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THE ADOPTION DECISION: A HUMAN CAPITAL APPROACH

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The adoption decision: A human capital approach

by

Gregory Dean Wozniak

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CHAPTER I. INTRODUCTION

The adoption of technological innovations is an element in the process of technological change. In a dynamic technological environment, disequilibria result from the introduction of innovative inputs. The decision to adopt an innovation is a reallocation decision made in response to disequilibrium. The efficiency of adjustment is determined by how agents respond to economic incentives. Differences in their capacity to be early adopters are attributed to differences in innovative ability, a single dimension of allocative ability. This study focuses on the role of innovative ability in the decision to adopt innovative inputs.

The Adoption Decision

The primary interest in technological progress has been in the areas of historical and broad ranging discussions, the measurement of technological progress, technological progress as a source of economic growth, rates of adoption and diffusion of technological improvements, and the adjustment to optimal quantities of innovative factors of production. The one aspect of the process of technological improvement which has generally been neglected in favor of pursuing these more macroeconomic issues is the decision to adopt an innovation. In a dynamic economic environment, the adoption of technological improvements is a key element in the process of technological change and is paramount to that process in a microeconomic context. Except for the invention and the development of innovations, no other stage of the process is more fundamental than the adoption of technological innovations.

A technological innovation or improvement is defined as a production technique, factor of production, or knowledge previously not available for use in production. The solution to the adoption decision problem is the decision either to adopt or reject the innovation. Adoption is the use of the technological improvement for the first time. The decision to adopt, i.e., the innovative decision, is the appropriate decision when considering the adoption of profitable innovations. Rejection implies the technological improvement is not used in production.

As a distinct economic decision, the adoption decision is the mechanism or process, within some profit maximizing framework, by which an agent chooses either to utilize (adopt) or not to utilize (reject) the technological innovation. This process entails a multiplicity of stages. Each serves a distinct function required to make those decisions. Like any decision, the adoption decision is a choice between alternatives. In the initial stage, an opportunity is provided by the introduction of a technological innovation and it becomes known. In general, to make adoption decisions, agents must keep well abreast of the availability of technological improvements, and obtain sufficient and accurate technical and market information about the improvements. With that information, they must be able to form expectations about the profitability of utilizing the improvements, and ultimately adopt and implement those improvements which they deem optimal.[1] Adopters are agents who have a faster rate of adoption relative to nonadopters, and therefore, are early adopters (innovators) because they are the first to adopt.

The incentive to adopt is the potential increase in profit derived from the use of the technological innovation. This increase in profit is not necessarily a rise in profit from the previous period. What is meant instead is that profit will be greater when the innovation is adopted than when it is rejected. Nothing spurs innovation (or any other reallocation) more than the possibility of increased profit. Adoption of an innovation is the reaction to take advantage of the opportunity its introduction makes available. The opportunity, i.e., increased profit, results from an increase in production or decrease in costs when utilizing the innovation. In making the adoption decision, any costs of utilizing an innovation must be taken into account. These include the direct cost of the innovation as a factor of production and the indirect costs which may arise from replacing the current production techniques, or converting the production process to be compatible with the innovation.

It should be clear that it is unnecessary for an agent to have decided against adopting an innovation in order to be a "nonadopter". A nonadopter is considered to be any agent who does not use an innovation. This may occur because the agent has decided to reject the innovation or because he is unable to reach a decision on whether to adopt or not. The latter results either form a lack of information about the introduction of the innovation or from being unable to meet the time constraint to be among the early adopters. If the agent is unaware of the innovation, he does not have the opportunity to adopt. On the other hand, if a decision-maker does not have sufficient time to reach a decision, the innovation will not be adopted. In either case, the agent is a nonadopter just as if he had decided to reject the innovation.

In analyzing the adoption of an innovative input, there is no concern with an index or measure of the level of technology in use or with the rate of utilization of the innovation after adoption. Also, the adoption decision is made in a single time period. This period immediately follows the introduction of the innovation. This is in contrast to optimal allocation decisions and the diffusion of innovations which may take several time periods.

The organizational structure of the farm permits us to center the analysis on the primary decision-maker. In most firms, the structure of management decision-making is quite complex. But, if only single operator farms are considered, the individual who decides whether or not to adopt an innovation is clearly defined. Furthermore, the chain of authority from the "adopter" of an innovation to the production worker, who will implement the innovation, in the typical firm is significantly different from that in an agricultural firm. In most agricultural operations the ultimate decision-maker and the production worker are the same person, the operator.

Objectives of the Study

The primary objectives of this study are to develop a model of the decision to adopt a single technological innovation and to explain the probability of the early adoption of that innovation. The model emphasizes the role of innovative ability and a measure of the economic incentive to be informed about innovations. The hypotheses to be tested are that the probability of adopting profitable innovations increases with an agent's innovative ability and that producers operating at larger scales of production have more incentive to be informed about new technologies used in production, and hence, are more likely to adopt those innovations than operators with smaller scales of production.

The secondary objectives of this study are to extend the model of the decision to adopt a single innovation, to consider the utilization of the complementary technology of implanting growth hormones, and to explain the probability of the adoption of these interrelated innovations. Two hypotheses are to be tested in the joint decision model. First, innovations that can be implemented along with the currently utilized inputs are more likely to be adopted than those innovations that displace currently utilized inputs. Second, if complementary current innovations are adopted producers with a given level of innovative ability and scale of production are more likely to utilize innovative inputs several periods after they have been introduced.

The Innovation

The decision to adopt an innovative cattle feed additive, monensin sodium, is analyzed in this study. Rumensin (monensin sodium's trade name) is a factor augmenting technological innovation. Available for use since early 1976, Rumensin improves feed efficiency but is not a hormone or growth stimulant. Unlike other growth promoting drugs, it requires no withdrawal. Monensin sodium influences natural microbial activity within the rumen by making it more efficient in converting feed into energy for growth and maintenance. Its use changes natural rumen digestion so that more usable volatile fatty acids are released from dietary nutrients and made available for absorption by the animal. Cattle fed a ration of monensin sodium produce equal gains with more than 10 percent less feed at a cost of about 1.5 cents per head per day.

One characteristic of the innovation vastly simplifies the adoption decision: monensin sodium has zero costs of implementation. Its utilization is completely compatible with the current production process and will not displace any previously used techniques. Also, no fixed factors of production become obsolete or decline in value from changing over to the innovation. The only costs incurred in utilizing the innovation are the costs of making the decision to adopt and the per unit price of the innovation as an input.

Footnotes

[1]The decision to adopt is only meaningful if the innovation is implemented.

CHAPTER II. A TECHNOLOGICAL INNOVATION IN A THEORETICAL PRODUCTION MODEL

Technological change at the firm (micro) level can occur in many forms: continuous, discrete or a single change; factor biased or factor neutral; embodied or disembodied.[1] This chapter presents a theoretical model of the input decision for a profit maximizing firm that is considering the use of an innovation assumed to be a disembodied, single-factor augmenting, technological improvement. These assumptions seem to describe monensin sodium as an innovation in livestock feed. As in the standard neo-classical theory of the firm, perfect technical and economic information on all available inputs (input combinations), marginal products, and market and (or) shadow (imputed) prices is assumed. Conditions for optimal input allocation are then derived for several combinations of decision variables and compared. Finally, a graphical illustration is presented.

Theoretical Production Model[2]

As a disembodied technological change, the innovation I, is not tied significantly to any specific input, so it is consistent with the assumption of homogeneous factors of production. An innovation is single-factor augmenting if it has the effect of increasing the productive capacity of a particular factor of production, say N, while leaving other factors, say X, unchanged. However, this need not imply that there has been an intrinsic change in the quality of N. One can measure the factor of production in efficiency units. The augmented factor measured in the efficiency units can then be represented as the product of N and an efficiency index, η.

The relationship between inputs and output is represented as a production function. The production function is assumed to be a strictly quasi-concave function with continuous first-order and second-order partial derivatives. It is

$$Q = Q(X, N), \tag{2.1}$$

where Q is output, X is an m element vector of fixed and variable inputs and N is the m + 1st input. Let us define $\hat{N} = N\eta, \eta = \eta(I/N) \geq 1$, and $I/N = r$. The production function with the innovation incorporated can then be written as

$$Q = Q(X, \hat{N}) = Q[X, N\eta(I/N)] = Q[X, N\eta(r)]. \tag{2.2}$$

In Equation (2.2), the new input $\hat{N}$ is homogeneous of degree one in I and N. The efficiency index, $\eta(r)$, is a function of the rate of use of the innovation, i.e., I/N. If the innovation is adopted, the efficiency index is greater than one, and it is assumed to increase, but at a decreasing rate as r increases. If the technological innovation is not adopted, $\eta(r)$ equals one, and $\hat{N}$ equals N. Thus, the efficiency index can be thought of as being a function of the decision to innovate and r, the innovation per unit of N.

A rational producer will maximize profit from the production and sales revenue of output. Profit π, is the difference between sales revenue and total costs:

$$\pi = P_q Q - TC, \tag{2.3}$$

where P_q is the price of a unit of output. Total cost of production (TC) is given by the linear equation

$$TC = \sum_{j=1}^{m} P_j X_j + P_N N + P_I I + FC,$$

where P_j is the price of the jth factor of production in the vector of m factors, P_N is the price of N, P_I is the price of the technological innovation, and FC is fixed cost. Substituting the most general form of the production function[3] for Q and the total cost equation for TC into Equation (2.3) gives

$$\pi = P_q\{Q[X, N\eta(I/N)]\} - \sum_{j=1}^{m} P_j X_j - P_N N - P_I I - FC. \tag{2.4}$$

The first-order conditions for a profit maximum with respect to X, N and I are

$$\frac{\partial \pi}{\partial X_j} = P_q \frac{\partial Q}{\partial X_j} - P_j = 0, \tag{2.5}$$

$$\frac{\partial \pi}{\partial N} = P_q [\frac{\partial Q}{\partial \hat{N}}(N\frac{\partial \eta}{\partial r} \frac{\partial r}{\partial N} + \eta)] - P_N = 0, \tag{2.6}$$

$$\frac{\partial \pi}{\partial I} = P_q [\frac{\partial Q}{\partial \hat{N}}(N\frac{\partial \eta}{\partial r} \frac{\partial r}{\partial I})] - P_I = 0. \tag{2.7}$$

Equations (2.5), (2.6) and (2.7) require that inputs be utilized up to the point where the value of the marginal product of each input equals its price. Input demand functions can be obtained by solving (2.5), (2.6), and (2.7) for X, N and I as functions of input and output prices.

Alternatively, Equations (2.6) and (2.7) can be combined as

$$\frac{\frac{\partial Q}{\partial \hat{N}}(N\frac{\partial \eta}{\partial r}\frac{\partial r}{\partial N}+\eta)}{\frac{\partial Q}{\partial \hat{N}}(N\frac{\partial \eta}{\partial r}\frac{\partial r}{\partial I})}=\frac{P_N}{P_I} \tag{2.8}$$

This condition states that the ratio of the marginal products of N and I must be equated to the ratio of their prices for a profit maximum. By substituting $\partial r/\partial N = -IN^{-2}$ and $\partial r/\partial I = N^{-1}$, Equation (2.8) can be reduced to

$$\frac{\eta}{\frac{\partial \eta}{\partial r}} - r = \frac{P_N}{P_I}\ . \tag{2.9}$$

An interpretation of Equation (2.8) can be proposed to define the optimal $\hat{N}$.[4] If $\hat{N}$ was a vendible factor of production, the profit maximizing level of employment of $\hat{N}$ is that level where its value of marginal product equals its market price. But, because it is equal to the product of N and the efficiency index, $\eta(I/N)$, $\hat{N}$ is determined by the level of N and I.

Alternatively, changes in the use of N and I affect $\hat{N}$ through their indirect effect on η and through N's direct effect on the product of N and η. Also, the price of a unit of N measured in efficiency units is a function of the relative price P_N/P_I. These relationships suggest that the level of $\hat{N}$ is optimal if N and I are used up to the point where the marginal effect on $\hat{N}$ of the last dollar spent on N is equal to the marginal effect on N of the last dollar spent on I. This is equivalent to the first-order conditions for a profit maximum with respect to N and I represented in Equation (2.8).

The profit maximizing value of the efficiency index is also determined by levels of employment of N and I. Equation (2.9) can be transformed to define an economically relevant (possible profit maximizing) range of r (I/N). That range is where its marginal effect on η is non-negative.[5] The level of employment of the innovation per unit of N must be such that an increase in the use of the innovation does not cause η to fall, i.e., $\frac{\partial\eta}{\partial r}\,\frac{\partial r}{\partial I} \geq 0$. Given that $\partial r/\partial I$ is always positive, if r^M is where $\partial\eta/\partial r = 0$, and if there is an $r_i \leq r^M$, then $\eta(r_i) \leq \eta(r^M)$ for all r_i. Therefore, the profit maximizing η corresponds to an $\eta(r_i)$ where $r_i \leq f^M$. Intuitively, for a profit maximum with respect to $\eta(r)$, r must be constrained to be less than or equal to r^M if the cost of attaining a certain η is to be minimized. For some $r_j > r^M$, if r_i and r_j are such that $\eta(r_i) = \eta(r_j)$, then the cost of $\eta(r_i)$ is less than the cost of $\eta(r_j)$. The effect of r on η is illustrated in Figure 2.1 and Figure 2.2.

