the opportunity to randomly select subjects into different treatment groups. As a result, the estimated effects of a treatment on the outcome of interest cannot be generalized to the entire

Table 4.2: Descriptive statistics for pest-level variables

Variable	Mean (std. dev.)	Crabgrass	Broadleaf Weeds	Surface Insects	Subsurface Insects	Diseases
Predicted State		34.244 (37.115)	42.667 (36.206)	27.133 (29.260)	41.622 (33.235)	35.622 (28.618)
Pesticide Intensity		89.333 (57.838)	75.489 (48.604)	52.844 (56.360)	66.600 (44.120)	44.711 (46.100)
Preventive Intensity		80.644 (47.441)	26.333 (39.991)	43.756 (52.396)	46.711 (44.363)	26.578 (37.971)
Corrective Intensity		8.6889 (29.197)	49.156 (42.646)	9.0889 (17.814)	19.889 (28.795)	18.133 (25.516)
Strategy Bias		46.400 (56.640)	-16.333 (64.627)	16.622 (46.933)	5.089 (52.903)	-9.044 (37.076)
Price of Preventive Pesticide Input		1.0698 (0.7410)	0.5207 (0.2854)	1.2400 (0.5998)	2.0489 (0.6368)	3.102 (1.0310)
Price of Corrective Pesticide Input		1.2196 (0.3456)	0.5896 (0.4010)	1.1882 (0.3908)	2.3287 (0.6457)	2.9329 (1.1636)
Price Ratio of Corrective to Prev. Pesticides		1.7009 (1.4033)	1.2731 (0.8554)	1.5600 (3.4339)	1.2345 (0.5491)	1.1486 (1.4456)

population unless this nonrandom selection into different treatment groups is accounted for in the process.

Social researchers have recognized this sample selection problem, and estimation methods have been developed to correct for the bias caused by endogenous, nonrandom selection into groups by the subjects of an experiment. Prevalent in the economic and sociology literature are various applications of sample selection regression models. These models separate the subjects into two groups based on some binary decision (the treatment) and then account for this selection decision when estimating the model outcome. If the researcher is interested in the outcome for both treatment groups, using switching regression model that assigns the groups into separate

Table 4.3: Number of firms with strategy bias

	Crabgrass	Broadleaf Weeds	Surface Insects	Subsurface Insects	Diseases
Preventive Bias	31 (69%)	12 (27%)	18 (40%)	19 (42%)	9 (20%)
Corrective Bias	7 (16%)	28 (62%)	18 (40%)	20 (44%)	28 (62%)
No Strategy Bias	7 (16%)	5 (11%)	9 (20%)	6 (13%)	8 (18%)

outcome regimes is appropriate (Goldfeld and Quandt 1973). Since this study is concerned with the pesticide intensity for both IPM and non-IPM groups, the amount of bias for both corrective and preventive groups, and the structure of technology for two different technology groups, a switching regression model will be used. Furthermore, since the IPM (strategy bias) and technology decisions are endogenous to the LCO, the model must incorporate this treatment effect through the use of an endogenous switch (Maddala and Nelson 1975).

Standard Endogenous Switching Regression Model

The standard endogenous switching regression model is specified as (Maddala 1983):

$$\begin{aligned} y_i &= x_{1i} \beta_1 + u_{1i} & \text{iff } Z_i \beta_0 \geq u_i \\ y_i &= x_{2i} \beta_2 + u_{2i} & \text{iff } Z_i \beta_0 < u_i \end{aligned} \quad (4.1)$$

where y_i represents the outcome of interest for sampling unit i and $Z_i \beta_0$ represents the criterion function that separates the sampling units into two separate regimes. The disturbance terms have a trivariate normal distribution with zero means and a covariance matrix

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{1u} \\ \sigma_{21} & \sigma_{22} & \sigma_{2u} \\ \sigma_{u1} & \sigma_{u2} & \sigma_{uu} \end{bmatrix}.$$

The likelihood function is written as (Maddala 1983)

$$L = \Pi \left[\int_{-\infty}^{Z_i \beta_0} g(y_i - x_{1i} \beta_1, u_i) du_i \right]^{I_i} \left[\int_{Z_i \beta_0}^{\infty} f(y_i - x_{2i} \beta_2, u_i) du_i \right]^{1-I_i} \quad (4.2)$$

where $I_i = 1$ iff $Z_i \beta_0 \geq u_i$ and $I_i = 0$ otherwise. The bivariate normal density functions of (u_{1i}, u_i) and (u_{2i}, u_i) are represented by g and f respectively.

With an endogenous criterion function, u_i is assumed correlated with u_{1i} and u_{2i} and thus σ_{1u} and σ_{2u} are parameters to be estimated. The disturbances u_{1i} and u_{2i} are typically assumed uncorrelated because only one regime is normally observed for each agent. Thus, the fact that σ_{12} does not appear in the likelihood function does not result in an estimation problem, since σ_{12} is assumed to be zero in most applications. All of the parameters of the model are estimated by maximizing the log-likelihood function (4.2).

Researchers have developed and applied variants of this standard endogenous switching model to analyze a wide range of issues. Spilerman (1972) studied interregional migration by applying a mover/stayer model that incorporates the decision to migrate. Lee (1978) modeled the effects of joining a union on wage rates, while more recently van Ophen (1993) studied the effects of public and private sector employment decisions on wages in the Netherlands. Another application to income differentials includes the study of education choice and the resulting incomes by Willis and Rosen (1979). Maddala (1983) develops a disequilibrium model of supply and demand using a switching regression framework. And in a recent publication in the sociology literature, Powers (1993) uses a variant of the endogenous switching model to estimate

the effect of family structure on early family formation.

What sets apart this study from those listed above is that, for any single economic agent, the disturbances for the five observations may be correlated both within and across regimes. Thus, the two regimes are specified as error component models and a two-step estimation procedure is used rather than the full-information maximum likelihood method.

Two variations on the standard model are developed below: (1) an endogenous switch composed of a random effects probit model that allows for interdependence between the five IPM decisions within each firm; and (2) a heteroscedastic error component model that allows for random effects both within and across regimes. In the first step, the parameters of the IPM (strategy bias) decision are estimated using a random effects probit model. The inverse Mill's ratio, calculated from the estimated parameters, is inserted into the two regimes to account for the nonrandom, endogenous selection decision. The pesticide intensity parameters and the strategy bias parameters are then estimated using estimated generalized least squares (EGLS) techniques. EGLS allows for correction of heteroscedasticity and for estimation of the correlation between disturbances within each firm, even across regimes.

Random Effects Probit Model for the IPM Decision

Error components models with continuous dependent variables have received much attention in the econometric literature. Until recently, however, the methods of estimating error components models with discrete data and the small sample properties of these methods has received very little attention. When using panel data, the error term is normally decomposed into two components: one component captures the unit or time specific disturbance, leaving a second disturbance component that satisfies the OLS properties. Thus, if the two components are $IID(0, \sigma^2)$, then the error components specification is a "parsimonious way of modeling positive correlation among observations within sampling units" (Guilkey and Murphy 1993, p. 301).

Reviews of probit models using panel data are provided by Maddala (1987) and Hsiao (1986 ch.7), while Guilkey and Murphy (1993) investigate the small sample properties of three different estimation methods for random effects probit models.

Different estimation methods for random effects probit models are distinguished by the manner in which the correlation between disturbances within a sampling unit is handled. Robinson (1982) showed that maximum likelihood (ML) methods provide consistent estimators even if the correlation between observations within a sampling unit are ignored. But since the coefficient standard errors are biased (Guilkey and Murphy 1993), the standard errors must be corrected in the manner suggested by Avery, Hansen, and Hotz (1985) to obtain correct results for hypothesis testing. Thus, the purpose of using the additional information on the correlation between observations in the estimation process is solely to improve the efficiency of the estimates, since consistent estimators can be obtained by ignoring the correlation. Guilkey and Murphy have shown in a simulation study that these corrected probit estimators perform quite well, even with small sample sizes.

Heckman (1976) proposed an asymptotically efficient ML method that takes into account the correlation between observations. Maximizing the log-likelihood function requires evaluating a complex integral, which may become very difficult for cases where the number of observations per sampling unit is large. Butler and Moffitt (1982) suggest using Hermite integration along with the BHHH maximization algorithm as a computationally efficient method for obtaining the ML estimators. This computational algorithm, along with the assumption of equicorrelated disturbances, makes evaluation of the integral tractable. Butler and Moffitt (1982) derive the log likelihood function for the equicorrelated random effects probit model.

Equicorrelation means simply that the correlation between disturbances within a sampling unit are some constant, resulting in all of the off-diagonal elements of the sampling unit

covariance matrix being equal. This assumption may be fairly safe if there are only a few observations per unit in a longitudinal data set (Chamberlain 1984) or, in the case of this study, the disturbances may be equicorrelated because the non-pesticide inputs are shared equally across all pests.

This assumption of equicorrelated disturbances should be tested. As Avery, Hansen, and Hotz (1983) note, ML will provide inconsistent estimates of the parameters if the covariance matrix is misspecified. Thus, in an attempt to improve the efficiency of the estimates, the researcher must be careful when specifying the covariance matrix or the consistency of the estimates will be lost. Two estimation methods that allow for a more general specification of the relationship between disturbances have been proposed. Avery, Hansen, and Hotz (hereafter referred to as AHH) develop an orthogonality condition (OC) estimator that is computationally tractable and possesses desirable large sample properties. This OC estimator, along with a nonlinear generalized least squares (NGLS) estimator developed by Chamberlain (1984), allow for both an unrestricted covariance matrix and interdependence between the random effects and the exogenous variables for all T observations.²⁶

The OC estimator for a random effects probit model is a member of the family of nonlinear instrumental variables estimators. The motivation for developing OC estimators came from the difficulty of implementing NGLS in the presence of heteroscedastic and correlated disturbances. The NGLS estimator is found by minimizing the weighted sum of squares of residuals

$$\frac{1}{N} \sum_{i=1}^N H(y_i, x_i, \beta)' \Omega_i^{-1} H(y_i, x_i, \beta) \quad (4.3)$$

where H is a T-dimensional vector of disturbances and $\Omega_i = E(H_i H_i' | x_i)$. Solving (4.3) requires

²⁶These two estimators are not as asymptotically efficient as ML.

estimates of Ω , which in turn requires consistent estimates of the parameters and elements of the covariance matrix. Since obtaining consistent estimates for the covariance matrix is computationally difficult as the number of observations per sampling unit increases, AHH suggest the alternative OC estimator.²⁷ With the OC estimator, consistent estimators of the weighting matrix and of the coefficients do not require a consistent estimate of the covariance matrix (AHH 1983). The OC estimator simplifies the estimation by correcting for the serial correlation in a linear manner (Maddala 1987).

