# Adoption of Emerging Technologies Under Output Uncertainty

**Atanu Saha, H. Alan Love, and Robert Schwart**

A model of divisible technology adoption under incomplete information dissemination and output uncertainty is developed. We identify economic and subjective factors affecting technology adoption and its intensity. Empirical estimation employs a mixed dichotomous-continuous framework with nonrandom sample selection. Producers' adoption intensity is conditional on their knowing about and deciding to adopt the new technology. Using survey data on bST (bovine somatotropin) adoption among Texas dairy producers, we find that larger and more educated operators are likely to adopt more intensively. Traditional dichotomous adoption models without sample selection significantly overestimate the adoption rate.

*Key words*: adoption, bST, emerging technologies, sample selection, uncertainty.

The literature on technology adoption under uncertainty can be divided into two broad streams: static adoption behavior of individual firms and aggregate adoption models that emphasize technology diffusion over time. Feder, Just, and Zilberman provide a comprehensive survey of this literature. In the present paper, we develop a model of an individual producer's decision to adopt a divisible technology in the presence of risk. We explore factors affecting adoption and intensity of adoption.

Our analytical model and its empirical application are framed in the context of bST (bovine somatotropin) adoption, a yield-enhancing growth hormone. Research suggests that bST could increase milk production by 10–20% per cow, depending on management practices (Office of Technology Assessment). After reviewing the product for over nine years, the Food and Drug Administration (FDA) approved bST for commercial use in November 1993. While the decision was pending, the technology was in the center of considerable controversy (Kaiser, Scherer, and Barbano; Smith and Warland). On the day bST was approved, Steven Witt, president of the Center for Science Information, a biotechnology research group in San Francisco, said: "The safety of this product was established very clearly by every major scientific body years ago. But the social and economic impacts, especially for agriculture, are far less clear" (*New York Times*, p. 1, November 6, 1993). Our study attempts to assess such impacts. It identifies the socioeconomic profile of early adopters and estimates the probable increase in milk supply through adoption.

Although bST provides a natural backdrop for our study, the model is applicable to any divisible technology about which information dissemination is incomplete. Examples of such technologies include genetically engineered products, whose prevalence is likely to grow in the near future. Approval of bST makes milk the first genetically engineered food allowed by the government, and it is unlikely to be the last. Jeremy Rifkin, the head of the Foundation on Economic Trends, contends: "This is the beginning of food politics in this country. If Monsanto (developer of bST) succeeds with this product, they open the floodgates on the biotechnology age" (*New York Times*, p. 1, November 6, 1993). Given the scientific and political conflicts surrounding biotechnological products, their commercial use is likely to be preceded by a protracted period of tests, trials, and impact analysis. A distinguishing feature of the precommercial use or early-diffusion period

---

The authors are, respectively, assistant professor, assistant professor, and professor and extension economist, Department of Agricultural Economics, Texas A&M University.

The authors wish to thank the three anonymous reviewers for their helpful comments; the usual disclaimer applies. Texas Experiment Station Article Number: 31688.

Review coordinated by Steven Buccola.

*Amer. J. Agr. Econ.* 76 (November 1994): 836–846

is incomplete information dissemination among potential adopters. Our study departs from existing literature by focusing on the analytical and empirical implications of incomplete information in the adoption process.

The role of information assumes special significance in the case of new or emerging technologies. The importance of information gathering and learning-by-doing in the adoption process has been emphasized by a number of analysts including Rogers; Feder and Slade; Feder and O'Mara; Lindner; Stoneman; and, Kislev and Shchori-Bachrach. In tune with these studies, we argue that producers' choices are significantly affected by their exposure to information about the new technology. However, we depart from their modeling frameworks in an important aspect. Several of the papers have analyzed adoption in a dynamic framework in which the adopter updates information about the new technology through a process of learning-by-doing. With bST and other bioengineered technologies, however, the information-gathering process is precluded in the preapproval period. Consequently, a potential adopter's information about the new technology is based mainly on industry reports and other publications. Because of this diffusion process, an adopter's information depends on individual-specific attributes, the most important being education.

Incomplete information diffusion has important implications for empirical analysis. A substantial segment of applied adoption research has employed probit or logit analysis of survey data to identify adopters' and nonadopters' socioeconomic characteristics (Jamison and Lau; Lesser, Magrath, and Kalter; Kinnucan et al; Zepeda). We argue these studies may suffer from sample selection bias inherent in survey data. The question of "whether or not to adopt" is relevant only to a *nonrandom* subsample of respondents who have heard about the new technology. This implies that a separate sample selection equation—explaining binary outcomes "heard" versus "haven't heard"—needs to be estimated in addition to the adoption equation. Furthermore, awareness about the new technology will be a function of unobserved respondent attributes, which may be influential in the adoption decision. To address these issues, the sample selection and adoption equations should be jointly estimated, allowing for correlation between the two equations' errors.

While analytical models in the adoption literature consider degree of adoption to be the relevant choice variable, the underlying assumption in applied research is that producers allocate resources in an all-or-nothing fashion between the risk-free technology and a risky innovation. This assumption is evident from the dichotomous dependent variable characterizing logit or probit adoption models. Feder, Just, and Zilberman's comments are revealing:

> ...most adoption research has thus far viewed the adoption decision in dichotomous terms (adoption or nonadoption). But for many types of innovations, the interesting question may be related to the intensity of use (e.g., how much fertilizer is used per hectare or how much land is planted to HYVs). Future studies can rectify this problem by properly accounting for a more varied range of responses and by employing statistical techniques suitable for the variables considered" (p. 287–88).