Graphical Illustration

The conditions for a profit maximum with respect to N (along with N measured in efficiency units) and X are illustrated in Figure 2.3. Point A illustrates the solution to the allocation decision either prior to the introduction of the technological improvement, where $N = \hat{N}$ and $\eta = 1$, or after the introduction of the innovation, when it is rejected and $N = \hat{N}$, r and I are equal to zero, and $\eta = 1$. Point B illustrates the solution

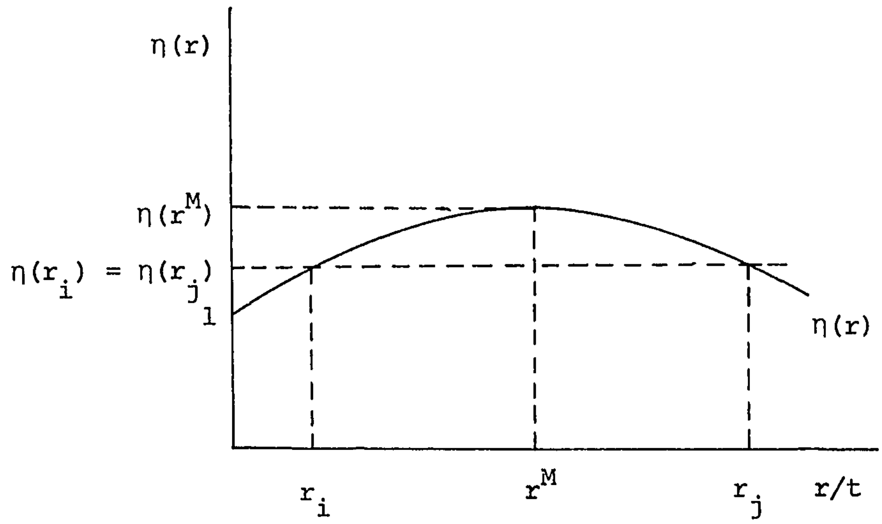

Figure 2.1. Optimal rate of use of the innovation

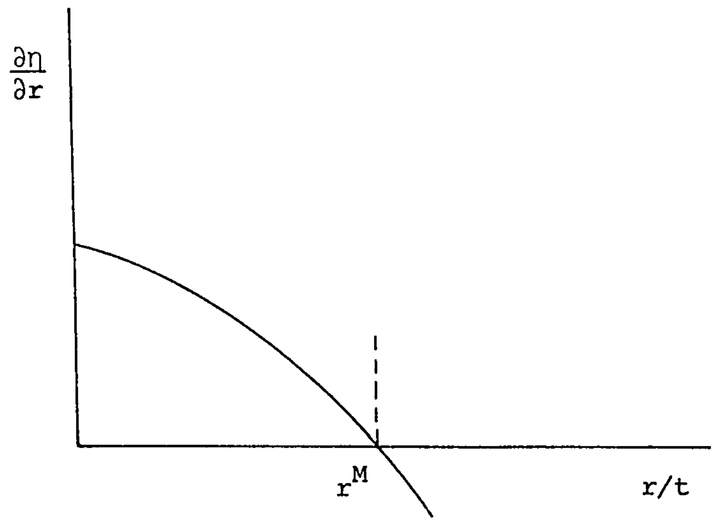

Figure 2.2. Diminishing effect of r on η

to the allocation decision when the innovation has been adopted and I and r are greater than zero, which implies $\eta > 1$. The adoption of the technological improvement augments N, causing its marginal product to rise such that $(\partial Q/\partial \hat{N})$ at point B is greater than $(\partial Q/\partial \hat{N})$ at point A. Therefore, holding all X_j's constant (X_0), the level of N will fall from N_0 to N_1 and equilibrium will shift from point A to point B.

This can be shown by rescaling the N axis so that a unit of output can be produced with less N and the same X_0. Now the unit of output produced at A requires the same X_0 and less N than it did before the introduction of the factor augmenting technological improvement. N_0 after the introduction of the innovation is less than N_0 before the introduction of the innovation because of the rescaling of the N axis. Alternatively, the technological improvement can be shown by simply "shrinking" the unit isoquant. Now, the new unit isoquant is Q_1 and the solution is at B, where X_0 and N_1 are used in the production of a unit of Q and $(P_j/P_{\hat{N}}) = (\frac{\partial Q}{\partial X_j}/\frac{\partial Q}{\partial \hat{N}})$.

The first-order conditions for a profit maximum with respect to N and I can be derived regardless of the form of the innovation, r or I. The choice of the appropriate decision variables is a function of the individual characteristics of the producers and other market and non-market factors. In an environment of less than perfect information, these variables affect the decision whether or not to adopt innovative inputs. The remainder of this study analyzes this decision.

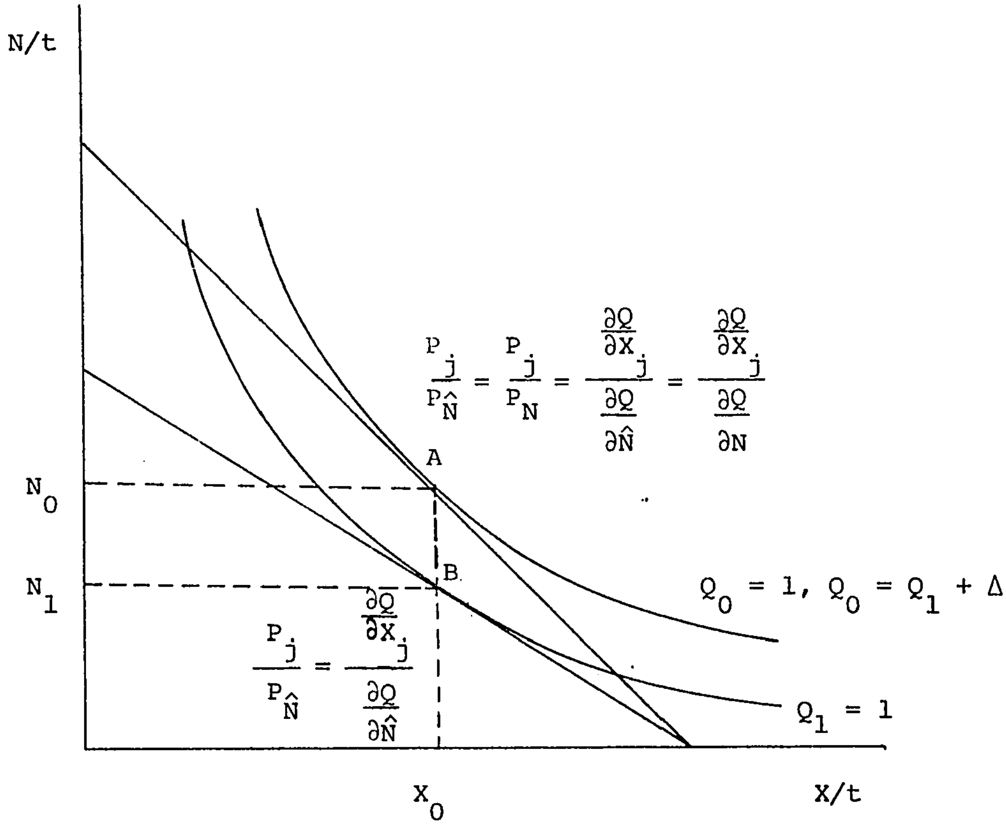

Figure 2.3. Tangency conditions for a profit maximum

Footnotes

[1]Detailed discussions of these concepts of technological change are presented in H. G. Jones, An Introduction to Modern Theories of Economic Growth (New York: McGraw-Hill, Inc., 1976), pp. 153-181; and P. A. Neher, Economic Growth and Development: A Mathematical Introduction, (New York: John Wiley & Sons, Inc., 1971), pp. 109-182.

[2]This section is based on the theory of the firm presented by J. Henderson and R. E. Quandt, Microeconomic Theory: A Mathematical Approach (New York: McGraw-Hill, Inc., 1971), pp. 52-102.

[3]The relevant specification of the production function for determining the profit maximizing input utilizations depends on the form in which the innovation is available. If the decision variables are X, N and r (instead of I), the first-order conditions for a profit maximum with respect to X and r can be reduced to $1/N\{[\eta/(\partial n/\partial r)] - r\} = P_N/P_r$. The price of a "unit" of r, $P_r = P_I N$. This expression is equivalent to Equation (2.9).

[4]If the production function is specified as $Q = Q[X, N(I, N)]$, the first-order conditions for a profit maximum with respect to N and I can be reduced to $(\partial\hat{N}/\partial N)/(\partial\hat{N}/\partial I) = P_N/P_I$. Also, $\hat{N}$ is homogeneous of degree k when $\hat{N}(tI, tN) = t^k N(I, N)$, where k is a constant and t is a positive real number.

[5]From Equation (2.9), if both inputs are used and have positive prices, $\partial\eta/\partial r \geq 0$.

CHAPTER III. THE INNOVATIVE ABILITY MODEL OF ADOPTION DECISIONS

Innovative ability may affect adoption decisions. In this chapter an innovative ability model of the adoption decision is developed. It predicts the probability of early adoption of innovations as a function of the producer's innovative ability and scale of production. It is assumed that innovative ability is related to the agent's level of education, experience, and information. The model is also extended to consider the adoption of complementary inputs and to consider the effects of attitude toward risk on the adoption decision.

The Adoption Decision and Input Allocation Decisions

When input usage is restricted to nonnegative quantities, an innovative ability model of the adoption decision can be developed from the standard neoclassical theory of the firm. One of the decisions of the profit-maximizing firm is the discrete decision of whether to adopt or not to adopt an innovation. If the profit-maximizing rate of utilization of an innovation is positive, the innovation will be adopted.

A graphical interpretation of the adoption decision is illustrated in Figure 3.1. The technological innovation "I" is measured on the vertical axis and the variable input N, which the innovation augments, is measured on the horizontal axis. When adoption occurs, the optimal rate of use of I and N occurs at a tangency of the isocost line CN_b to the isoquant Q_a, e.g., point A. When the innovation is rejected, the optimum

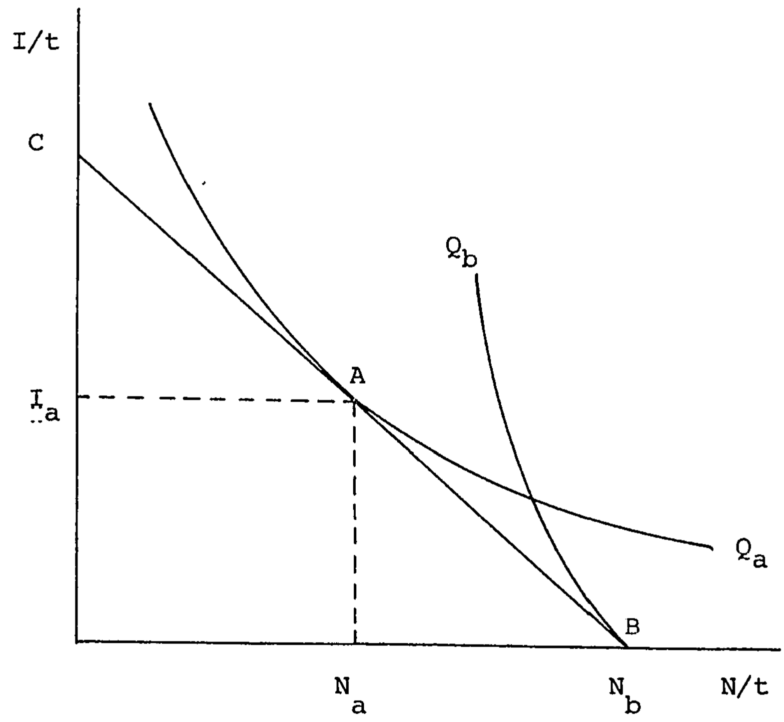

Figure 3.1. Tangency condition and corner condition for efficient input utilization

corresponds to a corner solution, e.g., point B.

In considering the adoption decision, it is useful to consider two decisions. First, choose the set of inputs whose utilization will maximize profits. Second, choose the optimal ratio of use for those inputs that are in the "optimal" set. "Adoption decisions" are made in the first decision. The second decision is similar to standard factor demand theory.

With imperfect information and uncertainty, adoption decisions of firms will differ. Not all operators of firms will be aware of potential innovations. Others will reach different decisions because of their different interpretation of the information and their expectations of future profitability. With economic uncertainty, attitudes of firm managers toward risk, risk preference, may be important for explaining who adopts innovations. A general treatment of decision-making under uncertainty would make the innovative ability model unnecessarily complex. The solution here is to assume that entrepreneurs are risk neutral. They are assumed to maximize expected profit.[1] At the end of this chapter, the attitude toward risk will be shown to be unimportant for adoption decision-making.

To maximize expected profit, $E[\pi]$, inputs should be utilized at such a rate that the ratio of their expected marginal products is equal to the ratio of their expected prices. If the only uncertainty is associated with the price of the innovative factor and with its effect on output, $E[\pi]$ will be maximized by utilizing inputs at the rate where the ratio of the marginal product of any of the noninnovative inputs N, $\partial Q/\partial N$, to the expected marginal product of I, $E[\partial Q/\partial I]$, is equal to the ratio of the price of N, P_N, to the expected price of I, $E[P_I]$.[2] When the use of I augments N, and the influence of I on $\partial Q/\partial N$ is not known with certainty, the (expected) marginal rate of technical substitution (ERTS) between N and I becomes the ratio of the two expected values, $E[\partial Q/\partial N]/E[\partial Q/\partial I]$. The expected profit maximizing input allocation condition for N and I can be expressed as

$$\frac{E[\partial Q/\partial N]}{E[\partial Q/\partial I]} = \frac{E[\eta-(\partial\eta/\partial r)r]}{E[\partial\eta/\partial r]} = \frac{P_N}{E[P_I]},$$

where $E[\eta-(\partial\eta/\partial r)r]/E[\partial\eta/\partial r]$ is the ERTS, and $P_N/E[P_I]$ is the slope of the (expected) isocost line. If the ERTS at all positive levels of I is greater than the slope of the expected isocost line, the innovation will be rejected. Conversely, adoption will occur only if the ERTS of N for I is equal to the slope of the expected isocost line. Because I augments N, adoption of the innovation implies that as the expected profit-maximizing level of I increases, the optimal ratio of I to N increases. With less than perfect information, entrepreneurs may differ in their ability to make innovative decisions.