Following the notations and derivations of AHH, the OC estimator is found by minimizing the criterion function given by

$$C(\beta) = \left[\frac{1}{N} \sum_{i=1}^N M(x_i, \beta) \right]' W_N \left[\frac{1}{N} \sum_{i=1}^N M(x_i, \beta) \right] \quad (4.4)$$

The first order conditions are

$$B_N \frac{1}{N} \sum_{i=1}^N M(y_i, x_i, \beta) = 0 \quad (4.6)$$

where B_N is a constant matrix that is "linked explicitly to the choice of the weighting W_N " (p.26) for a given choice of vector $M(y_i, x_i, \beta)$. AHH choose M such that the elements are the first derivatives of the likelihood function when the $E(u_i u_i' | x_i)$ is the identity matrix, with all observations treated symmetrically.

²⁷Chamberlain (1984) proposes a method for obtaining the covariance estimates and then obtains restricted NGLS estimates.

$$M(y_i, x_i, \beta) = \begin{bmatrix} M_0(y_i, x_i, \beta) \\ M_{+1}(y_i, x_i, \beta) \\ \vdots \\ M_{+t}(y_i, x_i, \beta) \\ M_{-1}(y_i, x_i, \beta) \\ \vdots \\ M_{-t}(y_i, x_i, \beta) \end{bmatrix} \quad (4.7)$$

where

$$M_0(y_i, x_i, \beta) = \sum_{t=1}^T \frac{f(x'_{it}\beta)x_{it}}{[1 - F(x'_{it}\beta)][F(x'_{it}\beta)]} h(y_{it}, x_{it}, \beta) \quad (4.9)$$

The vector x'_{it} includes elements that vary across the T observations within sampling unit i. M is a (k+8)-dimensional vector of "sample orthogonality conditions". The weighting matrix linked to this choice of M is

$$W_N = \begin{bmatrix} I_k & 0 \\ 0 & 0 \end{bmatrix} \text{ if } E(u_{it} | x_{it}) = 0 \quad (4.10)$$

That is, only the first k conditions M_0 are imposed. Under the additional assumption of strict exogeneity, all of the orthogonality conditions given in M are utilized. The weighting matrix is given as the inverse of

$$W_N^E = \frac{1}{N} \sum_{i=1}^N M_i M_i' \quad (4.11)$$

AHH propose both a Chi-square and a Wald-type test for strict exogeneity using results from Hansen (1982). If strict exogeneity holds, imposing all orthogonality conditions given in M will result in estimators that are more asymptotically efficient. The consistent parameter and covariance estimates are obtained by minimizing the criterion function (4.4) using the

orthogonality conditions specified in (4.5).

The approach taken in this study is to test for the assumption equicorrelation. If the equicorrelation assumption is rejected, unrestricted OC estimators will be obtained. If the equicorrelation assumption is not rejected, maximum likelihood methods using the procedure suggested by Butler and Moffitt will be used to obtain asymptotically efficient parameter estimates.

Once the parameter estimates are obtained, the inverse Mill's ratio for each observation is calculated and inserted into the pesticide intensity and strategy bias outcome regimes. These ratios are given as

$$\lambda_{it} = \frac{f(x_{it}\beta)}{F(x_{it}\beta)} \text{ for } I_{it} = 1$$

$$\lambda_{it} = -\frac{f(x_{it}\beta)}{1 - F(x_{it}\beta)} \text{ otherwise} \quad (4.12)$$

where $f(\cdot)$ and $F(\cdot)$ respectively are the probability and cumulative density functions for a normal distribution. Including these ratios in both regimes accounts for the nonrandom selection into groups.

Pesticide Intensity Outcomes

The pesticide intensity outcome for each pest is a function of netput prices, management knowledge, and the IPM sample selection variable. The disturbance terms among the five observations for each firm may be correlated since the five pesticide intensity outcomes are expected to be related. Failure to account for this correlation may result in inefficient parameter estimates. In addition, as Heckman (1976) shows, including the inverse Mill's ratio in the equations makes the disturbances heteroscedastic. Thus, generalized least squares (GLS) techniques must be employed to obtain parameter estimates that have desirable asymptotic properties.

Each regime is specified as an error components model. Hausman (1978) proposed a transformation to the variables to account for random effects within a sampling unit. Baltagi and Griffin (1988) extend this transformation to account for heteroscedastic disturbance terms. The Baltagi and Griffin method is used in this study to transform the variables, allowing for the random effects to occur across regimes for pesticide intensity outcomes, and then ordinary least squares procedures are used to obtain the parameter estimates.

Baltagi and Griffin propose the following transformation to correct for heteroscedasticity in a error components model:

$$(y_{it} - \theta_i \bar{y}_i) = (X_{it} - \theta_i \bar{X}_i) \beta + \epsilon_{it} \quad (4.13)$$

$$\text{where } \bar{y}_i = \sum_{t=1}^T \frac{y_{it}}{T}; \quad \bar{X}_i = \sum_{t=1}^T \frac{X_{it}}{T}; \quad \theta_i = 1 - \frac{\sigma_v}{\sigma_i}.$$

Since θ_i is unknown, σ_v and σ_i must be estimated. OLS residuals provide consistent estimates for σ_i . These estimates, combined with the estimated variance from the within regression of $(y_{it} - \bar{y}_i)$ on $(X_{it} - \bar{X}_i)$ provide estimates for θ_i .

In the first step, y_{it} is regressed on X_{it} to obtain the residuals $\hat{u}_{it}$. Write the equation for each firm $y_i = X_i \beta + \epsilon_i$ as

$$\begin{bmatrix} y_{i1} \\ \vdots \\ y_{im} \\ y_{i,m+1} \\ \vdots \\ y_{iT} \end{bmatrix} = \begin{bmatrix} X_{i,1} & 0 \\ \vdots & \vdots \\ X_{i,m} & 0 \\ 0 & X_{i,m+1} \\ \vdots & \vdots \\ 0 & X_{i,T} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \end{bmatrix}$$

where y_{it} and X_{it} are the natural logarithms of the dependent and independent variables and

(1...m) are the IPM observations and (m+1...T) are the observations for the non-IPM group.

Then, writing $y = [y_1 \ y_2 \ \dots \ y_N]'$, $X = [X_1 \ X_2 \ \dots \ X_N]'$, $\beta = [\beta_1 \ \beta_2]'$, $\epsilon = [\epsilon_1 \ \epsilon_2]'$, the OLS residual vector is $u = y - X\hat{\beta}$.

Next, the within regression of $(y_{it} - \bar{y}_i)$ on $(X_{it} - \bar{X}_i)$ produces $\hat{\sigma}_v^2$, which is a consistent estimate for σ_v^2 . Estimates for each sampling unit variance are then estimated as:

$$\hat{\sigma}_i^2 = T \left[\sum_{t=1}^T \frac{\hat{u}_{it}^2}{T} - \hat{\sigma}_v^2 \right] + \hat{\sigma}_v^2 \quad (4.14)$$

The transformation parameter is calculated as

$$\hat{\theta}_i = 1 - \left[\frac{\hat{\sigma}_v}{\hat{\sigma}_i} \right] \quad \forall \ i = 1 \dots N. \quad (4.15)$$

The variables are then transformed, substituting $\hat{\theta}_i$ for θ_i in (4.13) above. Baltagi and Griffin show that the OLS estimates for the two transformed regimes have the desirable asymptotic properties.

Strategy Bias Outcomes

The strategy bias estimates are obtained in a slightly different manner. First, two random effects probit models are estimated to account for the sample selection into the corrective and preventive bias groups. Using the inverse Mill's ratios from the probit models, strategy bias outcomes are estimated for each regime after transforming the variables to correct for random effects and heteroscedasticity. Note that the disturbances may be positively related within a regime, but not across regimes. Indeed, if the disturbances are correlated across regimes, the relationship would be negative. That is, positive errors for the preventive bias decision would

tend to be correlated with negative errors from the corrective bias decision, if a relationship exists. Thus, the Baltagi and Griffin transformation is performed on each regime separately rather than jointly, as in the pesticide intensity outcome model.

In summary, the estimation of the endogenous switching regression model requires the following steps: (i) estimation of a random effects probit model for the decision on whether or not to use IPM methods; (ii) calculation of the inverse Mill's ratio based on the random effects probit estimates; and (iii) estimation of the pesticide intensity and strategy bias outcomes by transforming the variables to correct for heteroscedasticity and random effects, and then using ordinary least squares techniques to obtain consistent and asymptotically normal estimates. In the next section, I report on the results of these estimation procedures.

4.3 ESTIMATION RESULTS

The IPM Decision

The preferred estimation method--corrected probit, equicorrelated ML, or orthogonality condition-- depends on the results of the equicorrelation hypothesis test. If the equicorrelation hypothesis fails to be rejected, then the equicorrelated ML method provides consistent and asymptotically efficient estimates. If the equicorrelation hypothesis is rejected, then the corrected probit or orthogonality condition estimators are preferred.

Bivariate probit estimates were obtained for the covariances between each pair of pests. These estimates and their standard errors are presented in Table 4.4. Also listed are the results of a chi-square test of the hypothesis that all of these covariances are equal and a likelihood ratio test for zero correlation between disturbances. Based on the covariance estimates, the hypothesis of equicorrelation failed to be rejected, while the hypothesis of zero correlation between all disturbances is rejected. Thus, the tests support the use of a random effects equicorrelated probit

Table 4.4: Error covariance estimates

	Annual Grasses	Broadleaf Weeds	Surface Insects	Subsurface Insects
Broadleaf Weeds	0.82252 (0.1781)			
Surface Insects	0.26200 (0.3865)	0.51948 (0.2844)		
Subsurface Insects	0.78352 (0.3839)	0.22738 (0.2871)	0.40937 (0.2200)	
Diseases	0.99812 (7.873)	0.54230 (0.6802)	0.56278 (0.4359)	0.54076 (0.2743)
Equicorrelation test: $X^2=8.729$, nine d.f. (0.5373 significance level)				
Random effects test: $X^2=16.650$, one d.f. (0.00004 significance level)				

Estimated standard errors in parentheses.