The model developed in the present paper analyzes the "how much to adopt" decision in conjunction with the "whether or not to adopt" choice. The model is comprised of three equations with correlated errors. The first two are the sample selection and the adoption versus nonadoption equations, both of which have dichotomous dependent variables. The third equation explains adoption intensity, a continuous variable. We show that including sample selection and adoption intensity in the model specification yields substantially different results and inferences compared to the traditional dichotomous specification.

## Model

A learning period preceeds any adoption decision. In this phase of the adoption process a producer's acquired information level determines whether or not he has heard about bST. The producer's optimal information is a function of information costs as well as individual characteristics such as education and age. When acquired information reaches a threshold level, the producer "hears" about bST.

Conditional on the producer hearing about bST, he decides in the second phase whether or not to adopt. The producer's subjective assessment of the new technology's yield plays a crucial role in this decision. Adoption is chosen only if the perceived net benefit of adoption outweighs its cost.

In the third phase, which need not be temporally distinct from the second, the producer decides what proportion of resources will be allocated to the new technology. The three adoption phases are formalized below.

*Phase One: Information Collection*

We posit that the producer's optimal information level is the outcome of an underlying utility maximization problem

$$(1)\qquad i^* \equiv i(\mathbf{d})$$

where $i^*$ denotes the optimal information level and **d** is a vector containing the producer's relevant economic and demographic characteristics. A producer hears about the new technology if

$$(2)\qquad i^*(\mathbf{d}) > i^0$$

where $i^0$ is the threshold information level. Clearly, the first phase is temporally separate from the one that follows. In the second phase, the producer's subjective perception regarding the bST yield distribution's moments is conditional upon acquired information, $i^*$.

*Phase Two: Whether or Not to Adopt*

The producer maximizes his expected utility of random wealth $\tilde{W}$ through optimal choice of the number of cows in traditional production and the number of cows to be treated with bST

$$(3)\qquad \max_{m,z} H \equiv \mathop{\mathrm{E}}_{i^*}\left[U\left(\tilde{W}\right)\right]$$
$$\equiv \mathop{\mathrm{E}}_{i^*}\left[U\left\{p\left(f(m)+g(z)\tilde{e}\right)-w\cdot(m+z)-r\cdot z\right\}\right]$$
$$\text{subject to: } m + z = x$$

where $\mathrm{E}_{i^*}$ denotes the expectation operator conditional on the producer's information $i^*$. Equation $\tilde{Q} \equiv f(m) + g(z)\tilde{e}$ denotes the producer's stochastic milk production function in which $m$ is the number of cows in traditional production and $z$ is the number of cows exposed to bST. Total herd size is denoted by $x$. Traditional milk production technology, $f(\cdot)$, is nonstochastic.[1]

However, output from cows exposed to bST is unknown before adoption and output uncertainty is captured by the stochastic part of the production function, $g(z)\tilde{e}$, where $\tilde{e}$ is a random variable. It is also assumed that $g(0) = 0$, implying the producer's wealth is nonrandom in the absence of adoption. The variable cost per cow is denoted by $w$, and $r$ is an additional unit cost associated only with cows exposed to bST. Examples of bST-specific cost items are: injections, special feed, additional management costs, and veterinarian fees.[2] Finally, $p$ denotes milk price which is known with certainty.

Assuming, for the moment, strictly interior solutions, the first-order conditions of (3) are given by

$$(4a)\qquad \mathop{\mathrm{E}}_{i^*}\left[U'(\cdot)\left\{pf_m(\cdot) - w\right\}\right] = 0$$

$$(4b)\qquad \mathop{\mathrm{E}}_{i^*}\left[U'(\cdot)\left\{pg_z(\cdot)\tilde{e} - (w + r)\right\}\right] = 0$$

where primes and subscripts denote derivatives of functions. We assume the second-order sufficient conditions for (3) are satisfied and let $m^*$ and $z^*$ denote the interior solutions to (3).

It is evident from first-order condition (4a) that $m$ and $z$ choices are "separable" in the sense that (4a) can be solved independently of (4b) for $m^* = m(p, w)$. That is, the optimal number of cows in the traditional production process is determined solely by output and input prices and is unaffected by risk considerations. This "separability" between the $m$ and $z$ choices allows us to focus on the optimal choice of $z$ in the remainder of the paper.

The first-order condition in (4b) assumes a strictly interior solution[3] for $z$. However, analysis of the adoption decision entails noninterior solutions. In particular, $z^* = 0$ is clearly possible; the condition under which $z^*$ is strictly positive is characterized by the following proposition. Proposition proofs are presented in the appendix.

[1] While traditional milk production is not completely risk-free, it is less risky than the untried bST technology. In the interest of analytical tractability we have assumed risk-free traditional milk production technology.

[2] Input prices are generally assumed to be nonrandom in the adoption literature because when actual adoption takes place adoption-related costs are known to the producer. However, as a consequence of incomplete information dissemination, this may not be true in the case of new and untried technologies when adoption involves technology-specific costs. As is evident from footnotes 4, 6, and 7, the treatment of bST-specific input cost $r$ as stochastic does not fundamentally change the main analytical results of this paper.

[3] A possible corner solution is $z^* = x^*$, implying 100% adoption; the sufficient condition for this outcome is given by $H_z(x^*, z^*) > 0$. However, we will not discuss this outcome since it is not the focus of our analysis.