The Innovative Ability Model

Innovative ability is the competence to search for, collect, interpret, and evaluate information efficiently in making innovative decisions.[3] In an environment of perfect information, innovative ability is not useful or valuable. But, in a world of less than perfect information, innovative ability is useful and commands a return as a factor of production.[4] The return is the cost savings derived from taking advantage of opportunities made available by the introduction of new technologies, i.e., adoption.[5] The economic gain is not necessarily an increase in profit over earlier periods; rather profit when the innovation is adopted is greater than when the innovation is rejected. In the innovative ability model, the hypothesis is that innovative ability increases the probability of adopting profitable innovations.

The basis for the innovative ability model of the adoption decision is developed by Nelson and Phelps, and Huffman. The models proposed by Nelson and Phelps are concerned with the rate of diffusion of a continually changing set of technological improvements.[6] Huffman utilizes a variable partial adjustment model to analyze the rate of adjustment to the optimal utilization of a single input.[7] Although these "rate of diffusion" and "adjustment" models are not concerned with the adoption of a single technological innovation they are relevant by providing theoretical principles for a one-period innovative ability model of the adoption decision.

In the "rate of diffusion" models the rate at which the available technology is diffused is hypothesized to be positively related to an index of average educational attainment, i.e., the degree of human capital intensity. In a one-period, single innovation adoption decision framework, this relationship would imply that as human capital intensity increases the probability of adopting the innovation increases. In the "adjustment" model the rate of adjustment to a disequilibrium caused by the introduction of a technological innovation and changing market conditions (relative prices) is hypothesized to be determined by allocative ability. As allocative ability increases, the rate of adjustment to disequilibrium increases. Or, as allocative ability increases, the more complete adjustment will be at any given time in the adjustment process. In this model, allocative ability is a function of a vector of economic variables: the educational level of decision-makers, the activity of agricultural extension, and the scale of production.

In general, the decision to utilize any set of inputs is determined by allocative ability, i.e., the efficiency of decision-makers in the search, collection, interpretation, and evaluation of information in making input allocation decisions.[8] If decision-makers with more allocative ability are more efficient in gathering and interpreting information they will be aware of more sources of information and be more efficient in processing information and making allocative decisions than decision-makers with less allocative ability. In an adoption decision context, the adoption or rejection of a single technological improvement, which is an element in the "optimal" set of inputs, depends on innovative ability, a single dimension of allocative ability.[9]

When superior new technology becomes available, old input combinations are no longer optimal. A disequilibrium will be created between actual and optimal rates of (some) input usage. The adoption decision can be viewed as a reallocation made in response to this disequilibrium. An "adjustment" model can provide the framework for the innovative ability model of the adoption decision. The introduction of a technological innovation at time t increases the stock of available technology and creates a disequilibrium in the "optimal" set of inputs Z^*. Given $I \varepsilon Z^*_t$ and making the simplifying assumptions that the only difference in the "optimal" set of inputs between t and t-1 is availability of the innovation at time t and that the set of inputs utilized at t-1 is optimal, the appropriate reallocation decision made in response to the disequilibrium $(Z^*_t - Z^*_{t-1})$ is to adopt the innovation. If adoption occurs adjustment is complete; the set of inputs utilized in time t is the "optimal" set of inputs; $Z_t = Z_t^*$, and the expected value of profits is maximized. Conversely, if the innovation is incorrectly rejected no adjustment to disequilibrium occurs; the set of inputs utilized will not be "optimal"; $Z_t \neq Z_t^*$, and the expected value of profits will not be maximized. Thus, by definition there is no partial adjustment to disequilibrium in the adoption decision.

The efficiency of the adjustment process is determined by how producers respond to economic incentives. Differences in the performance of these human agents in responding to innovations are attributed to differences in innovative ability.[10] Thus, agents with greater innovative ability are hypothesized to have larger probabilities of adoption than agents with lesser innovative ability.

The Effects of Education, Experience, Information and the Scale of Production on the Probability of Adoption

Education renders productive services by augmenting skills and knowledge useful in economic endeavors. As a single dimension of allocative ability, innovative ability requires decision-making skills and knowledge. One of the economic benefits of education, in terms of the adoption of technological innovations, is to enhance innovative ability which increases the probability of adoption.[11] Education provides the opportunity to improve allocative decision-making efficiency and contributes to the productive capabilities required to make innovative decisions by augmenting a person's capacity to think systematically and creatively about techniques. This enables him to use his rational faculties in the process to consciously modify his environment. Education fulfills this role by enhancing one's ability to be creative and flexible in a dynamic technological environment, to conceptualize the consequences of possible alternative actions, and to gather and process information relevant to making innovative decisions.

A dynamic technological environment, as the source of economic expansion, requires a labor force that is creative and adaptable, and has the capacity to adjust. In a broad sense, education enhances workers' ability to learn and helps them meet the creativity and flexibility requirements of an advancing technology. As an agent in a dynamic technological environment, the increased ability to learn augments one's capacity to adjust to disequilibria arising in that environment.[12] The ability to conceptualize the results of actions being contemplated and comprehend the effects of adopting technological improvements is also enhanced by education. This allows for a more critical evaluation of the productive characteristics and costs of adopting innovations, enabling producers to more easily distinguish those improvements whose adoption provides an opportunity for economic gain from those that do not.[13] Education also augments one's ability to receive, decode, and understand information relevant to making innovative decisions. Producers with more education should be aware of more sources of information, and be more efficient in evaluating and interpreting information about innovations than those with less education. Thus, it is hypothesized that when faced with adjusting inputs to include a technological innovation, producers with more education are more likely to be adopters than operators with less education.[14]

The effect of exprience on innovative ability is similar to that of education. Each work activity produces goods or services and provides work-related learning opportunities. Learning new skills and perfecting old ones while on the job, like education and other training, enhances productivity.[15] Furthermore, if the development of certain skills is more easily accomplished from experience working practical problems, the time an individual spends working at a particular job may contribute to the skills necessary to perform that job. In a dynamic technological environment where innovative inputs are appearing (and relative prices are changing), producers must continually make allocative decisions, i.e., decide whether to adopt or not to adopt new inputs. Having experience in making innovative decisions, therefore, makes producers more efficient in carrying out the tasks necessary to make those decisions, tasks such as, the gathering and interpretation of information relevant to making innovative decisions. This creates an incentive to acquire more information.[16] So, when faced with adjusting inputs to include a technological innovation, it is hypothesized that those producers with more experience are more likely to be innovative than producers with less experience.

Information may enhance the efficiency of making adoption decisions.[17] In the world of less than perfect information, the introduction of a technological improvement does not imply knowledge of its availability. Information pertaining to the innovation must be acquired by producers in making adoption decisions. Of the many sources of information available to farmers, agricultural extension and private agricultural supply firms are the most germane and the most interesting for analyzing the adoption decision. Agricultural extension, a major source of information on technological improvements in the agricultural sector, was established for the purpose of advancing agricultural welfare by spreading technological information on innovative production techniques and new factors of production. Private agricultural supply firms perform considerable research and extension activity of their own with the objective of improving their competitive position in the market place. The information provided by these firms may not be totally objective with respect to information on expected performance, but it seems likely to be one important source of information on how and when to use new technology. The hypothesis is that when faced with adjusting inputs to include a technological innovation, producers who acquire more information relevant to making innovative decisions are more likely to be innovators than operators who acquire less information.

It is also hypothesized that the scale of production is a measure of the incentive to be an informed economic agent and economies of scale in information usage suggest the probability of adoption is positively related to the scale of production.[18] The size of the activity or the scale of production where the innovation will be adopted gives one measure of the potential economic gain from adoption.[19] The loss from failing to take advantage of the opportunity of economic gain from the introduction of the technological innovation increases as the scale of production increases. The availability of new technologies creates demand for information useful in making innovative decisions. As the scale of production increases, the relative incentive to be better informed about innovations and to choose the "optimal" set of inputs increases. This implies scale economies in the use of information. Therefore, producers with larger scales of production derive greater economic benefits from being aware of technological advancements in inputs or techniques used in production and from adopting those improvements than producers with smaller scales of production.

The model of the adoption decision can be extended to consider complementary innovations; for example, the use of monensin sodium and growth hormone implants. These innovations need not, however, become available at the same time. The adoption decision must be developed in the context of one decision within a set of jointly determined variables. Alternatively, the decision to adopt (utilize) one technological innovation (complementary-input) may be conditional on the utilization (adoption) of another complementary-input (innovation). When innovations become available at different points in time, adoption becomes a multiple period decision which adds to the complexity of the decision.

It has been hypothesized that agents with more innovative ability have larger probabilities of "early adoption" than agents with less innovative ability. The decision to utilize an "earlier innovative" factor of production several periods after its introduction, however, may not be an adoption decision as defined in this hypothesis. It clearly is not if the decision to adopt was made immediately after its introduction. Thus, innovative ability will have no effect on the probability of utilizing an innovation several periods after it is available; i.e., innovative ability is not hypothesized to explain the process by which innovations are diffused. When analyzing this simultaneous decision, it is hypothesized that producers with a given level of innovative ability and scale of production are more likely to be adopters of current innovations if they are utilizing "earlier innovative" inputs (which complement the innovations) than if they are not. This also implies that producers with a given scale of production have larger probabilities of utilizing an "earlier innovative" input if they adopt a complementary current innovation than if they reject it regardless of their innovative ability. This hypothesis provides an opportunity to verify the early adoption implications of the innovative ability model of adoption decisions.

The Attitude Toward Risk in the Innovative Ability Model

Throughout the development of the innovative ability model it had been assumed that producers are neutral in their attitude toward risk. However, if producers are risk averse, it would be useful to know how the implications of the innovative ability model would be changed. The effect of attitudes toward risk on adoption is developed in the context of first-degree stochastic dominance (FSD).

Hadar and Russell propose a theorem for ordering uncertain prospects regardless of the specifications of the utility function.[20] Consider the probability density functions defined on profits (π), $f_1(\pi_i) = p_1(\pi_i)$ and $f_2(\pi_i) = p_2(\pi_i)$, $i = 1,2,\ldots,n$. The function $f_2(\pi_i)$ is said to be at least as large as $f_1(\pi_i)$ in the sense of FSD if and only if

$$F_2(\pi_i) \leq F_1(\pi_i)$$

for all values of π_i in the range (R), where $F_k(\pi_i) = \sum_{s=1}^{i} f_k(\pi_s)$ are the respective cumulative probability distributions, for $k = 1,2$. This dominance condition states that the value of the cumulative probability distribution of the preferred prospect F_2 never exceeds that of the inferior prospect F_1. Also, U_I can be defined as the set of all bounded and strictly increasing functions that possess a continuous first derivative at each point in the domain R. A utility function can be denoted by $u = \phi(\pi)$ where $\phi \varepsilon U_I$. For any two probability functions f_1 and f_2, f_2 is preferred to f_1 for all utility functions in U_I if and only if f_2 is larger than f_1 in the sense of FSD. The expected utility associated with $f_k(\pi_i)$ is given by

$$E[U_k(\pi)] = \sum_{i=1}^{n} p_k(\pi_i)\phi(\pi_i),$$

where $E[U_2(\pi)] \geq E[U_1(\pi)]$ for all $\phi \varepsilon U_I$ if and only if the dominance assumption holds, i.e., if $F_2(\pi_i) \leq F_1(\pi_i)$ for all π in R. Alternatively, f_2 is preferred to f_1 if and only if f_2 is stochastically larger than f_1. The proof of the theorem relies on the dominance assumption and the positivity of the marginal utility of π.[21] The implication of the theorem is that the odd moments in f_2, the preferred distribution, are larger than the respective moments in f_1. The first moment, $E[U(\pi)]$, is the most relevant in the application of the concept of FSD to the innovative ability model of adoption.[22]

The preferred probability density function f_2 can be derived by redistributing probabilities in f_1 from lower payoffs to higher payoffs. This redistribution of the probabilities can be interpreted as if an area of f_1 was removed at lower payoffs and then added to the probability function at higher payoffs. These probability functions are illustrated in Figure 3.2.