Coefficients and standard errors obtained by bivariate probit ML estimation.

model.

The IPM decision, as specified in (3.5) and (3.6), is a function of netput prices, management knowledge, and specific pest effects. Since this decision is based on the relative rather than the absolute prices between corrective and preventive pesticides, the price ratio of corrective to preventive pesticides is used instead of the absolute netput prices. This price ratio is the only variable that is not constant across all pests.

The parameter estimates and standard errors of the IPM decision model are presented in Table 4.5. The log-likelihood value for the IPM model is -123.8153. The random effects equicorrelated ML estimates are listed in the first column of Table 4.5, and the probit estimates that do not take into account the error covariances between pests are listed in the second column. Estimates of the coefficient standard errors given in parentheses are uncorrected for error correlations; the standard errors in brackets are corrected for error correlations following the

Table 4.5: Parameter estimates for the IPM decision

Variable	Coefficient ¹ (Std. error)	Coefficient ² (Std. error) [Corrected std. error]
Crabgrass intercept	-0.20058 (0.2410)	-0.32972 (0.6076) [0.7638]
Broadleaf weeds intercept	-1.2587** (0.2238)	-1.38333 (0.5958) [0.7588]
Surface insects intercept	-0.88481** (0.2331)	-0.99965 (0.5926) [0.7621]
Subsurface insects intercept	-0.83365** (0.2314)	-0.9452 (0.5932) [0.7416]
Diseases intercept	-1.4905** (0.2533)	-1.60157* (0.6132) [0.7325]
Pest control/insurance price	-0.00162 (0.0023)	-0.00202 (0.0060) [0.0074]
Maintenance/mowing price	-0.00020 (0.0006)	-0.00013 (0.0014) [0.0015]
Skilled labor price	0.00540 (0.0077)	0.00554 (0.0178) [0.0206]
Unskilled labor price	0.05935** (0.0212)	0.06623 (0.0556) [0.0720]
Fertilizer price	0.18880 (0.1280)	0.14976 (0.3002) [0.2824]
Equipment price	0.00007 (0.00004)	0.00008 (0.00009) [0.0002]
Corrective-to-preventive pesticide price ratio	0.16625** (0.0397)	0.21860* (0.0982) [0.0912]
Management knowledge	-0.01302** (0.0037)	-0.01151 (0.0088) [0.0134]
Covariance	0.63105** (0.0415)	N/A

Notes: Dependent variable is the no-IPM decision (0 or 1).

¹Random effects probit assuming equicorrelation.

²Standard probit maximum likelihood estimators.

* statistically significant at $\alpha=.05$; ** statistically significant at $\alpha=.01$.

method of AHH. Almost all of the uncorrected standard errors are biased downwards. This lends empirical support for the Monte Carlo results of Guilkey and Murphy (1993). The gain in efficiency achieved by taking into account the equicorrelation between pests is quite substantial. This result differs from those obtained by Guilkey and Murphy (1993). In their simulation using 50 sampling units and 5 time periods, the corrected probit standard error estimates and the equicorrelated ML estimates are very similar.

The two output prices for pest control/insurance and maintenance/mowing are not significant in explaining the decision on whether or not to use IPM methods. Regarding input prices, skilled labor is not a significant determinant, while the prices for equipment and fertilizer are almost significant at $\alpha = .05$. The most important determining factors are the prices of unskilled labor, the corrective-to-preventive pesticide price ratio, the level of management knowledge, and the type of pest. Firms are more likely to use IPM methods to treat diseases and broadleaf weeds, less likely with surface and subsurface insects, and least likely with crabgrass. For any pest, the higher the level of management knowledge, the higher the probability that IPM methods will be used. This result supports the research of Pingali and Carlson (1985), who found that schooling and experience lead to higher levels of IPM practices. IPM theory also suggests that labor, through scouting for pests, is a substitute for chemical means of pest control. This hypothesis is supported by these findings; as the price of unskilled labor increases, the probability of using IPM methods decreases. The probability also decreases as the price of corrective pesticides relative to the price of preventive pesticides increases. As it becomes relatively cheaper to treat pests preventively, less IPM methods will be used.

The strategy bias effect is evident in the input price of unskilled labor and the pesticide price ratio. As the price of under-predicting pest damage rises relative to over-predicting pest damage, the firm shifts its planned action upwards from the action associated with the expected

state. If pest damage is under-predicted, more unskilled labor and corrective pesticides must be hired. As this penalty increases relative to the penalty for over-predicting pest damage, the firm shifts the planned pesticide intensity upwards from the expected pest damage to maximize expected profits. For a lawn care firm, this action results in applying preventive pesticides to more turf area than is expected to be damaged. In other words, the firm decides against IPM methods in favor of the cheaper preventive pesticide applications.

Strategy Bias Outcomes

Using the functional form specified in (3.8), the parameters of the preventive and corrective strategy bias outcomes are estimated. For both the preventive and corrective bias outcomes, only the adjustment for heteroscedasticity is used since no positive correlation between the disturbances is evident. The corrective bias outcome is estimated using the method described in Section 4.2.

The coefficients and standard errors are listed in Table 4.6. The adjusted R^2 is 0.27 and 0.37 respectively for the preventive and corrective bias regimes. Of special interest are the interaction effects of management knowledge on the level of bias. In all cases, as management knowledge increases, the effect of the input prices on strategy bias diminishes as the theory would suggest. For the preventive bias regime, increases in the preventive pesticide price and decreases in the corrective pesticide price lead to lower levels of strategy bias. For the corrective bias group, non-pesticide input prices rather than pesticide prices are the important determinants of the level of bias. These results suggest that the corrective bias group is substituting IPM inputs for pesticides based on the prices it faces in the market.

The negative significant coefficient for the Inverse Mill's ratio for the corrective bias group suggests that firms engaging in corrective strategy bias have a larger bias than is expected for the general population. For the preventive bias group, the negative coefficient for the Inverse

Table 4.6: Strategy bias results

Variable	Corrective Bias: Coefficient (std. error)	Preventive Bias: Coefficient (std. error)
Intercept	0.3608 (1.624)	4.8020** (1.987)
Pest Control/Insurance Price	-0.2151 (0.896)	0.3007 (1.015)
Mgmt. Knowledge interaction	0.0218 (0.056)	0.0070 (0.046)
Mowing/Maintenance Price	-0.5581 (0.483)	-0.9045 (0.592)
Mgmt. Knowledge interaction	0.0429 (0.028)	0.0324 (0.031)
Skilled Labor Price	0.8904 (0.594)	-0.4839 (0.591)
Mgmt. Knowledge interaction	-0.0256 (0.038)	0.0568* (0.024)
Unskilled Labor Price	0.6546 (0.951)	1.4741 (1.080)
Mgmt. Knowledge interaction	-0.0169 (0.048)	-0.1238** (0.045)
Fertilizer Price	1.2279 (0.655)	-1.2438 (1.069)
Mgmt. Knowledge interaction	-0.0534 (0.036)	0.0313 (0.047)
Equipment Price	0.5134** (0.160)	0.1117 (0.189)
Mgmt. Knowledge interaction	-0.0299* (0.013)	-0.0110 (0.008)
Preventive Pesticide Price	-0.5447 (0.518)	-0.8237** (0.255)
Mgmt. Knowledge interaction	0.0232 (0.020)	0.0369** (0.015)
Corrective Pesticide Price	-0.0948 (0.534)	0.6770 (0.364)
Mgmt. Knowledge interaction	-0.0021 (0.021)	-0.0327* (0.015)
Inverse Mill's Ratio	-0.6455** (0.269)	-0.4277 (0.264)

Notes: Dependent variables are the levels of corrective and preventive bias;
coefficients obtained using GLS.

* statistically significant at $\alpha=.05$; ** statistically significant at $\alpha=.01$.

Mill's ratio suggests that firms engaging in preventive bias have a smaller bias than would be expected for the general population.

Pesticide Intensity Outcomes

For each regime, pesticide intensity is a function of the netput prices, management knowledge, and the Inverse Mill's ratio as given by equation (3.7). Netput prices are assumed exogenous to the firm. Firms face a price in the market for each input and output and decide only on the level, not price, for each netput. If this assumption does not hold, then the regressors will be correlated with the disturbance term and the resulting parameter estimates will be inconsistent. However, based on personal experience in the lawn service industry on Long Island and information provided by industry leaders (see Section 3.1), this assumption about exogenous prices seems reasonable for the case of the Long Island lawn service firm.

The parameters are estimated using the natural logarithms of the dependent and independent variables. The test statistic for the hypothesis for the hypothesis of no difference between ex post and ex ante technology is $F_{(8,205)} = 1.8428$ (.0709 significance level). Since this hypothesis is rejected at the 7% significance level, the model was re-estimated without imposing the equal slopes constraints. The conclusion is that differences exist between ex ante and ex post technologies and therefore the sufficient condition for asymmetric input penalties holds in this case.

The coefficients and standard errors are listed in Table 4.7. The selection into the group is the only statistically significant factor (at $\alpha = .01$) in determining pesticide intensity for the non-IPM group. The price ratio of corrective-to-preventive pesticides is statistically significant at $\alpha = .10$. The higher the price of corrective pesticides to preventive pesticides, the higher the pesticide intensity outcome. For the IPM group, the higher the price of pest control/insurance output, unskilled labor, fertilizer, and the pesticide price ratio, the higher the pesticide intensity

Table 4.7: Pesticide intensity results

Variable ¹	IPM regime Coefficient (std. error)	Non-IPM regime Coefficient (std. error)
Intercept	-3.8527 (4.637)	2.3304 (3.745)
Pest Control/Insurance Price	2.0965* (0.943)	-0.1847 (1.121)
Mowing/Maintenance Price	-2.1518* (0.996)	0.3901 (0.998)
Skilled Labor Price	-1.0087 (0.843)	0.1866 (1.162)
Unskilled Labor Price	4.7584** (1.302)	-0.1397 (1.119)
Fertilizer Price	2.5726** (0.966)	-0.4013 (1.447)
Equipment Price	0.6614 (0.355)	0.0111 (0.180)
Corrective to Preventive Pesticide Price Ratio	0.5633* (0.262)	0.2867 (0.172)
Management Knowledge	-0.7667 (0.551)	-0.0227 (0.638)
Inverse Mill's Ratio	-0.6547 (0.359)	0.8549** (0.269)

Notes: Dependent variable is pesticide intensity; coefficients obtained using GLS.