PROPOSITION 1. *Adoption will be an optimal choice if the expected net marginal benefit of adoption exceeds its marginal cost:*[4] $g_z(z = 0)\bar{e}(i^*) > (w + r)$, *where* $g_z(z = 0)\bar{e}(i^*) \equiv \underset{i^*}{E}[g_z(0)\tilde{e}]$.

Observe that in the above inequality, $g_z(z = 0)\bar{e}(i^*)$ is the producer's perceived marginal bST-induced increase in milk production. This perception is dependent on the producer's acquired information level $i^*$. Clearly, $\bar{e}(i^*)$ will vary among producers depending on $i^*$, which in turn is determined by sociodemographic producer characteristics.

An interesting and apparently counter-intuitive implication of proposition 1 is that neither the "riskiness" of the new technology (expressed through higher-than-first moments of $\tilde{e}$) nor the dairy producer's attitude toward risk (risk aversion or risk neutrality) plays a role in the adoption versus nonadoption decision.[5] However, it is evident from what follows that these factors do play significant roles in the "how much to adopt" decision.

### *Phase Three: How Much to Adopt*

Any meaningful analysis of phase three must rest on the underlying assumption that the inequality in proposition 1 is satisfied, that is, $z^*$ is strictly positive. Here, we focus on exploring the adoption-intensity response to perceived higher riskiness in bST yield. As before, the producer's perceptions about the degree of risk are assumed to be dependent on acquired information level $i^*$.

Let an increase in parameter $\gamma^e(i^*)$ denote a mean preserving spread (MPS) in the distribution of $\tilde{e}$, in the Rothschild-Stiglitz sense. Then

PROPOSITION 2. *If the producer's risk preference is characterized by constant absolute risk aversion (CARA), then a MPS in the distribution of* $\tilde{e}$ *will lead to a decrease in adoption intensity, i.e.,* $\partial z^*/\partial \gamma^e < 0$.[6]

The above proposition suggests that a decrease in the perceived "riskiness" of bST yield will induce a higher level of adoption. It seems reasonable to assume that the more informed a producer is about the new technology, the lower is his uncertainty about its yield; that is, $\partial \gamma^e(i^*)/\partial i^* < 0$. This inequality, in conjunction with proposition 2, implies

$$(5) \qquad \frac{\partial z^*}{\partial i^*} > 0\cdot$$

Consequently, any economic or demographic factor which leads to a higher acquired information level will have a positive effect on adoption intensity. Formally,

$$(6) \qquad \frac{\partial z^*}{\partial d_i} \overset{s}{=} \frac{\partial i^*}{\partial d_i}$$

where $\overset{s}{=}$ denotes "same sign as" and $d_i$ is the $i$th element of parameter vector $\mathbf{d}$, which captures the producer's economic and demographic characteristics.

The principal implication of (5) and (6) is that diffusion of technology-related information, and measures that expedite this diffusion, will have a positive effect on adoption level by reducing the subjective uncertainty surrounding the new technology.

## Empirical Analysis

In developing the empirical framework, a few intermediary steps are necessary to link the analytical and estimation models. Recall from the discussion of Phase 1 and equation (1) that a producer hears about the new technology only if the acquired information level crosses a given threshold; that is, if

$$(7) \qquad Y^{H*} \equiv i^*(\mathbf{d}) - i^0 > 0.$$

For purposes of estimation, (7) can be expressed as

$$(7') \qquad Y^{H*} \equiv \mathbf{X}^{\mathbf{H}} \cdot \boldsymbol{\beta}^{\mathbf{H}} + \varepsilon^H > 0$$

where $\mathbf{X}^{\mathbf{H}}$ is a vector of regressors containing the sociodemographic producer characteristics which determine his acquired information level, and $\boldsymbol{\beta}^{\mathbf{H}}$ is a vector of parameters to be estimated; $\varepsilon^H$ is an error term. To the econo-

---

[4] If bST-specific unit costs were random and denoted by $\tilde{r}$, then the inequality in proposition 1 would be replaced by: $g_z(z = 0)\bar{e}(i^*) > [w + \bar{r}(i^*)]$, where $\bar{r}(i^*) \equiv E_{i^*}[\tilde{r}]$.

[5] This will not be true if the producer's profit is random in the absence of adoption.

[6] Under input price risk, if the parameter $\gamma^r$ denotes a MPS in the distribution of $\tilde{r}$, it can be shown that $\partial z^*/\partial \gamma^r < 0$ holds under CARA

metrician, $i^*(\mathbf{d})$, $i^0$, and consequently $Y^{H*}$, are not observable. What is observed is the producer's response to the question of whether he has heard about bST. Let $Y^H$ denote an indicator variable which equals 1 if the producer has heard about bST, i.e., $Y^{H*} > 0$, and zero otherwise.

Turning now to Phase 2, recall from proposition 1 that the producer chooses to adopt if the perceived adoption benefit, net of costs, is positive. That is[7]

$$(8)\quad Y^{A*} \equiv g_z(0)\,\bar{e}\,[i^*(\mathbf{d})] - (w + r) > 0.$$

Again, $\bar{e}$ is not observable since it is the producer's subjective perception about bST's yield. Observable elements in the inequality are: sociodemographic characteristics $\mathbf{d}$, scale of operation $x$, and prices $r$ and $w$. These observable elements are captured in the vector of regressors $\mathbf{X^A}$ in the equation

$$(8')\quad Y^{A*} \equiv \mathbf{X^A} \cdot \boldsymbol{\beta}^{\mathbf{A}} + \varepsilon^A > 0.$$

As before, since $Y^{A*}$ is not observable, we denote by $Y^A$ the binary indicator variable which equals 1 when $Y^{A*} > 0$ and zero otherwise. In other words, $Y^A = 1$ if the producer's response is "yes" to the question of whether or not he plans to adopt bST.