Since the productivity of an innovation is not known with certainty, output when utilizing the innovation will be a random variable and profits when utilizing the innovation, π^A, will be stochastic. For those producers maximizing the expected utility of profits, the innovation will be adopted only if the expected utility of profits from adoption

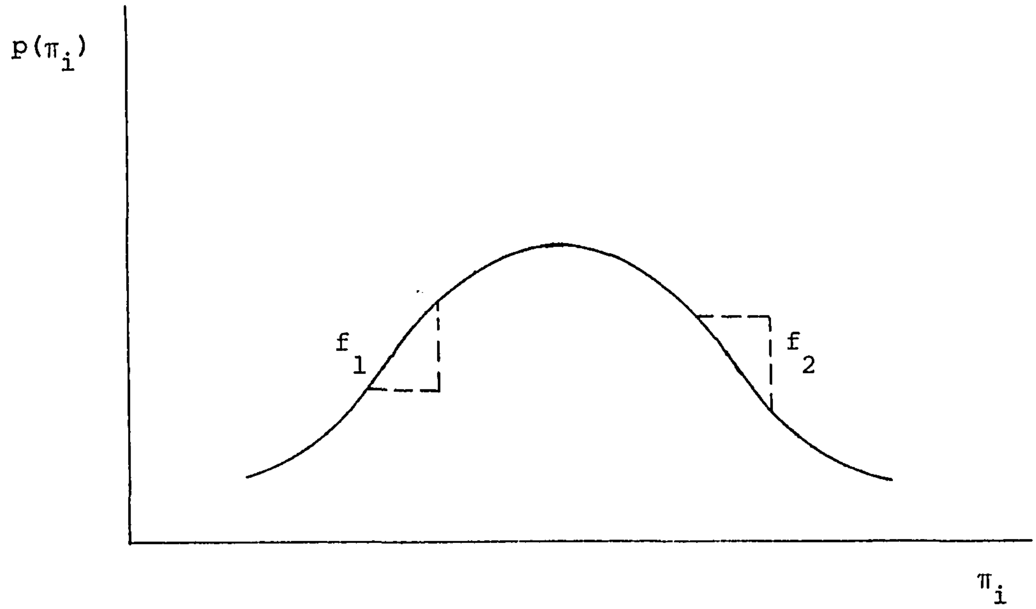

Figure 3.2. Redistribution of probabilities from lower payoffs to higher payoffs

(utilizing) the innovation, $E[U(\pi^A)]$, is greater than the expected utility of profits when the innovation is rejected, $E[U(\pi^R)]$. The probability density function defined on π^A, conditional on innovative ability IA, is $f_k(\pi_i|IA_k)$, where i = 1,2,...,n, and k = 1,2,...,t, and where the level of innovative ability k increases as k approaches t. The cumulative probability distribution corresponding to the probability function of the kth level of innovative ability is $F_k(\pi_i)$. Letting the probability density function conditional on a minimum level of innovative ability

$k = 1$ be $f_1(\pi_i|IA_1)$, the corresponding cumulative probability distribution is $F_1(\pi_1)$. Producers with more innovative ability are able to gain greater benefits from adoption. This implies that an increase in innovative ability redistributes probabilities toward higher payoffs, i.e., increases the probabilities of greater benefits. For some increase in innovative ability to a level above $k = 1$, say to $k = 2$, the probability density function and cumulative probability distribution would be $f_2(\pi_i|IA_2)$ and $F_2(\pi_i)$, respectively. The cumulative probability distribution of this redistribution of probabilities is such that $F_1(\pi_i)$ lies everywhere above $F_2(\pi_i)$.

For the probability of adoption to increase as innovative ability increases, i.e., for the expected utility of profits from adoption to rise with increases in innovative ability regardless of the specifications of the utility function, the distribution $f_2(\pi_i|IA_2)$ must be stochastically larger than $f_1(\pi_i|IA_1)$. In terms of FSD the value of the cumulative probability distribution of the preferred prospect $F_2(\pi_i)$ never exceeds that of the inferior prospect $F_1(\pi_i)$. That is

$$F_2(\pi_i) \leq F_1(\pi_i),$$

where for all values of π_i the probability of gaining π_i or less is not larger with $F_2(\pi_i)$ than with $F_1(\pi_i)$. Or, as innovative ability increases, the probability of gaining more than π_i is not smaller with $F_2(\pi_i)$ than with $F_1(\pi_i)$, for every π_i. By the transitivity of preferences, as innovative ability increases from the minimum level to some level t, where t > 1, all such prospects will be preferred to the prospect corresponding to the minimum level of innovative ability. In general,

$$F_{t-n}(\pi_i) \leq F_1(\pi_i),$$

where $n < (t-1)$, and

$$F_t(\pi_i) \leq F_{t-1}(\pi_i) \leq F_{t-2}(\pi_i) \leq \ldots \leq F_{t-(t-2)}(\pi_i) \leq F_{t-(t-1)}(\pi_i).$$

Alternatively, increases in innovative ability cause rightward shifts in the probability function so that $f_{t+n}(\pi_i | IA_{t+n})$ is at least as large as $f_t(\pi_i | IA_t)$ in the sense of FSD. In other words, f_{t+n} is preferred to f_t regardless of the specifications of the utility function. This implies that increases in innovative ability increase the expected utility of profits from adoption $E[U(\pi^A)]$. Hence, an increase in the difference of $E[U(\pi^A)]$ and $E[U(\pi^R)]$, resulting from an increase in the level of innovative ability, increases the probability of adoption regardless of the producer's attitude toward risk.

The application of the concept of FSD eliminates the effects of the attitude toward risk in making adoption decisions. This supports the use of the expected profit maximization criteria for making adoption decisions developed in the innovative ability model where producers were assumed to be risk neutral.

Footnotes

[1]Alternatively, the adoption decision can be based on the difference between expected profit when the innovation is adopted, $E[\pi^A]$, and expected profit when the innovation is rejected, $E[\pi^R]$. Holding the output rate constant, the cost savings (factor augmenting) nature of the innovation suggests expected profit should rise when adoption occurs, i.e., when $E[\pi^A] > E[\pi^R]$. This implies that adoption occurs only if $E[\pi^A] \geq E[\pi^R]$ and, conversely, that rejection occurs only if $E[\pi^A] < E[\pi^R]$.

[2]The marginal products of N and I are derived in Chapter II as first-order conditions for a profit maximum.

[3]In another sense, innovative ability is the capacity to be "productive" with new inputs and to anticipate that capacity. Innovative ability then becomes relevant in considering the effects of attitudes toward risk on the adoption decision.

[4]The return to education and other factors which enhance innovative ability are benefits normally not accounted for. This is brought out by T. W. Schultz, "The Increasing Economic Value of Human Time," American Journal of Agricultural Economics 54 (December 1972):847.

[5]The cost savings effect of adoption can be trasnformed directly into an effect on profits by holding output constant for a given output price.

[6]R. R. Nelson and E. S. Phelps, "Investment in Humans, Technological Diffusion, and Economic Growth," American Economic Review 56 (May 1966): 69-75.

[7]W. E. Huffman, "Allocative Ability: The Role of Human Capital," Quarterly Journal of Economics 91 (February 1977): 59-77; and W. E. Huffman, "Decision Making: The Role of Education," American Journal of Agricultural Economics 55 (February 1974):85-97.

[8]W. E. Huffman, "Decision Making," p. 85.

[9]F. Welch, "Education in Production," Journal of Political Economy 78 (January/February 1970):46.

[10]T. Schultz, "The Value of the Ability to Deal with Disequilibria," Journal of Economic Literature 13 (September 1975): 827, 834.

[11]Nelson and Phelps, p. 69.

[12]Nelson and Phelps, p. 69; and Welch, p. 47.

[13]Nelson and Phelps, p. 70.

[14]This interpretation of the effects of education is far from some "ad hoc" ones which have been proposed. An hypothesis that education makes decision makers less "conservative" is presented by A. A. Romeo, "Interindustry and Interfirm Differences in the Rate of Diffusion of an Innovation," Review of Economics and Statistics 57 (August 1975): 315. This requires one to ask what "conservative" means in economic decision-making. Such ambiguities do not arise if the effects of education on the efficiency of decision-making are developed strictly in terms of changes in productivity.

[15]G. S. Becker, Human Capital (New York: National Bureau of Economic Research, Inc., 1975), p. 37; Schultz, "Disequilibria," pp. 831-845; and Schultz, "Human Time," p. 847.

[16]G. J. Stigler, "Information in the Labor Market," Journal of Political Economy 70 (October 1962, Suppl.): 96; and G. J. Stigler, "Economics of Information," Journal of Political Economy 69 (June 1961):216.

[17]Huffman, "Allocative Ability," pp. 63-64; Huffman, "Decision Making," p. 87; and N. Khaldi, "Education and Allocative Efficiency in U.S. Agriculture," American Journal of Agricultural Economics 57 (November 1975):653.

[18]The effects of scale of production on allocative ability are discussed by W. E. Huffman, "Allocative Ability," p. 64; W. E. Huffman, "Decision Making," pp. 87, 93; and Khaldi, pp. 651, 654-656.

[19]Stigler, "Economics," p. 219.

[20]The development of the concept of stochastic dominance in this section relies on J. Hadar and W. R. Russell, "Stochastic Dominance and Diversification," Journal of Economic Theory 3 (September 1971):288-305; J. Hadar and W. R. Russell, "Rules for Ordering Uncertain Prospects,"

American Economic Review 59 (March 1969): 25-34; and G. Hanoch and H. Levy, "The Efficiency Analysis of Choices Involving Risk," Review of Economic Studies 36 (July 1969): 335-346.

[21]J. Hadar and W. R. Russell, "Stochastic Dominance," p. 290.

[22]The concept of FSD has been applied to "learning" and its effect on choosing optimal input levels by L. D. Hiebert, "Risk, Learning, and the Adoption of Fertilizer Responsive Seed Varieties," American Journal of Agricultural Economics 56 (November 1974): 764-768. Hiebert hypothesizes that "learning" creates adjustments in the input levels which eliminate allocative mistakes. It is then argued that these adjustments redistribute probabilities from lower payoffs to higher payoffs, thereby increasing the expected utility of net income from modern production. Because this change in (rate of) input utilization affects the net income from modern production, this "learning" may be more accurately described as an allocative effect. The probabilities, in the innovative ability model of adoption, are conditional on one aspect of allocative ability and not on the levels of inputs utilized.

CHAPTER IV: DATA AND EMPIRICAL SPECIFICATIONS OF THE INNOVATIVE ABILITY MODEL OF ADOPTION

This chapter presents the data used for fitting the empirical models, the empirical definitions of the variables, and the empirical specifications of the innovative ability model of adoption. The data are individual Iowa farmers raising cattle for slaughter in 1976. The first empirical specification is the linear probability model. Several problems of estimation and prediction, however, suggest that one should look for alternative models. Two alternatives which are transformations of the linear probability model (of binary choice) are the probit and logit transformations.[1] The logistic probability model is then extended to consider the joint adoption of complementary inputs, i.e., the decision to adopt a current innovative input and the decision to utilize an earlier innovation, a growth hormone implant, are treated as joint decisions. In a "conditional" logistic model, the probability of adopting momensin sodium is dependent on the utilization of an implant; and conversely, the probabiltity of utilizing an implant is dependent on the adoption of monensin sodium. In a "joint probability" logistic model, the adoption of the current innovation and the utilization of the complementary, earlier innovation are simultaneous decisions, i.e., the probability model is formulated as a system of simultaneous equations.

Data and Variables

The Iowa Family Farm Research Project Survey is the source of data for this study.[2] The sample survey of farms and farm households in all of Iowa's 99 counties was conducted in the spring of 1977 and collected information only for farms with at least $2,500 gross farm sales in 1976. The survey was designed to provide information on the characteristics of Iowa farms and farm families, on their information sources for decision-making, and on their research needs. The operator was identified as the primary decision-maker for the farm business. An adopter (nonadopter) is defined as an operator using (not using) monensin sodium in feeding cattle for slaughter.

The following variables were taken from or derived from the survey information:

Education: Years of schooling completed by the farm operator provides a direct measure of the educational level of the decision-maker.

Experience: Experience is measured by the number of years an operator has been farming on his own. It is derived by subtracting the year in which the operator began farming on his own from the year the survey was taken, 1976. The survey did not ask about the number of years the farm operators had been feeding cattle.

Information: Two information variables measuring farm operators' contact with agricultural extension service and private input supply firms are derived. Data on farmers' specific information about the use of monensin sodium were not collected in the survey, but data on the "frequency" of contact of operators with media and personal sources of information about markets, about the introduction of new products or procedures, and about the use of new products and procedures were obtained.[3] These data are used to derive the two information variables.

These frequency of contact data are subjective, qualitative measures of how often operators make contact with information sources. They take on integer values from 0 to 3 which correspond to four classifications of frequency of contact: no contact, little contact, some contact, and frequent contact. The frequency of contact by speaking to agricultural extension personnel about the use of new products and procedures is used as the measure of the amount of information obtained from agricultural extension service. The amount of information obtained from private agricultural supply firms is measured by the frequency of contact by speaking to private input supply firm personnel.[4]

Scale of Production: The survey provides a direct measure of this variable. The economic incentive for being informed about alternative technologies (the availability of monensin sodium) for feeding cattle is measured by the number (if five or greater) of head of cattle fed on the farm which were sold for slaughter in 1976.

Adoption: A dummy variable for adoption of the technological innovation monensin sodium is defined to take on the value 1 if the innovation is adopted, or 0 if the innovation is not adopted.

Implant: A dummy variable for the use of implants is defined to take on the value 1 if any growth hormone is implanted, or 0 if no growth hormone is implanted.

Empirical Specifications for the Adoption of a Single Innovation

The outcomes from the decision to adopt an innovation are dichotomous. Either the innovation is adopted or it is rejected. This is similar to an individual's decision to enter (not to enter) the labor force, to buy (not to buy) a car or some other durable good, to have (or not to have) a child. Thus, the concern is not with the rate of utilization after adoption. The first empirical specification of the innovative ability model of the adoption of a single innovation is the linear regression model.