* statistically significant at $\alpha=.05$; ** statistically significant at $\alpha=.01$.

¹Natural logarithms of the variables are used to estimate the parameters.

outcome. Higher prices of mowing/maintenance output and skilled labor and higher levels of management knowledge lead to a lower pesticide intensity outcome.

The implications of strategy bias for resource allocation are measured through the coefficients on the Inverse Mill's ratios. These coefficients suggest that the results for each regime depend not only on differences in prices, but also on the strategy bias decision. In the case of the IPM group (corrective strategy bias), pesticide intensity is relatively lower than would

be expected for the general population, given the values of prices and the level of management knowledge. Just the opposite is true for the non-IPM group, where pesticide intensity is relatively higher than would be expected for the general population. Preventive strategy bias leads to an absolute increase in the use of polluting inputs in this case.

In summary, the results of the empirical model applied to the LCO support the theoretical concept of strategy bias. Evidence is found that a comparative advantage is gained by engaging in strategy bias, with the level of strategy bias diminishing as management knowledge increases. And in this case, strategy bias results in differences in relative resource allocation and the increased use of polluting inputs. In the next chapter, I turn attention to using the results for policy analysis.

5. POLICY ANALYSIS

The results of the empirical model for the decision on whether or not to use IPM methods and the resulting pesticide intensity outcome provide for interesting policy analysis. The purpose of this chapter is to discuss how alternative policies can be expected to affect producer incentives and consequently, the intensity of pesticide use by a LCO. In the first section, the development of current lawn pesticide regulations is reviewed. This policy-making process has historical parallels with agricultural pesticide policy development and is shown to be theoretically consistent with a cost-effective agency decision model. The discussion provides a motivation for the current focus on pesticide-reducing policies. The effects of taxes and selected regulations on pesticide intensity by a LCO are identified in the second section.

5.1 POLICY DEVELOPMENT

Parallels with Agricultural Policy²⁸

It was not until after World War II that pesticide use in agriculture became widespread. As some early USDA researchers had warned, this increased pesticide use resulted in social costs which offset, to some degree, the benefits of increased crop yield. Contamination of groundwater and surface water, worker illness from exposure, unintended poisoning of fowl and wildlife, and potential illness from pesticide residues on food are the most serious of these costs associated with pesticide use. As public awareness of these problems increased, regulations that focused on reducing exposure to pesticides were enacted.

This concern about pesticides led scientists to investigate the tradeoffs involved in using

²⁸For a detailed account of the politics of agriculture pesticide policy development, see Bosso (1987).

pesticides to increase crop yields. The biggest problem confronting these researchers was the difficulty in measuring and assessing the risk to society. Without a concrete risk estimate, comparing the costs and benefits of reduced pesticide use to obtain the optimal level of pesticide use (in terms of social welfare) was very difficult. Consequently, multidisciplinary research by natural and social scientists concentrated on developing new pesticides and production methods that reduced risk without reducing crop yields and profits. The emphasis switched from reducing pesticide exposure to reducing pesticide use. This research led to the development of integrated pest management (IPM) methods.

The IPM approach to pest control utilizes a combination of chemical, biological, cultural, and genetic controls and, perhaps most importantly, information gathering activities. These activities include frequent scouting of the fields for pests, investing in education, and taking advantage of previous experience. Studies of farm production technology have supported the idea that substitution possibilities exist between pesticides and IPM inputs in producing many crops. The more surprising result from some of these studies is that IPM methods cost very little to implement on many crops. As a result of this research, IPM in agriculture has seen a steady increase in recent years.

According to recent USDA figures, total farm pesticide use on major crops has remained relatively stable at about 450 million pounds of active ingredient per year (Environmental Almanac, 1992). This amount represents a 200 million pound decline from the peak experienced in 1976. Part of this decline is attributed to the 3.9% decline in farm acreage during the period from 1975 to 1985, but clearly the substitution of IPM inputs for pesticides reduced the pesticide intensity per acre and played a significant role in reducing farm pesticide use.

In stark contrast to this trend in farm pesticide use, both the acreage treated and the intensity of pesticide use on lawns increased in urban areas during the 1980's. This growth is

analogous to the growth in production and pesticide use in the agricultural sector following World War II. To many health regulators and citizens, perhaps the biggest concern regarding this shift towards more lawn pesticide use is the fact that agricultural pesticides are now applied in highly populated areas.

Just as in agricultural policy, the first emphasis at the state level has been placed on minimizing the health risk to workers and consumers exposed to pesticides. These regulations have focused on the dissemination of information to reduce the number of consumer and worker pesticide exposure occurrences. Table 5.1 includes a list of several of these use and application laws for a sample of states. If lawn pesticide regulations follow the development of agricultural policy, the next step is to consider policies that focus on reducing use rather than exposure to pesticides.

Cost-Effective Decision Model

A cost-effective agency decision model also provides a motivation for analyzing pesticide-reducing policies. The hypothesis is that policies that control exposure reduce health risk initially at lower cost than policies that reduce pesticide use. If these exposure policies have diminishing marginal returns, however, additional risk reduction may be achieved most effectively through the use of pesticide-reducing policies. Thus, as citizens desire a reduction in the risk level over time, both pesticide-reducing and exposure control policies are used to cost-effectively control health risk from pesticides.

Several researchers have formalized this cost-effective agency decision process. The cost-effective objective is to minimize cost subject to meeting a certain risk level. Following Crouch and Wilson (1981), health risk is explained as a product of environmental and demographic variables. Assuming that these parameters have a joint lognormal distribution and taking the log of health risk, denoted R , the Crouch and Wilson model is written as

Table 5.1: Use and Application Laws for a Sample of States

REGULATION / STATE	NJ	NY	PA	CT	OH
Applicator Testing	✓	✓	✓	✓	✓
Storage Requirements	✓	✓	✓	✓	✓
Transportation Requirements	✓	✓	✓	✓	✓
Written Contracts		✓			
Customer Prenotification	✓	✓			
Neighbor Prenotification		✓			
Sign Posting	✓	✓		✓	✓
Business Licensing	✓	✓	✓	✓	✓
DIY Sign Posting				✓	

$$R = \sum_{i=1}^n X_i \quad (5.1)$$

where X_i is the log of the i th explanatory parameter. The mean and variance of the log of health risk is written as

$$\mu_R = \sum_{i=1}^n \mu_i; \quad \sigma_R^2 = \sum_{i=1}^n \sigma_i^2 + \sum_{i \neq j} r_{ij} \sigma_i \sigma_j \quad (5.2)$$

where μ_i and σ_i^2 are the mean and variance of X_i , respectively. The mean, μ_R , is the best-guess estimate of the log of health risk, and the variance of the log risk is a measure of the uncertainty of the estimate.

As noted above and as emphasized by Lave (1982) among others, risk assessments are subject to uncertainty due to errors in measurement and extrapolation. Lichtenberg and Zilberman (1988) propose a cost-effective framework that uses a safety rule to explicitly

incorporate this uncertainty into the risk management decision. Let S represent the desired safety level, such that S equals the probability that the health risk does not exceed some maximum allowable level, denoted R_o . Let R_s denote the level of log risk exceeded with probability $1-S$. Denoting F_s as the value of the standard normal which is exceeded with probability $1-S$, R_s is expressed as

$$R_s = \mu_R + F_s \sigma_R = \sum_{i=1}^n \mu_i + F_s \left[\sum_{i=1}^n \sigma_i^2 + \sum_{i \neq j} r_{ij} \sigma_i \sigma_j \right]^{\frac{1}{2}} \quad (5.3)$$

Implementing the safety rule requires that R_s not exceed R_o . Uncertainty, weighted by the desired safety level, has been incorporated into the risk assessment model through the use of the second term on the right side of (5.3).

The agency objective is to choose a set of policies that minimize cost subject to meeting the safety level of risk.

$$\text{Min } C(k) \quad \text{s.t. } R_s(k) < R_o \quad (5.4)$$

where k is a vector of policies. Each policy imposes social costs but also reduces the mean and/or variance of a risk variable. Thus, each policy carries with it a risk/cost tradeoff. Lichtenberg and Zilberman show that at the optimum, the marginal cost of reducing risk will be equal across all policies.

Lichtenberg, Zilberman, and Bogen (1989) applied this model to analyze pesticide regulations to reduce groundwater contamination. Pesticide health risk is the product of the amount of pesticides applied, the number of worker and consumer exposure occurrences, the uptake rate, and the dose-response rate. Thus, pesticide health risk is a linear function of the logarithms of these four variables,

$$R_s = \sum_{i=a,e,u,r} \mu_i(K,v) + F_s \left(\sum_{i=a,e,u,r} \sigma_i^2(K,v) + \sum_{i \neq j} r_{ij} \sigma_i(K,v) \sigma_j(K,v) \right)^{\frac{1}{2}} \quad (5.5)$$

where μ_a is the mean log amount of pesticides applied, μ_e is the mean log of worker and consumer exposure occurrences, μ_u is the mean log of the uptake rates, μ_r is the mean log of the dose-response rates, and σ_i is the standard deviation of these variables. Most state policies (e.g., lawn sign posting and storage and disposal requirements) are aimed at reducing the mean amount of pesticide exposure occurrences. Federal regulations, on the other hand, often focus on reducing the uncertainty (variance) of a variable. An example is the requirement of more research on the dose-response relationship before a pesticide can be registered. A list of lawn pesticide policies and their effects on risk parameters is presented in Table 5.2.