Finally, it can be recalled from the discussion of Phase 3 that a producer's intended adoption intensity, $z^*$, is a function of sociodemographic characteristics as well as the subjectively formed moments $\bar{e}\,[i^*(\mathbf{d})]$ and $\gamma^e[i^*(\mathbf{d})]$ of the uncertain yield distribution. Again, these subjective moments are not observed by the econometrician but underlying characteristics $\mathbf{d}$ are observed. The Phase 3 estimation equation is

$$(9)\quad Y^P \equiv \mathbf{X^P} \cdot \boldsymbol{\beta}^{\mathbf{P}} + \varepsilon^P$$

where $Y^P$ is adoption intensity expressed in terms of percentage of herd exposed to bST, $\mathbf{X^P}$ is the vector of regressors and $\varepsilon^P$ denotes an error term. Unlike $Y^H$ or $Y^A$, the dependent variable in (9) is continuous and observable.

Although the estimation model is given essentially by (7′), (8′), and (9), the issue of sample selection needs to be addressed in order to complete the empirical framework. We saw in the preceding section that a producer's decision to treat a portion of his herd with bST (Phase 3) is conditional on having decided to adopt bST (Phase 2), which in turn is conditional upon having heard about bST (Phase 1). In terms of the estimation equations, this means $Y^P$ and $\mathbf{X^P}$ are observed only if $Y^A = 1$ and $Y^H = 1$, while $Y^A$ and $\mathbf{X^A}$ are observed only if $Y^H = 1$. We assume that the disturbance terms of the equation system (7′), (8′), and (9) are distributed as trivariate normal: $\{\varepsilon^P, \varepsilon^A, \varepsilon^H\} \sim TVN\,(0, 0, 0, \sigma^2, 1, 1, \psi^H, \psi^A, \rho)$, where $\psi^H = corr(\varepsilon^H, \varepsilon^P)$, $\psi^A = corr(\varepsilon^A, \varepsilon^P)$ and $\rho = corr\,(\varepsilon^A, \varepsilon^H)$. Under these assumptions, the conditional probability of adoption is given by

$$(10)\quad \mathrm{prob}\left(Y^A = 1 \mid Y^H = 1\right) = \mathrm{E}\left[Y^A \mid (i^* - i^0) > 0\right] = \Phi(\mathbf{X^A}\boldsymbol{\beta}^{\mathbf{A}}) + \rho\lambda(\alpha)$$

where

$$\alpha = -\mathbf{X^H}\boldsymbol{\beta}^{\mathbf{H}},\ \lambda = \frac{\phi(\alpha)}{1 - \Phi(\alpha)}$$

and $\Phi$ and $\phi$ denote the cumulative distribution function (cdf) and probability density function (pdf) of a univariate normal distribution. The result in (10) follows from the definition of the expectation of a truncated bivariate normal.[8] Equation (10) suggests that probit or logit estimation of $Y^A$ on $X^A$ would lead to inconsistent estimates of $\boldsymbol{\beta}^{\mathbf{A}}$. The inconsistency would stem from an omitted variable since the second term in the right-hand side of (10) would be ignored. Importantly, the estimate of the marginal effect on the probability of adoption of a regressor common to the two vectors $\mathbf{X^H}$ and $\mathbf{X^A}$ would also be biased. In particular, if $x_j$ denotes a regressor common to $\mathbf{X^H}$ and $\mathbf{X^A}$, its marginal effect on the conditional adoption probability is given by

$$(11)\quad \frac{\partial\mathrm{prob}\left(Y^A = 1 \mid Y^H = 1\right)}{\partial x_j} = \phi(\mathbf{X^A}\boldsymbol{\beta}^{\mathbf{A}})\beta_j^A + \rho\beta_j^H(\lambda\alpha - \lambda^2).$$

[7] Under input price risk, $Y^{A*} \equiv g_z(0)\bar{e}[i^*(\mathbf{d})] - \{\bar{r}\,[i^*(\mathbf{d})] + w\} > 0$ replaces (8).

[8] If $x$ and $y \sim \phi_2\,(\mu_x, \mu_y, \sigma_x, \sigma_y, \rho)$, then: $\mathrm{E}[x \mid y > a] = \mu_x + \rho\sigma_x \cdot \lambda(\alpha_y)$, where

$$\alpha_y = \frac{a - \mu_y}{\sigma_y},\quad \lambda(\alpha_y) = \frac{\phi(\alpha_y)}{1 - \Phi(\alpha_y)},$$

and $a$ is the truncation point.

If the sample selection issue is not addressed, the second term in the right side of (11) will be ignored, providing a biased estimate of a regressor's marginal effect. The degree and direction of bias is sample-dependent and cannot be determined a priori.