Linear probability model[5]

In the linear probability model, the dependent variable in the model of the adoption decision is

$$y_1 = \begin{cases} 1 \text{ if the innovation is adopted} \\ 0 \text{ if the innovation is rejected.} \end{cases}$$

It is a linear function of a vector of explanatory variables Z, that is,

$$y_1 = Z\beta + \varepsilon, \qquad (4.1)$$

where

y_1 is the T x 1 vector of observations on the dependent variable,

Z is the T x (1+k) matrix of observations on the explanatory variable,

β is the (1+k) x 1 vector of coefficients, and

ε is the T x 1 vector of disturbance terms.

The standard least-squares (LS) assumptions for ε are[6]

$$E[\varepsilon] = 0,$$

$$E[\varepsilon\ \varepsilon'] = \sigma^2 I.$$

Thus,

$$E[y_1] = Z\beta. \qquad (4.2)$$

The least-squares estimator is

$$\hat{\beta} = (Z'Z)^{-1}Z'y_1.$$

Given the dichotomous (1 or 0) nature of the dependent variable, $E[y_1]$ can be interpreted as the proportion of all producers with a given set of z's who will adopt the innovation. As a conditional expectation of y_1 on Z, $E[y_1|Z]$ may be interpreted as the conditional probability that adoption occurs given Z. The value of $\hat{y}_1 = Z\hat{\beta}$ can be interpreted as an estimate of this conditional probability.

A linear probability specification of the adoption decision model, however, has several statistical problems when estimated by classical least-squares.[7] They are heteroskedasticity and nonnormality of the error term and predictions potentially outside the range of 0 to 1. First the binary nature of the dependent variable implies $\varepsilon_t = y_{1t}-Z_t\beta$, so, if $y_{1t} = 0$, then $\varepsilon_t = -Z_tb$ with probability $1 - Z_tb$, or if $y_{1t} = 1$, then $\varepsilon_t = 1 - Z_tb$ with probability Z_tb. The discrete distribution of the disturbance is

	ε_t	$p(\varepsilon_t)$
$y_{1t} = 0$	$-Z_t\beta$	$1 - Z_t\beta$
$y_{1t} = 1$	$1 - Z_t$	$Z_t\beta$

The variance of ε_t is

$$E[\varepsilon_t^2] = (-Z_t\beta)^2(1-Z_t\beta) + (1-Z_t\beta)(Z_t\beta)$$

$$= (Z_t\beta)(1-Z_t\beta),$$

and from (4.2),

$$E[\varepsilon_t^2] = E[y_{1t}](1-E[y_{1t}]).$$

Thus, the variance of ε_t differs systematically with $E[y_{1t}]$, and hence with Z_t. The disturbances ε_t are heteroskedastic. They violate the least-squares assumption of homoskedasticity.[8] The effect of heteroskedasticity is to make the classical least-squares estimator of β inefficient, although it remains unbiased and consistent.

When disturbances in a regression model are heteroskedastic, generalized or weighted least-squares is an efficient estimation procedure. The weighted least-squares (WLS) estimator for β in (4.1) can be obtained by applying a two-step procedure. Because the variances of the disturbances are unknown, they must be estimated before WLS can be applied. One method of obtaining these values is to first fit (4.1) by LS and then use $\hat{y}_{1t} = Z_t\hat{\beta}$ to estimate the variances as $\hat{\sigma}_t^2 = \hat{y}_{1t}(1-\hat{y}_{1t})$.[9] The estimate of the variance-covariance matrix, Ω_*, is then

$$\Omega_* = \begin{bmatrix} \hat{\sigma}_1^2 & 0 & \cdots & 0 \\ 0 & \hat{\sigma}_2^2 & \cdots & 0 \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ 0 & 0 & \cdots & \hat{\sigma}_T^2 \end{bmatrix}.$$

The WLS estimator for β is

$$\hat{\beta}_* = (Z'\Omega_*^{-1}Z)^{-1}(Z'\Omega_*^{-1}y_1).$$

Second, the distribution of ε_t is binomial; it is not normal.

This means that computed values of t and F statistics used in testing hypotheses and constructing confidence intervals do not have t and F distributions, respectively.[10]

Third, forecasts of y_{1t}, $\hat{y}_{1t}$, from the linear probability model may fall outside the 0-1 interval. This problem arises because $Z_t\hat{\beta}$ or $Z_t\beta_*$ are unrestricted, so some values of $\hat{y}_{1t}$ may exceed 1 and others may be less than 0.[11] Thus, the dichotomous dependent variable model developed in a linear probability framework (LS or WLS) allows for predicted values of y_1 which are outside the unit interval and which are inconsistent with an interpretation as the probability of adoption.

The statistical problems of the linear probability model estimated by both LS and WLS are potentially serious. Thus, other estimation procedures must be considered. Probit and logit estimation procedures attempt to solve the statistical problems of the linear probability model by transforming the dependent variable.

Probit model[12]

The probit model is associated with a cumulative normal probability function. It has had extensive application in biology; for example, in studies of critical drug dosages. In these studies, the hypothesis is that the critical dosage is normally distributed and the proportion of animals killed depends on the dosage. Animals will die only if the dosage level reaches or exceeds the critical level. Let W be a normally distributed index of the critical level of a drug expressed as a linear function of the dosage, and define F(W) as a cumulative distribution function. Let p be the proportion of animals killed, then F(W) = p.

The probit transformation is $W_t = F^{-1}(p_t)$, where $F^{-1}(\ )$ is the inverse function of $F(\ )$.

For applying the probit transformation to the adoption decision, define $W_t = Z_t\beta$ as an index positively related to the probability of adoption and measuring the t^{th} producer's attitude toward adoption. The probit specification for the conditional probability of adoption is

$$P_t(A|Z_t\beta) = F(Z_t\beta) = F(W_t), \tag{4.3}$$

where $F(\ )$ is the cumulative normal distribution. In the innovative ability model, W_t is a linear function of education (z_1), experience (z_2), information (z_3), and scale of production (z_4). If there is a critical value of W_t, W_t^*, for each producer which is distributed N(0, 1), values of y_{1t} (the adoption decision) are determined as

$$y_{1t} = \begin{cases} 1 \text{ (adoption)} & \text{if } W_t \geq W_t^* \\ 0 \text{ (rejection)} & \text{if } W_t < W_t^* \end{cases} .$$

When many different factors determine W_t^*, the central limit theorem can be applied to justify the assumption that W_t^* has a normal distribution.[13]

The standard normal cumulative distribution can be used to compute the probability that each W_t is greater than or equal to any arbitrary W_t^* so that

$$\begin{aligned} P_t(y_{1t} = 1|W_t) &= P_t(W_t \geq W_t^*|W_t) = F(W_t), \\ P_t(y_{1t} = 0|W_t) &= P_t(W_t < W_t^*|W_t) = 1-F(W_t). \end{aligned} \tag{4.4}$$

Equation (4.3) can then be rewritten as

$$P_t(A|Z_t\beta) = F(Z_t\beta) = (2\pi)^{-1/2} \int_{-\infty}^{Z_t\beta} e^{-w^2/2}dw, \tag{4.5}$$

where (the variable of integration) $w = (x-\mu)/\sigma$ when x is distributed $N(\mu,\sigma^2)$, and W_t^* is distributed $N(0, 1)$.

Let us arrange the observations in the adoption decision problem so that the first m producers are adopters and the remaining T-m producers are nonadopters, then the likelihood function can be written in the log form as

$$\sum_{t=1}^{m} \log F(Z_t\beta) + \sum_{t=m+1}^{T} \log[1-F(Z_t\beta)]. \tag{4.6}$$

The maximum likelihood estimates of β can then be obtained by maximizing (4.6) with respect to β.

From (4.3) and (4.4), the conditional expectation of y_{1t} in the probit model can then be expressed as

$$E[y_{1t}|Z_t\beta] = P_t(y_{1t} = 1|W_t) = F(W_t). \tag{4.7}$$

The estimated expectation of (4.7) is

$$\hat{E}[y_{1t}] = F(\hat{W}_t) = F(Z_t\hat{\beta}), \tag{4.8}$$

where $\hat{E}[y_{1t}] = \hat{y}_{1t}$ is the predicted probability that a producer, given the values of the z's, is an adopter and is equivalent to the probability that a standardized normal variate is less than or equal to $Z_t\beta$. Because F(W) is a cumulative normal distribution, $E[y_{1t}|Z_t]$ in (4.7) falls within the unit interval and is justifiably interpreted as a probability.

The impact of marginal changes in independent variables on the probability of adoption is greatest at the midpoint of the distribution; i.e., where $P_t(A) = 0.5$, a small change in Z brings about a relatively large change in $P_t(A)$.[14]

Logit model[15]

The logit model is associated with the cumulative logistic probability distribution of adoption. Define the probability of adopting the innovation as

$$P(A) = (1 + e^{-Z\beta})^{-1}, \qquad (4.9)$$

then

$$1/P(A) = 1 + e^{-Z\beta},$$

$$[1/P(A)] - 1 = e^{-Z\beta},$$

and

$$[\frac{P(A)}{1-P(A)}] = e^{Z\beta}. \qquad (4.10)$$

Taking the logarithms of both sides of (4.10) gives the logit model:

$$\log[\frac{P(A)}{1-P(A)}] = Z\beta. \qquad (4.11)$$

The left-hand variable in (4.11) is the logit corresponding to the probability of adoption; i.e., the log of the odds on adoption.[16] It is a monotonically increasing function of the probability P(A) and is bounded between $-\infty$ and $+\infty$.

The parameters of the logit model represented in (4.11) can be estimated by replacing the probability on the left-hand side with its approximation. One approximation $\hat{P}(A)_{ijk\ell}$ is the observed relative frequency of adoption by producers with a certain set of characteristics $Z_{ijk\ell} = (z_{1i}, z_{2j}, z_{3k}, z_{4\ell})$, where $i = 1,2,\ldots,m$; $j = 1,2,\ldots,n$, $k = 1,2,\ldots,p$, and $\ell = 1,2,\ldots,q$. Those producers with the $Z_{ijk\ell}{}^{th}$ set of characteristics have an i^{th} level of z_1, a j^{th} level of z_2, a k^{th} level of z_3, and ℓ^{th} level of z_4. Letting $n_{ijk\ell}$ represent the number of producers with the set of characteristics $Z_{ijk\ell}$ and $f_{ijk\ell}$ represent the number of producers within this set of producers who have adopted the innovation, then[17]

$$\hat{P}(A)_{ijk\ell} = f_{ijk\ell}/n_{ijk\ell}.$$

The logit probability model can then be estimated in the form:

$$\log\left[\frac{(f_{ijk\ell}/n_{ijk\ell})}{1-(f_{ijk\ell}/n_{ijk\ell})}\right] = \log\left[\frac{f_{ijk\ell}}{n_{ijk\ell}-f_{ijk\ell}}\right] = Z_{ijk\ell}\beta^{-1} \tag{4.12}$$

Difficulties may arise in applying (4.12) because of small "cell" sizes. If the elements of Z are continuously measured variables, many (if not all), of the m·n·p·q cells may have only one element. With one element per cell, $\hat{P}(A)_{ijk\ell}$ equals either 0 or 1, and interpreting it as a relative frequency is unrealistic. An alternative method for dealing with small cell sizes is to categorize some or all of the continuous variables. But cells with few observations will continue to be a potential problem.[18] However, a logit estimation technique with credible small sample properties is available.

The logit model can be restated using the cumulative logistic probability function so that small cell sizes are not a problem. The likelihood function for an individual observation (one observation per cell) is[19]

$$L(y_1,y_2,\ldots,y_T|x_1,x_2,\ldots,x_T) = \prod^{T}[F(\ )]^{y_t}[1-F(\ )]^{1-y_t}, \quad (4.13)$$

where F( ) is the asymmetric form of the cumulative logistic probability function

$$F(\ ) = \frac{1}{1 + e^{-Z\beta}} .$$

Equation (4.13) can be maximized to obtain an estimator for β, and the estimated probability of adoption is

$$\hat{P}(A) = \frac{1}{1+e^{-Z\beta}} .$$

Empirical Specifications for the Adoption of Interrelated Innovations

Many producers must consider more than one innovation in an adoption decision because the decisions are interrelated. Failure to take account of the joint decision in conducting the empirical analysis will lead to biased and inconsistent parameters of a single equation model. The joint occurrence is the utilization of an earlier innovative factor of production which complements monensin sodium, the implantation of a growth hormone. The first empirical specification of the innovative ability model of the adoption of interrelated innovations is the conditional logistic model.

Conditional logistic model

The conditional probability functions expressed in an asymmetrical univariate logistic formulation are

$$P(A|y_2 = 1) = \frac{1}{1+e^{-(Z\beta_1+y_2\alpha_2)}}, \tag{4.14}$$

$$P(X|y_1 = 1) = \frac{1}{1+e^{-(Z\beta_2+y_1\alpha_1)}}, \tag{4.15}$$

where

$$y_2 = \begin{cases} 1 & \text{if the complementary input is utilized} \\ 0 & \text{if the complementary input is not utilized,} \end{cases}$$

P(X) is the probability of utilizing the complementary input, α_i, with i = 1,2, is the bivariate interaction effect between the two innovations, and all other variables are as previously defined. These conditional probability functions correspond to structural equations (of the logistic formulation) in a simultaneous equations context. The logistic estimators, obtained by treating each of the "jointly dependent" dichotomous variables in turn as an exogenous explanatory variable in each of the conditional probability equations, are "conditional estimators." Equation (4.14) represents the probability of adopting the technological innovation conditional on the utilization of the complementary factor of production. The probability of utilizing the complementary factor of production conditional on the adoption of the technological innovation is represented in (4.15). Maximizing the likelihood functions formed from (4.14) and (4.15), as in (4.13), yields estimators of the coefficients β_1 and β_2, and estimators of the coefficients on the conditioning endogenous variables y_1 and y_2. The estimates of the bivariate interaction effects α_1 and α_2 must be adjusted by a factor of (division by) 2 to allow for the rescaling appropriate to the method of conditional estimation.[20] These conditional estimates are analogous to the ordinary least squares estimates of coefficients in a linear structural equation from a system of such equations. Improved estimators can be obtained by a "full information" maximum likelihood method of estimating the joint probability function.