Absent from the current policy portfolios are regulations which encourage a reduction in the amount of pesticides used. Assuming this risk parameter (X_a) is controllable and the agency objective is to minimize the cost of risk-reduction, the null hypothesis is that policies which affect X_a are inefficient compared to current policies in achieving the current level of health risk. The agriculture literature has suggested that X_a -reducing (IPM) policies can be implemented on some crops at very small loss in welfare, implying that current policies may be inefficient in reducing risk.²⁹ However, since the lawn production problem differs from the production problem for most agricultural crops, the results from the agriculture experience are not directly transferable to the case of reducing lawn pesticide use. What is needed is additional research into the cost of lawn pesticide-reducing policies, with the agriculture success stories illustrating the potential return on such a research investment.

Policies that may reduce pesticide use include direct factor taxes on pesticides and inputs

²⁹Some studies have found that profits actually increase with the implementation of IPM methods.

Table 5.2: Risk Affects for a Sample of Regulations

REGULATION / PARAMETER	X_a	X_e	X_u	X_r
Applicator Testing	?	Mean	-	-
Storage Requirements	-	Mean	-	-
Transportation Requirements	-	Mean	-	-
Pesticide Labelling	-	Mean	-	-
Customer Prenotification	-	Mean	-	-
Banning a Pesticide	-	-	Mean	Mean
Sign Posting	-	Mean	-	-
Dose-response Research	-	-	-	Var

that are complements with pesticides, subsidies for substitute inputs, an output tax on lawn care service, and command-and-control regulations such as mandatory pesticide applicator licensing and direct controls on pesticide use per acre. The results of the empirical model are used in the next section to determine how these different policy options affect the producer decisions to use integrated pest management techniques and thereby reduce the pesticide intensity on the total area treated by the LCO.

5.2 POLICY EVALUATION

Uncertainty about naturally-occurring pest damage cannot be removed from the system. One actor must bear the uncertainty. In the professional lawn care market, the consumer has shifted the uncertainty to the producer. By accepting the uncertainty, the LCO has an incentive to use preventive pest treatment methods. These methods have lowered total resource costs for the firm, but increased the use of polluting inputs to treat any given pest population. If the goal is to reduce pesticide use by lawn care firms, policies must be designed to provide the proper

incentives for producers to change behavior.

In this section, results from the empirical model are used to measure policy effects on IPM use and pesticide intensity levels by producers. Three types of policies are considered: (i) a government mandate that disallows preventive strategy bias and thereby requires use of IPM methods, (ii) taxes on netput prices, and (iii) education and training programs that provide an incentive to use more IPM methods and less pesticides. These policies provide incentives for firms to reduce pesticide use but, by increasing production costs, most likely increase the use of do-it-yourself pesticides as consumers substitute DIY products for professional services. While measuring these changes in homeowner do-it-yourself pesticide use is beyond the scope of this study, it is important to remember that the policy effects as reported in this section should be interpreted as only one component of a comprehensive policy impact assessment.

The pesticide intensity model estimated in Chapter 4 allows us to predict the decrease in producer pesticide intensity if all firms were to use IPM methods at the given prices. For example, a policy could be implemented whereby pesticide treatments applied before a specific date for a specific pest must not exceed the county extension agent's predicted level of pest damage. This policy would eliminate preventive strategy bias and thereby mandate the use of IPM methods. The change in pesticide intensity that would occur if a pest currently treated on a non-IPM program were treated with IPM methods is calculated as (Maddala 1983 p.261)³⁰

$$y_{1i} - X_i\beta_2 - \sigma_{2\epsilon} \frac{\phi(X_0\beta_0)}{\Phi(X_0\beta_0)} \quad (5.6)$$

In the current sample of 45 firms, the average reduction in pesticide intensity for those pests treated with non-IPM methods if all firms switched to using IPM methods is 11.65. In other

³⁰The sign on $\sigma_{2\epsilon}$ is reversed to reflect the difference in the definition of the inverse Mill's ratio.

words, on average 11.65 percent less turf area would have been treated with pesticides if firms had not engaged in preventive strategy bias. The total reduction in lawn area that would be treated with pesticides is 670 acres. This reduction in producer pesticide intensity assumes no changes in output or input prices. To the extent that firms could pass along the increased costs of production associated with using IPM methods, the total reduction in pesticide intensity would depend upon the price elasticity of demand for LCO pest control and the resulting increase in DIY pesticide intensity. If the current sample is representative of the total population of 550 firms, then the total area of turf treated with pesticides would be reduced by 8,189 acres. The potential³¹ and actual amount of turf treated with pesticides and the reduction in treated area if IPM methods are used for all pests is listed in Table 5.3. The amounts are listed for firms in the sample and extrapolated to the entire population of 550 firms.

Table 5.3: Preventive strategy bias effect on pesticide use

	Sample	Population
Maximum potential area treated with pesticides (acres)	9,152.8	111,663.9
Total area treated with pesticides (acres)	5,565.3	67,896.7
Reduction in turf area treated with pesticides by eliminating preventive strategy bias (acres)	670	8147.6
Percent reduction in turf area treated with pesticides by eliminating preventive strategy bias	12%	12%

A command-and-control regulation dictating the use of IPM methods and corrective pesticide applications is one option to reduce pesticide use. Economists often argue, however,

³¹The potential amount of turf that could be treated with pesticides is defined as treating 100% of output with pesticides for all five pests.

that a direct tax on pollution is the most cost-effective policy instrument to achieve a certain level of reduction in aggregate pollution levels. For non-point source pollution such as pesticides, the polluter often cannot be identified and therefore a tax on pesticide runoff or leachate becomes difficult or impossible to administer. In this case, a tax on the potential source of pollution--the use of pesticides--is often thought to be the next best alternative. Pesticide use could also be affected by taxing pest control output and other inputs besides pesticides, as well as command-and-control regulations that mandate higher levels of turfgrass experience and education.

Each tax or regulation may effect both the probability of using IPM methods and the potential pesticide intensity outcome. The change in probability that a firm will use IPM methods to treat pest damage resulting from a marginal change in a netput price or the level of management knowledge will be called the marginal treatment effect. Writing the expected probability of not using IPM methods as $\Phi(\beta'_0 X_0)$, the marginal treatment effect is (Greene 1990)

$$MTE = \frac{\partial \Phi(\beta'_0 X_0)}{\partial X_k} = \phi(\beta'_0 X_0) \beta_k \quad (5.7)$$

where X is the vector of explanatory variables in the model. Using (5.7) and the means of the explanatory variables, the marginal treatment effects were estimated for all netput prices and the level of management knowledge. Table 5.4 lists these effects, along with the standard errors of the estimates.³²

The marginal treatment effects shed light on how taxes provide an incentive for firms to change behavior. First, firms are not expected to change their probability of using IPM methods in response to marginal changes in the prices of pest control/insurance and mowing/maintenance outputs or a change in the price of skilled labor. Increases in the price of fertilizer, however,

³²Following Greene (1990), the asymptotic covariance matrix is given as $G \text{Var}[B] G'$, where $G = \frac{\partial MTE}{\partial \beta} = \phi I - \phi(\beta'_0 X_0) \beta_0 X'_0$.

Table 5.4: Marginal treatment effects

Variable	Marginal Treatment Effect	Standard Error
Pest Control/Insurance Price	-0.00062	0.00089
Mowing/Maintenance Price	-0.00008	0.00022
Skilled Labor Price	0.00207	0.00294
Unskilled Labor Price	0.02273**	0.00810
Fertilizer Price	0.07229	0.04906
Equipment Price	0.00003	0.00001
Corrective to Preventive Pesticide Price Ratio	0.06366**	0.01540
Management Knowledge	-0.00498**	0.00141

* statistically significant at $\alpha=.05$; ** statistically significant at $\alpha=.01$.

will increase the probability that a firm will not use IPM methods. Thus, a tax on fertilizer to reduce nitrate pollution will lead to the increased probability of engaging in preventive strategy bias and, therefore, decrease the probability of using IPM methods. A marginal change in the price of corrective pesticides relative to preventive pesticides will also decrease the probability of using IPM methods. Thus, the behavioral model suggests that taxing preventive pesticides, at least relatively more than corrective pesticides, will provide an incentive for producers to increase the use of IPM methods. A marginal increase in the price of unskilled labor also leads to an increased probability of not using IPM methods. Since higher prices for labor lead to increased pest scouting costs, this labor price effect is easily explained by IPM theory. Marginal increases in the price of equipment also have a significant negative effect on the probability of using IPM methods. The effect, however, is very small. Finally, marginal increases in the level of management knowledge increase the probability of using IPM, as expected from IPM theory and the empirical work of Pingali and Carlson (1985), among others.

The total effect on the expected potential change in pesticide intensity of a marginal change in one of the explanatory variables consists of two components (McDonald and Moffitt 1980). The first is the change in pesticide intensity for those in the regime, weighted by the probability of being in the regime. The second part is the change in the probability of being in the regime, weighted by the expected pesticide intensity if in the regime. The total effect of a marginal change in the value of an explanatory variable is written as (Poirier and Ruud 1981 p.253)

$$\frac{\partial E(y_{1i})}{\partial X_{ik}} = \beta_{1k} - \beta_{0k} \sigma_{1\epsilon} \frac{\phi(X_i \beta_0)}{\Phi(X_i \beta_0)} \left[X_i \beta_0 + \frac{\phi(X_i \beta_0)}{\Phi(X_i \beta_0)} \right] \quad \forall \text{ non-IPM observations} \quad (5.7a)$$

$$\frac{\partial E(y_{2i})}{\partial X_{ik}} = \beta_{2k} + \beta_{0k} \sigma_{2\epsilon} \frac{\phi(X_i \beta_0)}{1 - \Phi(X_i \beta_0)} \left[X_i \beta_0 + \frac{\phi(X_i \beta_0)}{1 - \Phi(X_i \beta_0)} \right] \quad \forall \text{ IPM observations} \quad (5.7b)$$

Using (5.7a) and (5.7b) and the means of the explanatory variables, the total potential effect on pesticide intensity resulting from a marginal change in each explanatory variable is calculated. Table 5.5 lists these effects.