The M-L estimates of parameters $\boldsymbol{\beta}^H$, $\boldsymbol{\beta}^A$, and $\rho$ can be obtained from maximizing the following log-likelihood function, which rests on the definition of conditional probability

$$(12)\quad \ln L = \sum_{Y^A=1, Y^H=1} \ln \Phi_2\left[\mathbf{X}^H\boldsymbol{\beta}^H, \mathbf{X}^A\boldsymbol{\beta}^A, \rho\right] + \sum_{Y^H=1, Y^A=0} \ln \Phi_2\left[\mathbf{X}^H\boldsymbol{\beta}^H, -\mathbf{X}^A\boldsymbol{\beta}^A, -\rho\right] + \sum_{Y^H=0} \ln \Phi\left[-\mathbf{X}^H\boldsymbol{\beta}^H\right].$$

Parameter values obtained by estimating (7′) and (8′) separately can be used as starting values in the maximization of (12). Maximum likelihood estimates of parameters $\hat{\boldsymbol{\beta}}^H$, $\hat{\boldsymbol{\beta}}^A$, and $\hat{\rho}$, can then be used in forming the regressors in the augmented "how much to adopt" equation. This augmented equation, based on the bivariate probit model with sample selection, is given by

$$(13)\quad Y^P = \mathbf{X}^P\boldsymbol{\beta}^P + \hat{\lambda}^H\theta^H + \hat{\lambda}^A\theta^A + \eta$$

where $\eta$ is the error term,

$$\hat{\lambda}^H \equiv \phi(W^H) \cdot \Phi\left[\left(W^A - \hat{\rho}Y^H\right)/\left(1-\hat{\rho}^2\right)^{1/2}\right]/\Phi_2,$$

$$\hat{\lambda}^A \equiv \phi(W^A) \cdot \Phi\left[\left(W^H - \hat{\rho}Y^A\right)/\left(1-\hat{\rho}^2\right)^{1/2}\right]/\Phi_2,$$

$$W^H \equiv -X^H\hat{\beta}^H,\ W^A \equiv -X^A\hat{\beta}^A.$$

Quantity $\Phi_2$ is the bivariate normal cdf $\Phi(W^H, W^A, \hat{\rho})$ whose pdf is denoted by $\phi_2$ (Limdep, 6.0, User's Manual, pp. 645–46). If the sample selection problem is not addressed, regressors $\lambda^H$ and $\lambda^A$ in (13) will be ignored and estimation would suffer from omitted variable bias.

Given cross-sectional data, the errors of (13) will most likely be heteroskedastic. If tests reveal that such is the case, coefficients in (13) can be estimated by the maximum likelihood method under the assumption that

$$(14)\quad \eta \sim N\left[0, \sigma_\eta^2(\mathbf{Z}^P)\right]$$

where $\mathbf{Z}^P$ denotes a subset of regressors of (13) influencing the disturbance variance.

*Application: bST Adoption in the Texas Dairy Industry*

Data requirements to estimate the model outlined above are rather onerous; in particular, specific data pertaining to the three phases of the adoption process are required. A data set on the Texas dairy industry provided the closest approximation to our requirements. The data are based on a telephone survey of Texas dairy producers undertaken in mid 1992 by Texas A&M Extension Service and conducted by the Public Policy Resources Laboratory. Respondents were asked whether or not they had heard about bST. If they had, they were asked whether they would adopt bST when approved by the FDA. If the response was "yes," they were asked what percentage of their herd they would expose to bST. Irrespective of the respondents' answers to the above questions, data on their age, education, farm size, etc. were gathered. Unfortunately, the data set contained little information on production costs and other economic characteristics. Summary statistics of the regressors used in the three estimation equations are presented in table 1.

Estimation was done with Limdep version 6.0. Relevant parameter estimates and asymptotic t-ratios are presented in table 2. Parameters of the awareness (Phase 1) and adoption (Phase 2) equations, $\boldsymbol{\beta}^H$ and $\boldsymbol{\beta}^A$, were estimated by maximizing (12) through a Davidson-Fletcher-Powell iterative procedure. Tests showed the errors of (13) were highly heteroskedastic. Thus, (13) was estimated by maximum likelihood under multiplicative heteroskedasticity (Harvey). Error variances $\sigma_\eta^2$ were assumed to be functions of herd size and efficiency. In terms of the notation in (14), these regressors constituted $\mathbf{Z}^P$.

Estimation results in table 2 concur, in the main, with predictions from the analytical model. They show that the two most important factors explaining whether or not a producer has "heard about bST" are his age and education. In the phase 2 regression equation, "herd size" is positive and significant. This suggests

**Table 1. Summary Statistics for Texas bST Adoption Data**

| Variable name | Explanation | Phase 1 equation | Phase 2 equation | Phase 3 equation |
|---|---|---|---|---|
| | | Mean (minimum, maximum) | | |
| Herd size | Number of cows in producer's herd | 247.30 (25, 6000) | 262.48 (25, 6000) | 344.72 (31, 6000) |
| Age | Dairy producer's age | 44.53 (20, 78) | 44.87 (21, 78) | 42.02 (21, 65) |
| Education | Years of producer's schooling[a] | 4.58 (1, 7) | 4.67 (2, 7) | 4.78 (2, 7) |
| Efficiency | Average daily milk production per cow (lbs.) | 51.20 (15, 80) | 51.46 (25, 78) | 52.99 (30, 78) |
| Experience | Years of producer operating experience | 18.48 (1, 52) | 18.75 (1, 52) | 16.79 (1, 50) |
| Expand | Dummy variable, equals 1 if producer expressed expansion plans, zero otherwise | 0.57 | 0.56 | 0.65 |
| Prior adoption | Dummy variable, equals 1 if producer adopted dairy innovations in the past, zero otherwise | 0.66 | 0.69 | 0.76 |
| | Number of observations | 314 | 264 | 139 |
| | % of respondents who are aware of bST | 84.08 | 100.00 | 100.00 |
| | % of respondents who will adopt bST | 44.27 | 52.65 | 100.00 |
| | % of herd to be exposed to bST | 19.01 | 22.61 | 42.94 |

[a] Data on education were contained in frequency classes: 1 indicated grades 0–4, 2 grades 5–8, 3 grades 9–11 or some high school, 4 indicated high school graduate, 5 some college, 6 college graduate, and 7 graduate work.

there may be a scale bias in bST adoption, and it is consistent with similar findings in other bST studies[9] (Kinnucan et al., Zepeda). The negative coefficient for "experience" suggests younger and less-experienced producers are more likely to be first adopters.