Joint probability logistic model

The probabilities corresponding to the joint occurrence or nonoccurrence of the two dichotomous variables, y_1 and y_2, can be represented parametrically by two main effects, $Z\tilde{\beta}_1$ and $Z\tilde{\beta}_2$, and by one bivariate interaction effect b_{12}. The joint probability function for each of the jointly dependent variables can be expressed in the symmetric logistic form as

$$P_{y_1=1}(y_2) = \frac{e^{Z\tilde{\beta}_1+u_2b_{12}}}{\sum_{i_1=1}^{2} e^{u_1(Z\tilde{\beta}_1+u_2b_{12})}},$$

$$P_{y_2=1}(y_1) = \frac{e^{Z\tilde{\beta}_2+u_1b_{12}}}{\sum_{i_2=1}^{2} e^{u_1(Z\tilde{\beta}_2+u_1b_{12})}}, \tag{4.16}$$

where $u_1 = +1$ if $y_1 = 1$ and $i_1 = 1$; $u_1 = -1$ if $y_1 = 0$ and $i_1 = 2$; $u_2 = +1$ if $y_2 = 1$ and $i_2 = 1$; and $u_2 = -1$ if $y_2 = 0$ and $i_2 = 2$. $\tilde{\beta}_1$ and $\tilde{\beta}_2$ are the coefficients of the exogenous variables in the main effects in the adoption equation and the utilization equation, respectively. These main effects are linear functions of the vector of exogenous explanatory variables, $Z = (z_1,z_2,z_3,z_4)$. The bivariate interaction effect, b_{12}, is assumed to be constant and independent of the values of any of the exogenous explanatory variables.

The joint probability likelihood function is derived by specifying (4.16) as a system of equations. Maximum likelihood estimators of the structural coefficients, $\tilde{\beta}_1$, $\tilde{\beta}_2$, and b_{12}, are obtained by maximizing the likelihood function with respect to those parameters simultaneously. These full information maximum likelihood estimators are consistent and asymptotically efficient.

Footnotes

[1]"Angular transformations" are alternative transformations. See M. Nerlove and J. Press, "Univariate and Multivariate Log-Linear and Logistic Models," (Rand Corporation, R-1306-EDA/NIH, December 1973), pp. 15-16. An alternative technique to estimate the logistic function was developed by J. Berkson, "Maximum Likelihood and Minimum Chi-Square Estimation of the Logistic Function," Journal of the American Statistical Association 50 (March 1955): 130-162.

[2]E. O. Hoiberg and W. E. Huffman, Profile of Iowa Farms and Farm Families: 1978 (Iowa Agricultural and Home Economics Experiment Station and Cooperative Extension Service Bulletin P-141, April 1978).

[3]Media information sources are journals, magazines, television and radio. Personal sources of information are conversations with agricultural supply firm personnel and attendance at field days or demonstrations sponsored by the extension service, farm supply companies or co-ops.

[4]Other measures of the availability of information were also specified in the empirical analysis. These were both individual variables and groups or indices of variables. No individual variables performed as well as those defined (used). The Cronbach alpha test for the reliability of an index indicated no index of information variable sources and/or types was as good a measure of the availability of information as those variables defined.

[5]A. S. Goldberger, Econometric Theory (New York: John Wiley & Sons, Inc., 1964), pp. 156-162.

[6]If Z is random, then ε and Z are assumed to be uncorrelated.

[7]For an outline of the problems associated with an ordinary linear regression specification of the binary dependent variable model see Goldberger, pp. 248-250, and J. Kmenta, Elements of Econometrics (New York: The Macmillan Company, 1971), pp. 425-427.

[8]Also, when $y_1 = 0$ or 1 the variance of ε is low in relation to when $y_1 = 0.5$.

[9]A consistent estimator of $\hat{E}[y_t](1-\hat{E}[y_t])$ is $\hat{y}_t(1-\hat{y}_t)$. See R. McGillivray, "Estimating the Linear Probability Function," Econometrica 38 (September 1970):775-776.

[10]A significance test can be performed on the $\hat{\beta}$'s if their asymptotic means and variance are known. This is pointed out by Kmenta, pp. 252-254; and H. Theil, Principles of Econometrics (New York: John Wiley & Sons, Inc., 1971), pp. 377-378.

[11]Although $\hat{y}_t(1-\hat{y}_t)$ may take on negative values, $\hat{E}[y_t](1-\hat{E}[y_t])$ cannot.

[12]For a complete development of the probit probability model see D. J. Finney, Probit Analysis (Cambridge: Cambridge University Press, 1971). The discussion of the probit model relies on Goldberger, pp. 250-251; R. S. Pindyck and D. L. Rubinfeld, Econometric Models and Economic Forecasts (New York: McGraw-Hill, Inc., 1976), pp. 245-247; and Theil, Principles of Econometrics, pp. 630-631.

[13]Theil, Principles of Econometrics, p. 630; and H. Theil, Economics and Information Theory (Amsterdam: North-Holland Publishing Company, 1967), p. 73.

[14]The same can also be said for the cumulative logistic probability distribution. See Pindyck and Rubinfeld, p. 249.

[15]The discussion of the logit model relies on Nerlove and Press, pp. 12-20, Pindyck and Rubinfeld, pp. 247-251; and Theil, Principles of Econometrics, pp. 632-635.

[16]One property of the linear logit specification is the perfect symmetry between the logits of the two alternatives, i.e., between adoption and nonadoption. By interchanging the outcomes of the two alternatives, the functional specification of the right-hand variables in unchanged, but the signs of the coefficients of the variables will be reversed because

$$\log\left[\frac{P(A)}{1-P(A)}\right] = -\log\left[\frac{1-P(A)}{P(A)}\right].$$

[17]It can be shown that $f_{ijk\ell}/\eta_{ijk\ell}$ is a maximum likelihood estimate of $\hat{P}(A)_{ijk\ell}$. See J. Berkson, "A Statistically Precise and Relatively Simple Method of Estimating the Bio-Assay and Quantal Response, Based on the Logistic Function," Journal of the American Statistical Association 48 (September 1953):565-566.

[18]Information is still lost unless the number of observations is very large.

[19]Nerlove and Press, pp. 16, 17, 57.

[20]Ibid., p. 77.

CHAPTER V. EMPIRICAL RESULTS

The purpose of this chapter is to present and discuss estimates of the empirical specification of the innovative ability model of adoption. First, estimates of the model for Rumensin adoption by least-squares, weighted least-squares, probit and logit procedures are presented and compared. Second, estimates of the two-equation adoption model, which considers both the adoption of Rumensin and the utilization of the complementary technology of implanting growth hormones, by conditional logit and joint probability logit procedures are presented and compared to the single equation results. The results generally support the innovative ability hypothesis and show consistency among the different estimation techniques.

The Adoption of a Single Innovation

This section presents estimates of the adoption model for Rumensin when its adoption is considered independently of other, earlier innovations. The expected signs of the coefficients of the explanatory variables and the results from fitting the model by four different estimation procedures are presented in Table 5.1.[1] The equations were fitted with a squared term included for the education and scale variables to permit nonlinear marginal effects of these variables. The experience variable is defined as the inverse of experience.[2]

Table 5.1. Expected signs and estimated coefficients of the innovative ability model of adoption for a single innovation, Iowa farmers, 1976[a]

Variables	Expected Sign	LS (1)	WLS (2)	Probit (3)	Logit (4)
ED	+	0.258	-0.02	0.795	0.70
		(3.05)*	(-1.04)	(2.96)*	(2.97)*
ED^2	-	-0.011	0.0009	-0.034	-0.03
		(-2.90)*	(0.86)	(-2.81)*	(-2.84)*
1/EXP	-	0.339	0.201	1.007	0.84
		(1.59)	(0.96)	(1.58)	(1.63)***
EXT	+	0.065	0.047	0.204	0.178
		(2.38)**	(1.77)	(2.39)**	(2.40)**
PRAGS	+	0.0336	0.0384	0.0945	0.0758
		(1.32)	(1.51)	(1.24)	(1.20)
SCALE	+	0.00184	0.00195	0.00529	0.0043
		(4.25)*	(4.66)*	(3.99)*	(3.92)*
$SCALE^2$	-	-0.0000015	-0.0000014	-0.0000043	-0.0000035
		(-2.28)**	(-2.16)**	(-2.13)**	(-2.15)**
INTERCEPT	?	-1.44	0.366	-5.91	-5.17
		(-3.02)*	(1.13)	(-3.89)*	(-3.80)*
R^2		0.169	0.189		
F		8.766	9.931		
- Log Likelihood Function					-178.05
Observations		310	306	310	310

[a]Figures in parentheses are t-ratios for the LS and WLS equations, and asymptotic t-ratios for the probit and logit equations.

*Significant at 1% level.

**Significant at 5% level.

***Significant at 10% level.

The estimates

Estimates of the innovative ability adoption model for Rumensin provide surprisingly similar results, although the statistical properties associated with the coefficients seem likely to be much different. The signs of the estimated coefficients are in strong agreement with expected signs, except for the experience variable. It implies that farms operators with the least experience have the highest probability of adopting Rumensin as a cattle feeding technology, and that as farmers' experience increases the probability of adoption decreases.

Given the violation of the assumption of the standard normal multiple regression model, the least-squares estimator is inefficient and the estimator is not normally distributed. Weighted least-squares, applied by using the predicted value from the least-squares (LS) equation of Table 5.1 to obtain an estimate of the variance-covariance matrix, should improve the estimator's efficiency.[3] Weighted least-squares (WLS) estimates are reported in Equation (2) of Table 5.1. The performance of the education, experience, and extension information variables has deteriorated, however, in going from LS to WLS. The signs of the coefficients of ED and ED^2 have been reversed and the t-ratios for 1/EXP and EXT are smaller. Thus, other statistical problems and/or specification errors may be more serious than heteroskedasticity.

The probit and logit estimates of the model appear in Equations (3) and (4), respectively, of Table 5.1. These estimates should have significantly improved statistical properties compared to LS and WLS estimates of the model. All of the signs of the estimated coefficients are in agreement with those expected in the innovative ability model of adoption, except for experience. The sign of the experience coefficient is, however, in agreement with the LS estimate. Except for the coefficient of private agricultural supply firm information, the coefficients of all the explanatory variables are significantly different from zero at the 10 percent level of better.[4]

In comparing the probit and logit results with the LS and WLS results, there are two notable changes in sign of the coefficients. These are the negative sign on the coefficient of education and the positive sign of the coefficient on education squared. Also, the LS estimation, even with the bias of the test statistics, seems to provide a "good" indication of the explanatory power of the innovative ability model of adoption. This is suggested by the comparison of the t-ratios of the variables included in the regression equations in Table 5.1 with the t-ratios of the variables not included: the former variables have the greatest (relative) significance between variables within an equation, are consistently the most (relatively) significant variables between estimation techniques, and are the same variables chosen when using the criterion for determining which variables to include in the LS estimation.

Implications of the estimates

In order to compare the implications of the probit and logit estimates with each other and with the implications of the LS and WLS estimates, the regression coefficients in Table 5.1 must be transformed into common units, the effect of a unit change in an explanatory variable on the probability of adoption. First the partial derivatives of the probability of adoption with respect to each explanatory variable in the probit and logit equations are obtained. These partial derivatives are then transformed to obtain the partial derivatives of the probability of adoption with respect to the explanatory variables in the estimated probit and logit equations. The estimated marginal effects from the LS and WLS estimations and the marginal effects derived from the probit and logit estimations are presented in Table 5.2, and implied adoption elasticities for the probit and logit models are presented in Table 5.3.

Table 5.2. Expected signs of the partial derivatives of the probability of adoption and their estimated values[a]

$\partial P(A)/\partial X$	Expected signs	LS	WLS	Probit	Logit
$\partial P(A)/\partial ED$	+	0.0085	0.00045	0.009	0.014
$\partial P(A)/\partial EXP$	+	-0.00067	-0.0004	-0.0007	-0.00076
$\partial P(A)/\partial EXT$	+	0.065	0.047	0.073	0.082
$\partial P(A)/\partial PRAGS$	+	0.0336	0.038	0.036	0.035
$\partial P(A)/\partial SCALE$	+	0.0015	0.0016	0.0017	0.0016

[a]All estimated values of the partial derivatives are evaluated at the variable's sample mean value. Estimates of coefficients used in the calculations are taken from Table 5.1.

Table 5.3. Estimated elasticities of the probability of adoption[a]

Elasticity	Probit	Logit
$\varepsilon_{P(A), ED}$	0.27	0.42
$\varepsilon_{P(A), EXP}$	-0.041	-0.045
$\varepsilon_{P(A), EXT}$	0.40	0.45
$\varepsilon_{P(A), PRAGS}$	0.085	0.083
$\varepsilon_{P(A), SCALE}$	0.50	0.47

[a]All estimated values of the elasticities of the probability of adoption are evaluated at the variable's sample mean value. Estimates of coefficients used in the calculations are taken from Table 5.1.