For the IPM regime, marginal increases in the prices of unskilled labor and fertilizer lead to increases in pesticide intensity, suggesting that pesticides are substitutes for these inputs in the production process. Thus, a tax on fertilizer with the objective of reducing nitrate pollution can be expected to result in increased pesticide pollution by producers, assuming that all other prices are held constant. A marginal increase in the ratio of corrective to preventive pesticide prices also increases pesticide intensity, suggesting that any tax on pesticides should be applied at a higher rate to preventive compared with corrective pesticides if the policy goal is to reduce pesticide intensity. An increase in the price of pest control/insurance and a decrease in the mowing/maintenance output price lead to increased pesticide intensity. The increase in pesticide

Table 5.5: Total potential pesticide intensity effects

Variable	IPM Regime	Non-IPM regime ¹
Pest Control/Insurance Price	2.0958	N/A
Mowing/Maintenance Price	-2.1519	N/A
Skilled Labor Price	-1.0065	N/A
Unskilled Labor Price	4.7824	N/A
Fertilizer Price	2.6490	N/A
Equipment Price	0.6614	
Corrective to Preventive Pesticide Price Ratio	0.6306	0.1959
Management Knowledge	-0.7614	N/A

¹Due to the large standard errors of the coefficients, only the potential effect of changes in the pesticide price ratio can be estimated with any confidence.

use that results from this increased pesticide intensity may be more than offset by the expected decrease in aggregate output. The Minnesota study mentioned in Chapter 3 found that the demand for professional lawn service is fairly elastic at the current price point and, therefore, a decrease in aggregate output should be expected with a marginal increase in the price of pest control. Marginal increases in the level of management knowledge decrease pesticide intensity as expected. Cooperative extension seminars and field training classes are examples of policies that would increase the level of management knowledge and thereby decrease pesticide intensity.

In the non-IPM regime, note that marginal increases in the corrective to preventive pesticide price ratio also has a positive effect on pesticide intensity. The marginal effects of the other explanatory variables cannot be presented with confidence, given the large standard errors of the estimators. The absence of marginal effects for the non-pesticide inputs is not surprising, given that only the pesticide prices are significant in determining the level of preventive strategy bias. If the non-IPM group over-predicted pest damage, then pesticide intensity is totally

determined by the decision to use preventive strategy bias and the important factors in determining the level of bias (i.e., the pesticide price ratio).

In summary, expected pesticide intensity is reduced for the non-IPM group when policies provide incentives to increase the probability that IPM methods will be used and to decrease the level of preventive bias. For the IPM group, expected pesticide intensity is reduced by policies that provide an incentive to substitute IPM inputs for pesticides. A significant determinant of both the probability of using IPM methods and the resulting level of pesticide intensity is the corrective to preventive pesticide price ratio. Thus, taxes that increase the price of corrective pesticides relative to preventive pesticides provide an incentive for firms to reduce pesticide use, while a proportionate tax on all pesticides may have little or no input substitution effect, providing only a smaller expected reduction in pesticide use due to an output effect. In addition, the results suggest that a tax on fertilizer to reduce nitrate pollution may, in fact, lead to increased pesticide pollution by producers. Policymakers, therefore, should jointly consider both nitrate and pesticide pollution when devising a policy portfolio. Finally, a policy that disallows preventive bias is expected to lead to a significant reduction in pesticide intensity by producers.

6. CONCLUSION

6.1 SUMMARY OF FINDINGS

Producers in many markets face uncertainty about production costs at the beginning of the production process. In this study, I propose that expected profit maximizing producers plan actions at the beginning of the process based on the expected penalties for over and under-predicting the uncertain event. If the expected penalty functions are asymmetric, as is commonly the case, input and output levels may deviate from the levels associated with the predicted state of nature. The conditions under which this shifting of resource levels, or strategy bias, may occur are set forth and empirically tested using data collected from a sample of professional lawn care firms. The empirical evidence supports the theoretical concept that firms engage in strategy bias to maximize expected profits. Strategy bias does occur in this lawn service market due to differences in ex ante and ex post technology that cause asymmetric penalties between over and under-predicting the level of naturally-occurring pest damage. In this case, preventive strategy bias results in a significant increase in the amount of turf area treated with pesticides, a polluting input.

The most important factors in determining whether or not IPM techniques are used are the price of unskilled labor, the corrective-to-preventive pesticide price ratio, the level of management knowledge, and the type of pest. For the non-IPM group, the most significant factor in determining pesticide intensity is the price ratio of corrective-to-preventive pesticides. For the IPM group, the output prices for pest control/insurance and mowing/maintenance, the input prices for unskilled labor and fertilizer, and the corrective-to-preventive pesticide price ratio are all significant determinants for the intensity of pesticide use.

The results suggest that policymakers can use economic incentives, such as taxes, to

encourage producers to use IPM practices and reduce the reliance on pesticides to control lawn pests. For example, a tax on preventive pesticides is expected to increase the probability of using IPM methods and decrease the intensity of pesticide use by individual firms. A tax on fertilizer, however, is expected to have the opposite effect on pesticide intensity. This result suggests that policymakers should jointly consider both nitrate and pesticide pollution when devising a policy portfolio.

Economic agents often decide to shift all or part of the uncertainty about future, exogenous events to other agents through the purchase of insurance. In the professional lawn care market, the consumer has shifted the uncertainty about naturally-occurring pest damage to the producer. I contend that in this market, the shifting of uncertainty to the producer occurs due to economic incentives. Producers are able to supply both insurance and the product that mitigates the effects of the insured event at a cost lower than the sum of the parts. Insurance and the complementary product are jointly produced, lowering total costs of production through the use of the relatively cheaper ex ante technology.

Shifting of uncertainty to the producer saves resources in this market. However, this savings may be offset by externality costs if the resulting change in resource allocation increases the use of polluting inputs. This cost-benefit tradeoff is present in this study and, thus, it is unclear whether the savings stemming from the joint production of insurance and pest control outweigh the costs of increased pesticide use. A comprehensive cost-benefit assessment is recommended in this case to account for the tradeoff between reduced resource costs of shifting the uncertainty to the producer and the additional costs resulting from the increased use of polluting inputs.

6.2 LIMITS AND SHORTCOMINGS

This study focuses on the behavior of risk-neutral producers operating in competitive markets whose main objective is to maximize expected profits in the face of uncertainty about the occurrence of an exogenous event that affects the cost of production. As a consequence of these assumptions, this study represents a simple starting point rather than a comprehensive conclusion regarding behavior under cost uncertainty. The general framework, however, does allow researchers to formulate alternative market structures and theories of producer behavior and then identify the implications for resource allocation using the same concepts of asymmetric penalties and strategy bias. Extending this general framework to incorporate the behavior of risk-averse producers is also desirable.

This research is also limited to the study of individual resource allocation decisions. Depending on the conditions prevailing in the market, the implications for resource allocation at the individual producer level may be different than for the system as a whole. While an individual producer may take prices as exogenous, clearly the combined action of these producers, and consumer responses to these actions may cause prices to change and thereby change the ultimate resource allocation patterns in the market. In the case of lawn care, how do resources shift from the professional service market to the do-it-yourself market to the do-nothing market in response to price changes? This study does not address this question, but only considers the penultimate resource allocation effects of individual producers.

Another limitation is the static framework used for analysis. As Pannell (1991) remarks in his review of the literature on pests and risk, static frameworks are often employed to make a problem tractable, but then it is often necessary to expand the analysis framework to allow for dynamic effects. For instance, a lawn care firm makes its pest control output decision at one point in time, the beginning of the season, but the input decisions are made over time throughout

the course of one growing season. Also, research has shown that pests develop a resistance to pesticides over time. How does this potential pest resistance affect the producer action? Are producers less likely to engage in preventive bias due to the future costs of this resistance? Future efforts to incorporate these dynamic effects into the asymmetric penalty framework should enhance the explanatory power of the model.

As with many research projects in the social sciences, data collection is often difficult, tedious, frustrating, and disappointing. Testing the theoretical concepts developed in this study requires detailed information on producer actions. While many efforts were made to insure that data were collected from a full representative sample of firms, the participation rates were very low. The extent of bias in the resulting sample with respect to the variables of the model are unknown although, if nonresponse bias exists, it most likely works against rather than in favor of supporting the model. The number of observations is sufficient to test the propositions of the behavioral model, but clearly for policy purposes, it would be desirable to have a much larger sample so that effects of policies could be estimated with more confidence. Given the cost-effectiveness of policies to reduce pesticide use on many agriculture crops, expanding the sample size for policy purposes may be an effective use of additional research funds.

6.3 IMPLICATIONS FOR FUTURE RESEARCH

The model of producer behavior under cost uncertainty applies to many situations. The concept of jointly producing insurance and the complementary product is undeveloped in the literature, but has several applications of current interest. The most notable is to the health maintenance organization which provides both health insurance and treatment should illness occur. The health provision and insurance industries are very large and complex, and thus applying the concepts developed in this study to this market will require considerable research

effort and resources. Nevertheless, since some of the theoretical concepts are evident, like an incentive to use cheaper ex ante technology and providing an overall savings in resources, modifying the model and assumptions to fit the health care market may prove to be very fruitful and rewarding.

Another general application is to the study of producer externalities and the policy instruments chosen to implement corrective policies. To the extent that asymmetric penalties exist, actual pollution levels will deviate from the policy target levels unless the strategy bias effects are taken into account when devising the regulations. The case of marketable pollution permits is a prime example. If markets for permits are sticky in the sense that trades cannot occur instantaneously and without transaction costs, then penalties may exist for the firm for not correctly predicting annual pollution levels. If the penalty for under-predicting is a fine and/or jail, and the penalty for over-predicting is having purchased too many permits, then in general the penalties will be asymmetric. Assuming that jail or the fine is the higher of the two penalties, firms will buy permits for a higher level of pollution than what they expect or predict. This preventive strategy bias may result in higher costs for achieving the targeted pollution level. In other words, the costs may exceed the benefits if the level was set based on some marginal cost-benefit criteria.