Phase 3 estimation results are most revealing. They show that herd size, education, plans to expand, and prior adoption experience have positive and significant influence, while experience has a negative and significant influence on adoption intensity. Coefficients associated with herd size and education are positive and generally significant in all three phases, implying that larger and more educated producers are not only more likely to be aware of and to adopt bST, but will expose a greater percentage of their herd to bST.

[9] For findings in the context of HYV adoption, see Binswanger; Parthasarathy and Prasad; Perrin and Winkelmann; and Jamison and Lau.

The insignificance of the education coefficient in the Phase 2 equation warrants comment. Recall that Phase 2 estimates are based on the subsample of respondents who have heard about bST. Phase 1 and 2 results show that, while education significantly increases the probability of hearing about bST, it has no significant effect on the conditional probability of adoption when only the subsample is considered.

Another issue to be considered is the appropriateness of the conditional model specification. The coefficient estimates associated with $\lambda^A$ and $\lambda^H$ in the Phase 3 equation shed light on the issue. If the null hypothesis that the coefficients of $\lambda^A$ and $\lambda^H$ are jointly equal to zero is not rejected, one may conclude that the adoption intensity equation could have been estimated separately, i.e., without recognizing that the dependent variable in this equation is observed only if the dependent variables in Phase 2 and Phase 1 equations both equal one. The F

**Table 2. Estimation Results**

| | Phase 1: Whether heard about bST | Phase 2: Whether to adopt bST | Phase 3: % of herd to be treated with bST |
|---|---|---|---|
| Constant | −1.2439 | −1.1992 | −67.3730 |
| | (−2.24) | (−2.08) | (−2.30) |
| Herd size | 0.0005 | 0.0009 | 0.0089 |
| | (1.28) | (2.13) | (6.10) |
| Age | 0.0145 | — | — |
| | (2.36) | | |
| Education | 0.3414 | 0.0988 | 7.2417 |
| | (3.77) | (1.35) | (2.30) |
| Efficiency | — | 0.0081 | 0.1793 |
| | | (0.87) | (0.69) |
| Expand | — | 0.1618 | 7.0240 |
| | | (1.08) | (1.89) |
| Experience | — | −0.0120 | −0.3553 |
| | | (−1.87) | (−4.01) |
| Prior adoption | — | 0.1865 | 23.7590 |
| | | (1.20) | (6.08) |
| $\hat{\lambda}^A$ | — | — | 58.1550 |
| | | | (5.11) |
| $\hat{\lambda}^H$ | — | — | −3665.30 |
| | | | (−8.60) |
| Number of observations | 314 | 264 | 139 |
| % of correct predictions | 84.40 | 64.77 | — |
| $\chi^2$ | 19.01 (d.f. = 3)[a] | 29.77 (d.f. = 6)[a] | 3475.98 (d.f. = 8)[a] |

Note: Numbers in parentheses are asymptotic t-statistics.
[a]The $\chi^2$ test statistics are for the null that all coefficients except the intercept are equal to zero.

test statistic for the null $H_o : \beta^P_{\lambda^A} = \beta^P_{\lambda^H} = 0$ was 330.29, clearly rejecting the null and vindicating the conditional model specification. Estimated correlation coefficients between the errors of the three estimation equations, (7′), (8′), and (9), were: $\hat{\rho} = corr(\varepsilon^A, \varepsilon^H) = 0.9832$; $\hat{\psi}^H = corr(\varepsilon^H, \varepsilon^P) = -0.1694$; and $\hat{\psi}^A = corr(\varepsilon^A, \varepsilon^P) = 0.2645$.

Parameter estimates from limited dependent variable models do not have the same interpretation as those from continuous dependent variable models. For example, the effect of any regressor, say $x_j$, on the probability of hearing about bST is not given by $\hat{\beta}^H_j$ but by the marginal effect, $\hat{\beta}^H_j \cdot \phi(\mathbf{X}^H \hat{\boldsymbol{\beta}}^H)$ evaluated at the sample means. Similarly, the marginal effect on the probability of adoption conditional upon the producer hearing about bST is given by (11). However, marginal effect magnitudes depend on measurement units. To facilitate comparison of the relative importance of various regressors in influencing the probability of adoption or of hearing about bST, we have converted the marginal effect estimates into elasticities. For example, for the Phase 1 equation, the probability elasticity of regressor $x_j$ is given by

$$\frac{\partial \text{prob}(Y^H = 1)}{\partial x_j} \cdot \frac{\bar{x}_j}{\text{prob}(Y^H = 1)} = \hat{\beta}^H_j \cdot \frac{\phi\left(\bar{\mathbf{X}}^H \hat{\boldsymbol{\beta}}^H\right) \cdot \bar{x}_j}{\Phi\left(\bar{\mathbf{X}}^H \hat{\boldsymbol{\beta}}^H\right)}$$

where overbars denote sample means. Similar procedures for probability elasticity estimation were adopted for Phase 2 and Phase 3 equations. Probability elasticity estimates for the continuous regressors are presented in table 3. Standard errors were computed using the delta method.