The hypothesis that operators with more education are more likely to be adopters than operators with less education is supported by the positive partial derivative of education (ED) in all models. In the probit (logit) model, the partial derivative of the probability of adoption with respect to education is 0.009 (0.014); i.e., an increase in the educational level of the average operator by one year will increase the probability of adoption by 0.9 (1.4) percentage points. This one additional year of education produces a 2.4 (3.7) percent increase in the probability of adoption. This implies that an operator with one year of education more than the average operator is 2.4 (3.7) percent more likely to be an adopter than the average operator. The least-squares estimation implies a smaller marginal effect of education on adoption.

In the probit and logit models, the effect of operator's education on the probability of adoption is maximized at 11.7 and 11.9 years of schooling, respectively. This implies that the average operator with 11.3 years of education is less than one year short of an education level that would maximize the effect of education on the probability of adopting Rumensin.[5]

The negative partial derivative of the probability of adoption with respect to the level of experience (EXP) in all equations fails to support the hypothesis that operators with more experience are more likely to be adopters than operators with less experience. The partial derivative of the probability of adoption with respect to a year of experience is approximately -0.0007 in the least-squares, probit and logit equations.[6] This negative impact of experience on the probability of adoption may be interpreted as more experienced operators being less adaptive and receptive to a dynamic technological environment. Or alternatively, the less experienced operators, who are also the younger operators, are more likely to adapt their productive techniques in favor of innovative factors of production.[7] This suggests that the effect of the low cost of "investing" in new technologies for the young and least experienced operators may offset the hypothesized effect of experience in making innovative decisions. As experience increases the probability of adoption decreases, although this effect as indicated by the estimated partial derivative of experience is very small. The more experienced operators are slower to adopt and the less experienced operators are the most likely to be adopters.

The positive partial derivative of the probability of adoption with respect to frequency of contact with agricultural extension information sources (EXT) supports the hypothesis that an increase in the frequency of contact with sources of information about the use of new products and procedures increases the probability of adoption. Although the estimated coefficients on PRAGS (frequency of contact with private agricultural supply firms' information sources) are positive in sign, none of the coefficients are significantly different from zero. Thus, those operators who obtain information about the use of innovative products or procedures from agricultural extension are more likely to be adopters than operators who obtain less information, but obtaining information from contacts with private agricultural supply firms is not a strong indicator of adoption.[8]

The larger effect of agricultural extension information contact on the probability of adoption may be partially explained by the role each information source plays in the adoption decision and diffusion process. Information obtained from agricultural extension sources about the use of new products and procedures may be regarded as being more credible or reliable than information obtained from private agricultural supply firms. Farmers may feel that input supply representatives are primarily interested in their firm's sales or profits, while agricultural extension is providing technical information as a part of a public information program. For extension to perform well in this task, operators must value and apply extension information in making production and innovative decisions. In terms of opportunity cost, farmers' willingness to have contact with extension implies that the information has value to them; empirical results show that operators with more frequent contact with agricultural extension are more rapid adopters. Alternatively, the nature of the adoption decision may dictate the relative impact of information sources on early adoption. Early in the diffusion process, agricultural extension may be more able to supply relevant information on an innovative input than can its possible or future suppliers. A higher frequency of contact with agricultural extension information sources than with private agricultural supply firms' information sources supports this interpretation of the relative effect of alternative information sources.[9]

In the logit equation, a likelihood ratio test can be used to evaluate the statistical hypothesis about the importance of the group of variables which are the measurable dimensions of innovative ability, ED, ED^2, 1/EXP, EXT and PRAGS. Twice the difference of the log likelihood when these variables are excluded from the equation and the log likelihood from the logit equation in Table 5.1 (-2[-189.6 + 178.05] = 23) is distributed asymptotically χ^2 with degrees of freedom equal to the number of restrictions (slopes set equal to zero) imposed. With the upper 1 percent level of significance for χ^2 with 5 degrees of freedom being 15.1, we can accept the hypothesis that innovative ability is a significant determinant of the probability of adoption. This supports the hypothesis of the innovative ability model of adoption that the greater an agent's innovative ability the greater the probability of adopting innovations.

The positive partial derivative with respect to scale of production

(SCALE) in all equations supports the hypothesis that producers operating at larger scales of production have a greater economic incentive to be informed about innovative feed additives; therefore, they are more likely to adopt the innovation than producers with smaller scales of production. Because the cost of information usage seems to be uncorrelated to the size of the cattle feeding operation the results for the scale variable also imply there are economies of scale in the utilization of information. This incentive for larger cattle feeders to be informed means that larger size may be viewed as substituting for less education and experience. The probability of adoption is positively related to the scale of production, presumably because the larger the scale of production the greater the time and expenditures allocated to information processing and the less time allocated to other decision-making alternatives. This allows larger cattle feeders access to a higher quality and/or quantity of information. All things equal, producers feeding a greater-than-average number of cattle are more likely to adopt the innovation than producers with a less-than-average number of feeder cattle. This implies that producers feeding more than 111 head of cattle for slaughter are more likely to be adopters than producers with fewer slaughter cattle.

In the probit and logit equations, the partial derivative of the probability of adoption with respect to scale of production is about 0.0017. For the average operator, this implies that an increase of 10 head of fed cattle would increase the probability of adoption by about 1.7 percentage points. The positive effect of SCALE on the probability of adoption diminishes as SCALE increases. The maximum positive effect occurs at 615 (614) head of cattle in the probit (logit) model. Thus, an average operator with 111 head of cattle is producing at an output rate that is far below the size that has the maximum positive effect on the probability of adoption. This may be one explanation for the low average probability of adoption of 0.38. If the average operator doubled the number of cattle fed, the probability of adoption would increase to 0.57 (0.56) in the probit (logit) model, which represents approximately a 50 percent increase in the probability of adoption.

A comparison of the response elasticities in Table 5.3 indicates that the probability of adoption is most responsive to a change in the scale of production than to a change in the educational level of the operator, or to a change in the level of the operator's experience. In the logit model, the probability of adoption for the average operator is more responsive to a change in his educational level, relative to a change in the scale of production, than in the probit model. A comparison of the information elasticities indicates the probability of adoption is more responsive to a change in the frequency of contact with agricultural extension information sources than to a change in the frequency of contact with private agricultural supply firms' information sources. The qualitative scale used to measure the information variables prohibits a comparison of their response elasticities with the other (quantitative) variable response elasticities.

The Adoption of Interrelated Innovations

This section presents logit estimates of the adoption model when it is expanded to consider the interrelated technologies of Rumensin and implanting of growth hormones.

The estimates

The results of estimating the conditional probability functions (for each of the dependent variables) and the joint probability functions are reported in Table 5.4. Equations (1) and (2) report the results of the conditional estimations of the univariate dichotomous logistic functions obtained by treating AMS and IMPT, in turn, as an exogenous explanatory variable in the other's conditional probability equation. Equations (3) and (4) report the results of the full information maximum likelihood estimation of the joint probability functions.

The comparisons of Equation (3) with (1), and (4) with (2), show very little difference between the conditional estimates and the more appropriate full information joint probability estimates. In Equations (1) and (3), all the coefficients of the variables, except for 1/EXP, PRAGS, and $SCALE^2$, are significantly different from zero at the 10 percent level or better. Only the coefficients of the scale of production, the scale of production squared, and the interaction term are significantly different from zero at conventional levels of statistical significance in Equations (2) and (4). All the coefficients of the variables in Equation (3) have the same sign as in Equation (1), and all the

Table 5.4. Conditional and joint probability estimates of the innovative ability model of adoption for interrelated innovations, Iowa farmers, 1976[a]

	Conditional estimates		Joint Probability Estimates	
	AMS (1)	IMPT (2)	AMS (3)	IMPT (4)
Main Effects:				
INTERCEPT	-5.46 (-3.79)*	-1.04 (-1.26)	-5.0 (-3.40)*	-0.71 (-0.55)
ED	0.73 (2.92)*	-0.015 (-0.22)	0.71 (2.9)*	-0.01 (-0.04)
ED^2	-0.032 (-2.86)*	0.0034 (0.36)	-0.031 (-2.85)*	0.0032 (0.33)
1/EXP	0.82 (1.44)	0.15 (0.28)	0.80 (1.48)	0.12 (0.23)
EXT	0.20 (2.58)*	-0.057 (-0.79)	0.20 (2.52)**	-0.059 (-0.81)
PRAGS	0.081 (1.22)	-0.017 (-0.25)	0.08 (1.2)	-0.015 (-0.23)
SCALE	0.0035 (3.04)*	0.0028 (2.46)*	0.0034 (3.0)*	0.0028 (2.43)**
$SCALE^2$	-0.0000026 (-1.54)	-0.0000032 (-1.90)***	-0.0000026 (-1.5)	-0.0000033 (-1.84)***
Interaction Effects:				
AMS		0.359 (5.04)*		0.36 (5.04)*
IMPT	0.362 (5.08)*		0.36 (5.04)*	
Log Likelihood Function	-164.6	-169.7	-347.8	

[a]Figures in parentheses are asymptotic t-ratios.

*Significant at 1% level.

**Significant at 5% level.

***Significant at 10% level.

coefficients of the variables with large (small) t-ratios in Equation (1) also have large (small) t-ratios in Equation (3). There is also conformity of signs, and magnitudes of t-ratios, of the coefficients of the variables between Equations (2) and (4). But all of the coefficients of the variables of the main effects in the IMPT equations, except for SCALE and $SCALE^2$, have the opposite sign as in the AMS equations.

The conditional estimates in Equations (1) and (2) can be interpreted as (analogous to the ordinary least-squares) estimates of the structural coefficients in a system of simultaneous equations. *A priori*, this does not imply that these estimates would or would not be close to the more appropriate full information estimates in Equations (3) and (4). If the coefficients of the variables of the main effects differ at all in magnitude, they differ only in the second or third digit of the corresponding coefficient estimate. The greatest differences in the coefficients occur for those with low t-ratios. The intercepts are expected to be sensitive to the method of estimation.

The interaction effect in each equation is positive and statistically significant at the 1 percent level. Differences do exist, however, between the conditional estimates and the joint probability estimate of the interaction effect. The matrix of estimated (single valued) joint probability interaction effects appearing in the last two rows of Equations (3) and (4) is symmetric. The corresponding matrix of the conditional estimates, obtained by estimating the AMS equation and the IMPT equation independently of each other, is not symmetric, although it nearly is. This slight lack of symmetry is the major weakness of the conditional estimates.

A comparison of the conditional estimates, and the joint probability estimates, with the results of estimating the logit equation in Table 5.1 shows all of the coefficients of the variables of the main effects have the same sign, all of the coefficients of the variables have approximately the same magnitude, and, except for PRAGS in both estimated equations and 1/EXP and SCALE^2 in the estimated conditional probability and joint probability equations, all of the coefficients of the variables are statistically significant at the 10 percent level or better.

The general agreement between the models of estimation does not imply that the logit estimates or even the conditional estimates are as "good" as the full information joint probability estimators. A more likely cause of this result is suggested by the conclusions drawn from the conditional logit analysis, i.e., the model, in both instances, may be misspecified when other jointly dependent variables are not included.[10] The remarkable agreement of the estimated univariate logistic model of the adoption decision with both the conditional estimates and joint probability estimates of the adoption equation in the multivariate logistic model also lends support to this argument.

Implications of the estimates

The importance of the variables that measure innovative ability in explaining the probability of adopting a current innovation can be seen by comparing the log likelihood when those variables are excluded from the conditional equation with the log likelihood of Equation (1) in Table 5.4: -2(-175.5 + 164.6) = 22.2 is distributed asymptotically χ^2 with 5 degrees of freedom, equal to the number of restrictions (the number of sloped set equal to zero) imposed. The upper 1 percent level of statistical significance for χ^2 with 5 degrees of freedom is 15.1. The hypothesis that innovative ability is a significant determinant of the probability of adoption can, therefore, be accepted. This supports the hypothesis that producers who have more innovative ability are more likely to be adopters of current innovations than those who have less innovative ability.

A log likelihood ratio test can be used to evaluate whether or not innovative ability is a significant determinant of the probability of implanting in Equation (2). The log likelihood for the equation when the measurable dimensions of innovative ability are deleted is 172.2. Again, twice the difference of the log likelihood (-2[-172.2 + 169.7] = 5.0) is distributed asymptotically χ^2 with 5 degrees of freedom. With the upper 10 percent level of statistical significance for χ^2 equal to 9.24, we cannot accept the hypothesis that innovative ability is a significant determinant of the probability of utilizing earlier innovative inputs. Therefore, the decision to utilize innovations several periods after their introduction can be distinguished from the adoption decision as defined by the innovative ability model. Thus, factors explaining the adoption decision (innovative ability variables) will not explain the diffusion of innovations.

The small t-ratio for the coefficient of the reciprocal of experience, in all equations, implies that experience has no effect on the probability of adoption. This and the positive, statistically significant coefficient of the reciprocal of experience in the logit equation in Table 5.1 fail to support the hypothesis that operators with more experience are more likely to be adopters than operators with less experience.

The positive and constant effect of the scale of production in the adoption equations supports the hypothesis that producers with larger scales of production are more likely to be adopters. The positive, but diminishing effect of the scale of production in the implant equations supports the hypothesis that producers with larger scales of production are more likely to utilize an earlier innovative input than producers with smaller scales of production. These results suggest that producers operating at larger scales of production have a greater economic incentive to be informed about superior technologies regardless of when they are introduced.