This study points out the importance of understanding incentives when designing public policies. Attention to the role that uncertainty plays in determining producer response is imperative when designing regulations, especially in the case of environmental externalities. In the case analyzed in this study, preventive bias alone caused a significant increase in the use of polluting inputs by individual producers. Policies designed to decrease preventive bias or the probability of engaging in preventive bias will provide the correct incentive to reduce the use of polluting inputs and achieve the policy goal. Failing to account for these strategy bias effects

when developing environmental policies, however, can result in ineffective and costly policy decisions.

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APPENDIX

APPENDIX A

Questionnaire and cover letter

LAWN SERVICE PRODUCTION METHODS SURVEY

Instructions

The information you provide will be used to determine the impact of pesticide regulations on lawn service businesses. All questions request information for the 1993 season. Please answer all questions in Sections A and B. If you provided lawn fertilization and pest control services during 1993, all questions in Section C should also be answered. Your return of this questionnaire will constitute your informed consent to participate in this study. Please return to: LCI Project, 505A Stokely Management Center, Knoxville, TN 37996-0550. Thank you for participating.

SECTION A: GENERAL INFORMATION

A1. Which services did you provide in 1993? (check all that apply)

- ☐ lawn fertilization and pest control
- ☐ lawn mowing/landscape maintenance (including aeration/dethatching)
- ☐ other _____

A2. What is your customer's average lawn size (in square feet)? ft²

A3. How many customers received lawn fertilization and pest control services on a regular basis during 1993?

A4. For the average size lawn, what was the annual price for your lawn fertilization and pest control service in 1993? \$

A5. How many customers received lawn mowing/landscape maintenance services on a regular basis during 1993?

A6. For the average size lawn, what was the annual price for your lawn mowing/landscape maintenance service in 1993? \$

A7. How many years of experience did you have in turfgrass management prior to 1993?

A8. How many years of agronomic education have you received beyond high school? . . .

SECTION B: LABOR AND EQUIPMENT

B1. How many vehicles were operated in 1993 for fertilization and pest control service? . _____

What was the average annual cost of operating one of these vehicles? \$ _____
(Include gas, maintenance, insurance, and lease or depreciation costs.)

B2. How many vehicles were operated in 1993 for lawn mowing/maintenance service? . . _____

What was the average annual cost of operating one of these vehicles? \$ _____
(Include gas, maintenance, and lease or depreciation costs.)

B3. How many mowers, aerators, dethatchers, and seeders did you own or lease in 1993? _____

What was the average annual cost of operating one of these units? \$ _____
(Include gas, maintenance, and lease or depreciation costs.)

B4. How many employees (including yourself) have passed the state pesticide exams
and are state licensed applicators? _____

What was the average weekly compensation for these employees? \$ _____

How many weeks, on average, were these workers employed during 1993? . . _____ weeks

On average, how many hours per week did these employees work during 1993? _____ hours

B5. In addition to the state licensed applicators, how many other employees, on average,
were engaged in the production of lawn pest control, mowing, and landscape
maintenance during 1993? _____

What was the average weekly compensation for these workers? \$ _____

How many weeks, on average, were these workers employed during 1993? . . _____ weeks

On average, how many hours per week did these employees work during 1993? _____ hours

SECTION C: FERTILIZER AND PEST CONTROL

Complete this section if you provided lawn fertilization and pest control services

C1. How many regularly scheduled applications did each customer receive in 1993?

☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ other _____

C2. On average, how many of these applications included: liquid fertilizer? _____

granular fertilizer? _____

broadleaf herbicide _____

C3. At what annual rate was nitrogen applied, on average, to each lawn in 1993?

☐ 3 lbs/1000 ft² ☐ 4 lbs/1000 ft² ☐ 4.5 lbs/1000 ft²

☐ 5 lbs/1000 ft² ☐ other _____ lbs/1000 ft²

C4. Please provide the nutrient analysis, bag/container coverage (in square feet), and cost for the primary granular and liquid fertilizers used.

	<u>Nutrient Analysis</u>	<u>Bag/Container Coverage</u>	<u>Cost per Bag/Container</u>
<i>example</i>	20-4-8	10,000 ft ²	\$ 6.50
granular	- -	_____ ft ²	\$ _____
liquid	- -	_____ ft ²	\$ _____

C5. What were your pre-season predictions for the percentage of your 1993 customers that would have infestations of the following pests?

Predicted crabgrass infestation: _____ % of customers

Predicted broadleaf weed infestation: _____ % of customers

Predicted surface insect infestation: _____ % of customers

Predicted grub infestation: _____ % of customers

Predicted disease infestation: _____ % of customers

Section C continued on next page

SECTION C (continued)

C6. For each product that you used during 1993, provide the product cost, the bag or container coverage (in square feet), and the percentage of customers who received corrective and/or preventive treatments.

	<u>Container Coverage</u>	<u>Price per Container</u>	<u>Customers Receiving Preventive Treatment</u>	<u>Corrective Treatment</u>
<u>Crabgrass Control:</u>				
Preemergent herbicide	_____ ft ²	\$_____	_____ %	_____ %
Fertilizer + preemergent herbicide	_____ ft ²	\$_____	_____ %	_____ %
Fertilizer + herbicide + insecticide	_____ ft ²	\$_____	_____ %	_____ %
Postemergent herbicide	_____ ft ²	\$_____	_____ %	_____ %
<u>Broadleaf Weed Control:</u>				
Broadleaf herbicide	_____ ft ²	\$_____	_____ %	_____ %
Fertilizer + broadleaf herbicide	_____ ft ²	\$_____	_____ %	_____ %
<u>Surface Insect Control:</u>				
Surface insecticide	_____ ft ²	\$_____	_____ %	_____ %
Fertilizer + surface insecticide	_____ ft ²	\$_____	_____ %	_____ %
Biological surface insect control	_____ ft ²	\$_____	_____ %	_____ %
<u>Grub/Subsurface Insect Control:</u>				
Grub/subsurface insecticide	_____ ft ²	\$_____	_____ %	_____ %
Fertilizer + grub insecticide	_____ ft ²	\$_____	_____ %	_____ %
Biological grub control	_____ ft ²	\$_____	_____ %	_____ %
<u>Disease Control:</u>				
Fungicide	_____ ft ²	\$_____	_____ %	_____ %
Fertilizer + fungicide	_____ ft ²	\$_____	_____ %	_____ %
Biological disease control	_____ ft ²	\$_____	_____ %	_____ %

Please return to: LCI Project, 505A Stokely Management Center, Knoxville, TN 37996-0550



NEW YORK STATE TURFGRASS ASSOCIATION, INC.

P.O. BOX 612, LATHAM, NEW YORK 12110 • 518-783-1229 • 800-873-TURF

December 3, 1993

Dear Manager/Owner:

You have been selected to participate in a study to determine the impact of pesticide regulations on lawn care business profits. To complete this study, information is needed on the amount of labor, equipment, fertilizer, and pesticides used in the production process. Please complete the enclosed questionnaire today and return it using the postage-paid envelope. Filling out the questionnaire should take approximately twenty minutes. No questionnaire contains any questions or markings to identify you as a respondent. The return envelope does contain an ID number to track survey response; however, this number will never be transferred to the questionnaire or used in any way to identify individual responses. This procedure insures that you will remain anonymous.

Since the results of this study will be used to inform policymakers of the impact of proposed regulations on industry profits, you can expect to benefit directly from participating in this study. I encourage you to take the time now to complete the enclosed questionnaire. If you have any questions, please contact the research staff directly by calling or writing:

Tom Yoder
Economics Department
505A Stokely Management Center
Knoxville, TN 37996-0550
(615) 974-3303
(615) 974-4601 FAX

Thank you for your willingness to participate in this important research effort.

Sincerely,

John Liburti
President

APPENDIX B

Survey Results

A1. Which services did you provide in 1993? (check all that apply)

	<u>Freq.</u>	<u>%</u>
lawn fertilization and pest control only.	8	17.8
both pest control and mowing/maintenance services.	22	48.9
both pest control and other services.	14	31.1
pest control, mowing/maintenance, and other services.	1	2.2

A2. What is your customer's average lawn size (in square feet)?

<u>Mean</u>	<u>St. dev.</u>
9620	12640

A3. How many customers received lawn fertilization and pest control services on a regular basis during 1993?

<u>Mean</u>	<u>St. dev.</u>
221.11	294.38

A4. For the average size lawn, what was the annual price for your lawn fertilization and pest control service in 1993?

<u>Mean</u>	<u>St. dev.</u>
444.80	589.05

A5. How many customers received lawn mowing/landscape maintenance services on a regular basis during 1993?

<u>Mean</u>	<u>St. dev.</u>
78.22	67.02

A6. For the average size lawn, what was the annual price for lawn mowing/landscape maintenance service in 1993?

<u>Mean</u>	<u>St. dev.</u>
1507.33	1490.20

A7. How many years of experience did you have in turfgrass management prior to 1993?

<u>Mean</u>	<u>St. dev.</u>
18.18	10.15

A8. How many years of agronomic education have you received beyond high school?

<u>Years</u>	<u>Freq.</u>	<u>%</u>
0	14	31.1
1	3	6.7
2	16	35.6
3	4	8.9
4	6	13.3
6	2	4.4

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B1. How many vehicles were operated in 1993 for fertilization and pest control service?

<u>Vehicles</u>	<u>Freq.</u>	<u>%</u>
1	24	53.3
2	11	24.4
3	7	15.6
4	1	2.2
5	1	2.2
8	1	2.2

What was the average annual cost of operating one of these vehicles?

<u>Mean</u>	<u>St. dev.</u>
4380.33	2592.51

B2. How many vehicles were operated in 1993 for lawn mowing/maintenance service?

<u>Vehicles</u>	<u>Freq.</u>	<u>%</u>
0	12	26.7
1	23	51.1
2	7	15.6
3	1	2.2
4	1	2.2
5	1	2.2

What was the average annual cost of operating one of these vehicles?

<u>Mean</u>	<u>St. dev.</u>
3193.33	2081.71

B3. How many mowers, aerators, dethatchers, and seeders did you own or lease in 1993?

<u>Mean</u>	<u>St. dev.</u>
6.13	3.47

What was the average annual cost of operating one of these units? (Include gas, maintenance, and lease or depreciation costs.)

<u>Mean</u>	<u>St. dev.</u>
997.11	998.86

B4. How many employees (including yourself) have passed the state pesticide exams and are state licensed applicators?