Not unexpectedly, education has the largest and most significant elasticities in Phases 1 and 3, underscoring the role of information in the adoption process—a point we emphasized in our analytical model.

The negative, although insignificant, elastic-

**Table 3. Probability Elasticity Estimates**

| | Phase 1 | | Phase 2 | | Phase 3 | |
|---|---|---|---|---|---|---|
| | with ss | w/o ss | with ss | w/o ss | with ss | w/o ss |
| Herd size | 0.0521<br>(1.33) | 0.0533 | 0.1107<br>(0.60) | 0.1538 | 0.0729<br>(6.08) | 0.0016 |
| Efficiency | | | 0.3557<br>(0.87) | 0.5635 | 0.2252<br>(0.70) | −0.5356 |
| Experience | | | −0.1929<br>(−1.86) | −0.2077 | −0.1408<br>(−4.06) | 0.1675 |
| Age | 0.1568<br>(2.39) | 0.1697 | | | | |
| Education | 0.3851<br>(4.06) | 0.3950 | −0.7267<br>(−0.39) | 0.1779 | 0.7988<br>(2.96) | 0.3748 |

Note:(*a*) Asymptotic t-ratios are in parentheses; (b) "with ss" denotes with sample selection, "w/o ss" denotes without sample selection.

ity of education in the Phase 2 equation may seem counterintuitive. However, the unconditional marginal effect (and probability elasticity) is positive for education in Phase 2. The negative sign appears only when the conditional marginal effect is considered, meaning that the second right-hand side term in (11) is negative and dominates the first term, which is positive.

An indicator of the explanatory power of the Phase 1 and Phase 2 bivariate probit equations is the percentage of correct predictions. This was found to be 84.40% and 64.77% in Phase 1 and Phase 2 equations, respectively. As a measure of overall fit, $\chi^2$ test statistics for the null that all coefficients except the intercept are zero were computed for each equation. In every case, the null was rejected at the 1% significance level.

*Consequences of Model Misspecification*

The consequences of not addressing the sample selection problem warrant attention. In table 3, we have included the probability elasticity estimates from the model without sample selection. The most significant differences occur in Phase 3, with sign reversals for the efficiency and experience regressors and substantial magnitude changes in the herd size and education elasticities.

To demonstrate the implications of estimating with sample selection, we used our own model and the traditional probit model without sample selection to predict the production impact of bST adoption. Equation (13) implies that the bST-induced percentage increase in milk production, evaluated at sample means is

$$\text{(15a) \% increase in } Q^{\text{with sample selection}} = \bar{\hat{Y}}^{P} \cdot \Delta$$

where $\bar{\hat{Y}}^{P}$ denotes the mean of the predicted values from (13) and Δ denotes the bST induced percentage increase in milk production per cow. Based on a recent Office of Technology Assessment report, Δ was taken to be 15%. From (13), $\hat{Y}^{P}$ was 0.34, which yields a 5.1% increase over the current (without-bST) level of average daily production.

To derive the corresponding figures from the traditional probit model without sample selection, we used

$$\text{(15b) \% increase in } Q^{\text{w/o sample selection}} = \mathrm{E}\left[\hat{Y}^{A}\right] \cdot \Delta$$

where $\mathrm{E}[\hat{Y}^{A}] \equiv \Phi(\bar{\mathbf{X}}^{A}\hat{\boldsymbol{\beta}}^{A})$. Note that $\hat{\boldsymbol{\beta}}^{A}$ in (15b) denotes the parameter estimates from the Phase 2 probit model without sample selection (in the interest of brevity these estimates are not reported); $\mathrm{E}[\hat{Y}^{A}] = 0.54$ , an 8.1% increase over the current production level.

It is clear from these figures that whether the sample selection issue is addressed makes a substantial difference in adoption impact estimates. In fact, the traditional probit analysis overestimates bST's production impact by 59%. Consequences of model misspecification are particularly important at a time when the dairy industry is burdened with considerable surplus production and when there are concerns about the distributional impact of bST adoption.

## Concluding Comments

We have presented a model of divisible technology adoption under output uncertainty. Our model departs from the extant adoption literature by underscoring consequences of incomplete information diffusion about a new technology. Although the paper's analytical model and its empirical application are framed in the context of bST (bovine somatotropin) adoption, the model itself is relevant for any emerging technology about which information diffusion is incomplete.

Our analytical results showed that the decision of whether to adopt bST is determined solely by the producer's perception of bST-induced yield and adoption costs. Risk attitude and perceptions about the degree of risk associated with the untried technology had no influence on the adoption decision. Risk factors, however, did influence the degree of adoption if the producer decided to adopt. Diffusion of technology-related information, and measures that expedite this diffusion, can have a positive effect on adoption intensity by reducing the uncertainty associated with the new technology.

In the early stages of diffusion, only a subset of producers are aware of the new technology. Thus, adoption estimates based on survey data may suffer from nonrandom sample selection bias, inasmuch as the adoption decision is relevant only to respondents who are aware of the new possibilities. Producers often must decide how intensively to utilize the new technology, and this question is relevant only to the subsample of producers who have decided to adopt. We have set out the mixed dichotomous-continuous estimation framework and specified the maximum likelihood function, based on relevant conditional probabilities, appropriate for such a problem.