The positive interaction effect of implanting in the adoption equation supports the hypothesis that producers who have adopted earlier innovative inputs (utilize inputs complementary to current innovations) are more likely to adopt current innovations than those who have not. This implies that innovations which can be implemented along with the currently utilized inputs are more likely to be adopted than those innovations which would displace currently utilized inputs.

The positive interaction effect in the implant equations suggests that the use of Rumensin increases the probability of implanting, all things being equal, even though the implant technology has been available for several periods. This supports the hypothesis that producers with a given level of innovative ability and scale of production have a higher probability of utilizing earlier innovative inputs several periods after they have been introduced if complementary current innovations are adopted than if they are not.

Footnotes

[1]The equation presented is the preferred estimated equation because all variables which are hypothesized to directly affect the probability of adoption in the innovative ability model appear and the interaction terms and nonlinear terms not appearing all have coefficients that are not statistically significant at conventional levels of significance. Therefore, no implications can be drawn about whether education complements or substitutes for either information source or experience in making adoption decisions. Also, the R^2's of the LS and WLS equations are "relatively" good considering the limited (binary) nature of the dependent variable. Although its meaning is unclear when the disturbances are binomial and discrete rather than continuously distributed, it is presented here as part of the linear probability estimates.

[2]Experience is constrained to be equal to or greater than one year. Appendix B reports the probit and logit estimations for an equation with an alternative definition of experience.

[3]The four observations where $\hat{y}$ from the LS predictions falls outside the interval 0-1 were removed because they imply negative values for estimates of the variance. The variables in the WLS estimated equation are transformed by dividing both the dependent and independent variables by σ.

[4]Again, the interaction terms and the nonlinear terms not included in the probit equation and the logit equation were not statistically significant at conventional levels of significance.

[5]The elasticity of the probability of adoption, with respect to the operator's educational level, is 0.27 (0.42) in the probit (logit) model; i.e., the logit model predicts the average operator's likelihood of adoption to be more responsive to a change in the educational level than the probit model.

[6]According to the elasticity of the probability of adoption, a 1 percent increase in the operator's level of experience will decrease the probability of adoption by 0.041 (0.045) percent in the probit (logit) model.

[7]The effect of age of a firm's president on the rate of diffusion of an innovation is in question. Opposite conclusions have been reached by S. Globerman, "Technological Diffusion in the Canadian Tool and Die Industry," Review of Economics and Statistics 57 (November 1975):431; and Romeo, p. 316.

[8]In the probit (logit) model, a 1 percent increase in the frequency of contact with agricultural extension information sources will increase the probability of adoption by 0.40 (0.45) percent. Irrespective of the low level of statistical significance of the coefficient on PRAGS, a 1 percent increase in the frequency of contact with private agricultural supply firms' information sources will increase the probability of adoption by 0.085 (0.083) percent in the probit (logit) model.

[9]The average operator "sometimes" has contact with agricultural extension information sources and "seldom" has contact with agricultural input supply firm information sources.

[10]Nerlove and Press, p. 81.

CHAPTER VI. SUMMARY AND IMPLICATIONS

In a dynamic economic environment the opportunity cost of not adjusting to changing economic conditions provides the signal to make reallocative decisions. The capacity to adjust quickly to a changing set of available inputs resulting from the introduction of a technological innovation, i.e., to be an early adopter of innovative inputs, is innovative ability, one dimension of allocative ability.

Summary

This study was concerned with the early adoption of an innovative cattle feed additive, monensin sodium. A rate of adoption (adjustment) model was transposed into a single period model of the adoption decision. The decision to adopt was specified as an adjustment to a disequilibrium in the "optimal" set of inputs. The probability of adoption was determined by the level of innovative ability and the scale of production. Education, experience, and the availability of information were hypothesized to be measurable dimensions of innovative ability.

The results indicated that increases in education and information enhance innovative ability, and thereby raise the probability of adoption. Operators with more education and those who acquire more information about the use of new products and procedures are more aware of innovative factors of production, are more efficient evaluating the productive characteristics and costs of those innovations, and are more likely to adjust their utilized set of inputs through adoption. The results suggested that the average operator (with 11.3 years of education) is less than one year short of an educational level that would maximize the effect of education on the probability of adoption. The estimated effect of increases in experience, however, did not support the hypothesis of the innovative ability model of adoption. The results also indicated that operators are more cognizant of innovative factors that can be applied in the larger scale activities of the operation. Also, scale economies in the usage of information exist, but the benefits realized by the average operator were small in relation to the potential benefits provided by larger scales of production. The results, however, did not indicate, either because of limitations of the data or the model, that the economic variables which are measurable dimensions of innovative ability substitute for or complement each other's contribution to innovative efficiency. Alternatively, this may suggest that the effects of these variables on one's ability to make innovative decisions are independent of one another.

Implications

In general, the results imply the following:

1) Education increases the probability of adoption and is a source of return to education which has received little theoretical attention.

2) The availability of information is necessary to make innovative decisions.

3) The dissemination of information by agricultural extension creates a benefit in the form of increased production and welfare.

4) The dissemination of information by private agricultural supply firms provides benefits to adopters analogous to those from agricultural extension information but also provides benefits to the firms. These benefits act as the incentive for firms to develop innovations and make available information pertaining to their use.

5) Operators with larger scales of production gain scale economies in information usage.

6) An increase in innovative ability increases the probability of adopting profitable innovations regardless of the agent's attitude toward risk. As an allocative skill, innovative ability allows agents to benefit from the disequilibria resulting from the introduction of new technologies, and reduces the probability of allocative error.

7) If an innovation can be employed along with current inputs it is more likely to be adopted than if it displaces currently utilized inputs.

This research expands the knowledge of how an agent's capacity to respond to disequilibria resulting from a dynamic economic environment is affected by one dimension of allocative efficiency. The implication is that decision-making is a human capital intensive activity. This suggests that the benefits derived from adopting new inputs creates an incentive for agents to acquire the ability to adjust to disequilibria resulting from the introduction of new inputs.

The implications of the innovative ability model of adoption suggest several topics for future research. The effect of education on making innovative decisions suggests education may play an important role in making household production decisions and asset portfolio decisions. The disequilibria resulting from the introduction of new types of assets and innovative ways of carrying out transactions create an incentive for agents to learn and adapt their activities. This is only one sector of economic activity which is being changed by the introduction of innovations.

The conclusion that an increase in innovative ability increases the probability of adoption regardless of the attitude toward risk of the adopter can be checked by using an alternative criterion for ranking uncertain prospects. In this approach, groups of agents are defined by a specified interval of risk aversion. The probability distributions of adopters can then be compared with the probability distributions of nonadopters within an interval of risk aversion. The hypothesis is that the level of innovative ability of the average adopter is at least as high as the level of innovative ability of the average nonadopter within each group of agents.

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I alone am responsible for any omissions or errors that remain in this dissertation.

APPENDIX A: TABLES OF FREQUENCIES OF ADOPTION AND NONADOPTION BY EDUCATION, EXPERIENCE, AND SCALE OF PRODUCTION

Table A.1. Frequencies of adoption and nonadoption by education

Years of education of operators	Frequency in sample	Adopters	Frequency of adoption	Nonadopters	Frequency of nonadoption
6-8	.22	13	.19	54	.81
9-10	.05	6	.35	11	.65
11-12	.58	79	.44	101	.56
13-14	.09	14	.48	15	.52
15-16	.04	6	.46	7	.54
17-18	.01	0	.00	4	1.00
TOTALS		118		192	

Table A.2. Frequencies of adoption and nonadoption by experience

Years of experience of operators	Frequency in sample	Adopters	Frequency of adoption	Nonadopters	Frequency of nonadoption
0-4	.05	9	.53	8	.47
5-9	.11	19	.56	15	.44
10-14	.07	10	.42	14	.58
15-19	.13	17	.44	22	.56
20-24	.17	17	.32	36	.68
25-29	.21	23	.36	41	.64
30-34	.10	11	.35	20	.65
35-39	.10	8	.26	23	.74
40-44	.03	2	.20	8	.80
≥45	.02	2	.29	5	.71
TOTALS		118		192	

Table A.3. Frequencies of adoption and nonadoption by scale of production

Number of cattle fed on the farm sold for slaughter	Frequency in sample	Adopters	Frequency of adoption	Nonadopters	Frequency of nonadoption
1-49	.46	28	.20	114	.80
50-99	.22	31	.45	38	.55
100-249	.19	32	.55	26	.45
250-499	.11	21	.64	12	.36
≥500	.03	6	.75	2	.25
TOTALS		118		192	

APPENDIX B: AN ALTERNATIVE SPECIFICATION OF THE INNOVATIVE ABILITY MODEL OF ADOPTION

The hypothesis of the innovative ability model of adoption is that increases in the level of experience have a positive effect on the probability of adoption. An equation with the level of experience and experience squared was specified in order to test for a nonlinear relationship between experience and the probability of adoption. The results of the probit and logit estimations of this specification are consistent with the results from the estimation of the probit and logit equations reported in Table 5.1; i.e., they fail to support the hypothesis.

In order to evaluate the effect of experience on the probability of adoption, the logit and probit coefficients can be transformed as described in the text. The negative partial derivative of the probability of adoption with respect to the level of experience (EXP) in the probit (logit) equation fails to support the hypothesis that operators with more experience are more likely to be adopters than operators with less experience. The partial derivative of the probability of adoption with respect to experience is -0.006 (-0.0055) in the probit (logit) equation. This negative impact of experience on the probability of adoption may be interpreted in the same way as the negative sign of the partial derivative of experience on the probability of adoption when the nonlinear effect of experience is specified by the reciprocal of experience.

The effect of an increase in the level of experience on the probability of adoption, however, does not approach zero as in the reciprocal form of the nonlinear relationship. Instead, the effect of an increase in experience is minimized at 30.6 (29.4) years of experience in the probit (logit) model. This range of the nonlinear relation corresponding to the diminishing effect of experience on the probability of adoption is 81 (75) percent of the sample range in the probit (logit) model. The relevant range of the effect of increases in experience on the probability of adoption is from zero years of experience to the number of years of experience where its effect on the probability of adoption is minimized. An alternative interpretation is that the effect of increases in experience on the probability of adoption is negative up to this minimum and then becomes positive. The period over which increases in experience have negative effects on the probability of adoption can be considered as a "learning period" and once that period is over, increases in experience increase the probability of adoption. This implies the average operator with 21.8 years of experience has a "learning period" of 30.6 (29.4) years in the probit (logit) model. This extensive "learning period" is required for experience to have a positive effect on the probability of adoption, and is a length of time well beyond the number of years the average operator has been farming on his own.

These interpretations are illustrated in Figure B.1. The first is illustrated by the curve ABD (A'B'D') for the probit (logit) equation. The "learning period" interpretation is illustrated by the curve ABC (A'B'C') for the probit (logit) equation.

Even though the first interpretation of the negative partial derivative of the probability of adoption with respect to experience

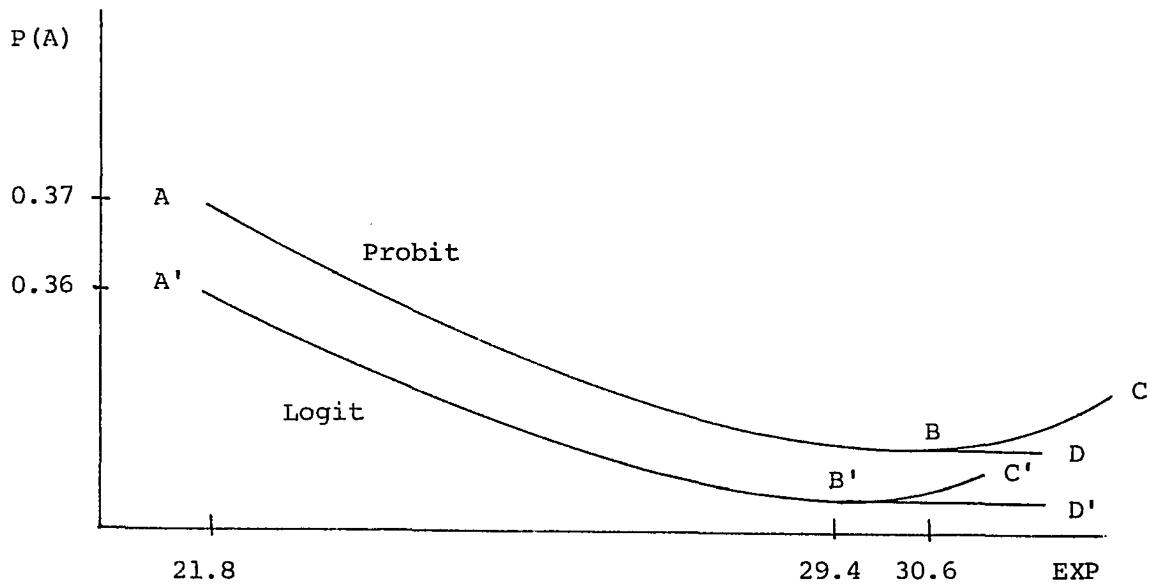

Figure B.1. Marginal effect of experience on the probability of adoption

seems more reasonable than the "learning period" interpretation, the whole range of the sample is not accounted for. The difficulty with the second interpretation is that the theoretical justification for a turning point is lacking. This implies an alternative form of the non-linear relationship between experience and the probability of adoption should be specified. The reciprocal of experience was chosen as the alternative.