<u>Employees</u>	<u>Freq.</u>	<u>%</u>
1	33	73.3
2	11	24.4
3	1	2.2

What was the average weekly compensation for these employees?

<u>Mean</u>	<u>St. dev.</u>
564.53	180.58

How many weeks, on average, were these workers employed during 1993?

<u>Mean</u>	<u>St. dev.</u>
38.87	7.80

On average, how many hours per week did these employees work during 1993?

<u>Mean</u>	<u>St. dev.</u>
42.29	9.92

B5. In addition to the state licensed applicators, how many other employees, on average, were engaged in the production of lawn pest control, mowing, and landscape maintenance during 1993?	<u>Mean</u> 3.22	<u>St. dev.</u> 2.94
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What was the average weekly compensation for these workers?	<u>Mean</u> 325.56	<u>St. dev.</u> 79.23
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How many weeks, on average, were these workers employed during 1993?	<u>Mean</u> 32.87	<u>St. dev.</u> 11.00
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On average, how many hours per week did these employees work during 1993?	<u>Mean</u> 40.98	<u>St. dev.</u> 8.10
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C1. How many regularly scheduled applications did each customer receive in 1993?

<u>Applications</u>	<u>Freq.</u>	<u>%</u>
3	2	4.4
4	3	6.7
5	25	55.6
6	8	17.8
7	3	6.7
8	1	2.2
9	1	2.2
10	1	2.2
13	1	2.2

C2. On average, how many of these applications included:

liquid fertilizer?

<u>Applications</u>	<u>Freq.</u>	<u>%</u>
0	35	77.8
1	3	6.7
2	2	4.4
3	2	4.4
4	2	4.4
7	1	2.2

granular fertilizer?

<u>Applications</u>	<u>Freq.</u>	<u>%</u>
0	1	2.2
1	4	8.9
2	4	8.9
3	3	6.7
4	16	35.6
5	14	31.1
6	2	4.4
10	1	2.2

broadleaf herbicide?

<u>Applications</u>	<u>Freq.</u>	<u>%</u>
0	3	6.7
1	13	28.9
2	14	31.1
3	6	13.3
4	5	11.1
5	3	6.7
8	1	2.2

C3. At what annual rate was nitrogen applied, on average, to each lawn in 1993?

<u>Rate</u>	<u>Freq.</u>	<u>%</u>
2.0	2	4.4
2.5	1	2.2
3.0	14	31.1
4.0	15	33.3
4.5	4	8.9
5.0	8	17.8

C4. Please provide the nutrient analysis, bag/container coverage (in square feet), and cost for the primary granular and liquid fertilizers used.

Granular fertilizer.

	<u>Mean</u>	<u>St. dev.</u>
Nutrient analysis	21.44	6.00
Coverage	10.81	2.85
Cost	9.80	3.01

Liquid fertilizer.

	<u>Mean</u>	<u>St. dev.</u>
Nutrient analysis	4.22	8.02
Coverage	12.36	38.95
Cost	9.72	32.32

C5. What were your pre-season predictions for the percentage of your 1993 customers that would have infestations of the following pests?

	<u>Mean</u>	<u>St. dev.</u>
Predicted crabgrass infestation:	34.24	36.70
Predicted broadleaf weed infestation:	42.67	35.80
Predicted surface insect infestation:	27.13	28.93
Predicted grub infestation:	41.62	32.86
Predicted disease infestation:	35.62	28.30

C6. For each product that you used during 1993, provide the product cost, the bag or container coverage (in square feet), and the percentage of customers who received corrective and/or preventive treatments.

	<u>Mean</u>	<u>St. dev.</u>
<u>Crabgrass Control:</u>		
Preemergent herbicide		
Coverage	13.88	23.58
Price	19.23	32.01
Preventive Treatment	39.07	46.18
Corrective Treatment	2.44	14.78
Fertilizer + preemergent herbicide		
Coverage	5.02	6.09
Price	7.06	10.06
Preventive Treatment	38.24	46.24
Corrective Treatment	0.42	2.24
Fertilizer + herbicide + insecticide		
Coverage	0.00	0.00
Price	0.00	0.00
Preventive Treatment	0.00	0.00
Corrective Treatment	0.00	0.00
Postemergent herbicide		
Coverage	22.27	67.46
Price	18.84	36.80
Preventive Treatment	3.33	16.33
Corrective Treatment	5.82	16.35
<u>Broadleaf Weed Control:</u>		
Broadleaf herbicide		
Coverage	70.18	66.54
Price	32.24	29.32
Preventive Treatment	20.78	36.41
Corrective Treatment	43.27	41.95
Fertilizer + broadleaf herbicide		
Coverage	3.82	17.97
Price	5.02	21.64
Preventive Treatment	5.56	21.66
Corrective Treatment	5.89	20.31
<u>Surface Insect Control:</u>		
Surface insecticide		
Coverage	12.76	18.72
Price	13.59	14.38
Preventive Treatment	30.87	42.13
Corrective Treatment	7.76	16.31

	<u>Mean</u>	<u>St. dev.</u>
Fertilizer + surface insecticide		
Coverage	2.46	5.02
Price	3.70	7.61
Preventive Treatment	12.89	31.03
Corrective Treatment	1.33	4.88
Biological surface insect control		
Coverage	0.00	0.00
Price	0.00	0.00
Preventive Treatment	0.00	0.00
Corrective Treatment	0.00	0.00
<u>Grub/Subsurface Insect Control:</u>		
Grub/subsurface insecticide		
Coverage	11.36	14.65
Price	20.47	19.06
Preventive Treatment	41.93	44.45
Corrective Treatment	19.00	28.77
Fertilizer + grub insecticide		
Coverage	0.54	2.14
Price	1.33	5.20
Preventive Treatment	4.78	18.68
Corrective Treatment	0.89	4.12
Biological grub control		
Coverage	0.00	0.00
Price	0.00	0.00
Preventive Treatment	0.00	0.00
Corrective Treatment	0.00	0.00
<u>Disease Control:</u>		
Fungicide		
Coverage	28.24	45.86
Price	59.69	81.47
Preventive Treatment	26.58	37.55
Corrective Treatment	17.40	25.27
Fertilizer + fungicide		
Coverage	0.49	3.24
Price	1.76	11.68
Preventive Treatment	0.00	0.00
Corrective Treatment	0.73	4.86
Biological disease control		
Coverage	0.00	0.00
Price	0.00	0.00
Preventive Treatment	0.00	0.00
Corrective Treatment	0.00	0.00

APPENDIX C

Data Methods

I. FIRM-LEVEL VARIABLES

Pest Control/Insurance Output: Average lawn size (in 1000 ft² units) times the number of customers receiving lawn fertilization and pest control services on a regular basis during 1993. (Questions A2 & A3)

Mowing/Maintenance Output: Average lawn size (in 1000 ft² units) times the number of customers receiving lawn mowing/landscape maintenance services on a regular basis during 1993. (Questions A2 & A5)

Output Ratio: Pest Control/Insurance output divided by Mowing/Maintenance output.

Price of Pest Control/Insurance Output: Annual price for average size lawn divided by the average lawn size (in 1000 ft² units). (Questions A4 & A2)

Price of Mowing/Maintenance Output: Annual price for average size lawn divided by the average lawn size (in 1000 ft² units). (Questions A6 & A2)

Output Price Ratio: Price of Pest Control/Insurance output divided by price of Mowing/Maintenance output.

Price of Skilled Labor Input: Average weekly compensation divided by the average number of hours worked per week. (Question B4)

Price of Unskilled Labor Input: Average weekly compensation divided by the average number of hours worked per week. (Question B5)

Price of Fertilizer Input: Cost per pound of granular nitrogen times the percent of total nitrogen applied in granular form plus the cost per pound of liquid nitrogen time the percent of total nitrogen applied in liquid form. (Questions C2 & C4)

Price of Equipment Input: Total cost of operating all vehicles and maintenance

equipment divided by the number of vehicles and equipment. (Questions B1, B2, & B3)

Management Knowledge: Sum of the years of experience in turfgrass management prior to 1993 and the years of agronomic education received beyond high school. (Questions A7 & A8)

Fertilizer Intensity: Average annual rate that nitrogen was applied to each lawn in 1993. (Question C3)

II. PEST-LEVEL VARIABLES

Predicted States: Pre-season predictions for the percentage of customers that would have infestations of crabgrass, broadleaf weeds, surface insects, grubs, and diseases. (Question C5)

Preventive Pesticide Intensities: Percent of customers receiving preventive treatment summed over all product types for each of the five pests. (Question C6)

Corrective Pesticide Intensities: Percent of customers receiving corrective treatment summed over all product types for each of the five pests. (Question C6)

Pesticide Intensities: Sum of the preventive pesticide and corrective pesticide intensities for each pest.

Preventive Biases: Preventive pesticide intensity minus the predicted state for each pest.

Corrective Biases: Predicted state for each pest minus the preventive pesticide intensity.

Price of Preventive Pesticide Input: Weighted average of the price per container divided by the container coverage for each pest. For combination fertilizer + pesticide products, the pesticide price is the total product price minus the fertilizer price.

Price of Corrective Pesticide Input: Weighted average of the price per container divided by the container coverage for each pest. For combination fertilizer + pesticide products, the pesticide price is the total product price minus the fertilizer price.

Price Ratio of Corrective to Preventive Pesticides: Price of corrective pesticide input divided by price of preventive pesticide input.

VITA

Thomas Neil Yoder was born in Millersburg, Ohio on December 31, 1961. He attended Walnut Creek elementary schools and graduated from Hiland High School, Berlin, Ohio in May, 1980. In August of the same year, he entered Bluffton College, Bluffton, Ohio, where he attended classes until the spring of 1982. He entered The Ohio State University at Columbus in September, 1982 and received his Bachelor of Science degree in Business Administration in June, 1984. From January, 1985 through June, 1990 he worked as a manager for Barefoot Grass Lawn Service, Incorporated, with his final position being manager of operations for the Northern New Jersey market. In August, 1990, he entered The University of Tennessee, Knoxville, and in December, 1994, received a Doctor of Philosophy degree in Economics.