Estimation results using survey data on Texas dairy producers provide intuition about the adoption process and support our analytical model. Larger and more educated producers are not only more likely to be aware of and to adopt bST, but also are likely to expose a greater percentage of their herds to bST. Plans to expand dairy operations and prior adoption experience had a positive and significant influence on adoption intensity. Ignoring the sample selection problem can yield a substantially biased estimate of bST's impact on milk production.

*[Received February 1993;*
*final revision received March 1994.]*

## References

Binswanger, H. *The Economics of Tractors in South Asia: An Analytical Review.* New York: Agricultural Development Council and the International Crops Research Institute for the Semi-Arid Tropics, 1978.

Feder, G., and R. Slade. "The Acquisition of Information and the Adoption of New Technology." *Amer. J. Agr. Econ.* 66(August 1984):312–20.

Feder, G., and G.T. O'Mara. "On Information and Innovation Diffusion: A Bayesian Approach." *Amer. J. Agr. Econ.* 64(February 1982):141–45.

Feder, G., R.E. Just, and D. Zilberman. "Adoption of Agricultural Innovations in Developing Countries: A Survey." *Econ. Develop. and Cultur. Change* 33(January 1984/85):255-98.

Harvey, A.C. "Estimating Regression Models with Multiplicative Heteroskedasticity." *Econometrica* 44(May 1976):461–65.

Jamison, D.T., and L.J. Lau. *Producer Education and Farm Efficiency.* Baltimore: Johns Hopkins University Press, 1982.

Kaiser, H.M., C.W. Scherer, and D.M. Barbano. "Consumer Perceptions and Attitudes Toward Bovine Somatotropin." *N. E. J. Agr. Res. Econ.* 21(April 1992):10–20.

Kinnucan, H., U. Hatch, J.J. Molnar, and R. Pendergrass. "Adoption and Diffusion Potentials for Bovine Somatotropin in the Southeast Dairy Industry." Alabama Agr. Exp. Sta. Bull., 1990.

Kislev, Y., and N. Shchori-Bachrach. "The Process of an Innovation Cycle." *Amer. J. Agr. Econ.* 55(February 1973):28–37.

Laffont, J.J. *The Economics of Uncertainty and Information.* Cambridge: MIT Press, 1990.

Lesser, W., W. Magrath, and R. Kalter. "Projecting Adoption Rates: Application of an Ex Ante Procedure to Biotechnology Products." *N. C. J. Agr. Econ.* 8(July 1986):159–74.

Limdep. *User's Manual and Reference Guide.* Version 6.0. Econometric Software Inc. Bellport, New York, 1992.

Lindner, R.K. "Farm Size and the Time Lag to Adoption of a Scale Neutral Innovation." Unpublished. Adelaide: University of Adelaide, Australia, 1980.

Parthasarathy, G., and D.S. Prasad. *Response to the Impact of the New Rice Technology by Farm Size and Tenure: Andhra Pradesh, India. Los* Baños: International Rice Research Institute, 1978.

Perrin, R., and D. Winkelmann. "Impediment to Technical Progress on Small Versus Large Farms." *Amer. J. Agr. Econ.* 58(December 1976):888–94.

Rogers, E. *Diffusion of Innovations*. New York: Free Press of Glencoe, 1962.
Rothschild, M., and J.E. Stiglitz. "Increasing Risk: I. A Definition." *J. Econ. Theory* 2(September 1970):225–43.
Smith, B.J., and R.H. Warland. "Consumer Responses to Milk from bST-Supplemented Cows." *Bovine Somatotropin and Emerging Issues: An Assessment*. Milton C. Hallberg, ed. Boulder: Westview Press, 1992.
Stoneman, P. "Intra Firm Diffusion, Bayesian Learning and Profitability." *Econ. J.* 91(June 1981):375-88.
U.S. Congress, Office of Technology Assessment. "U.S. Dairy Industry at a Crossroad: Biotechnology and Policy Choices." Washington DC, May 1991.
Zepeda, L. "Predicting Bovine Somatotropin Use by California Dairy Producers." *W. J. Agr. Econ.* 15(July 1990):55-62.

## Appendix

*Proof of Proposition 1*

The sufficient condition for $z^* > 0$ is given by

(A1) $H_z(m^*, z = 0) > 0$

When $z = 0$, the producer's wealth and associated marginal utility $U'[W(m^*, z = 0)]$ is nonrandom. Thus, when $z = 0$, (4b) reduces to

(A2) $$H_z(m^*, z = 0) = pE[g_z(0)\tilde{e}] - (w + r) = 0$$

since $U'[W(m^*, z = 0)] > 0$. The proof now follows from substituting (A2) in (A1).

*Proof of Proposition 2.* The proof of the proposition rests on theorem 2 in Jean-Jacques Laffont, p. 28. As a consequence of this theorem, it is sufficient to show that first-order condition (4b) is strictly concave in $\tilde{e}$ to prove the proposition. Let $h \equiv pg_z(\cdot)\tilde{e} - (w + r)$. Note under CARA that

(A3) $$E[U'' \cdot h] \equiv -\bar{A}E[U'h] = 0$$

where $\bar{A}$ is the nonstochastic Arrow-Pratt measure of risk aversion under CARA; the last equality in (A3) follows from (4b). Differentiating (4b) with respect to *e*

(A4) $$H_{ze} = pg_z(z^*)E[U'] + pg(z^*)E[U''h]$$

but by (A3) the second term in the right-hand side of (A4) is zero. Differentiating (A4) again with respect to *e*

(A5) $$H_{zee} = p^2 g_z(z^*)g(z^*)E[U''] < 0$$

under risk aversion.