Predicting Bovine Somatotropin Use by California Dairy Farmers

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An *ex ante* adoption model of bovine somatotropin (BST) is estimated with survey data of California milk producers. Theoretical justification is developed for incorporation of socioeconomic explanatory variables in a technology-adoption model. The advantages of a multinomial over a binomial *ex ante* model also are presented. The multinomial logit model is used to predict BST adoption, to test hypotheses on characteristics associated with knowledge and receptiveness towards BST, and to predict potential structural changes in the California dairy industry due to the release of BST technology.

Key words: bovine somatotropin, dairy, multinomial logit, technology adoption.

Who gains and who loses from technological change has been a topic of research since Griliches' paper first quantified technology diffusion. Cochrane coined the phrase "treadmill technologies" to describe the process of technology adoption in American agriculture. Diffusion models estimated by Bass, by Jarvis, and by Byerlee and Hesse de Polanco explained past adoption processes. Predicting adoption rates before a new technology is available, or *ex ante,* permits identification of potential gainers and losers for anticipation of policy implications.

Bovine somatotropin (BST) offers a unique opportunity to explore technology adoption *ex ante.* Kronfeld reports milk production increased by 15% (±8.4%) over full lactation in nine long-term BST research experiments. The properties of this naturally occurring hormone have been known for decades, but recent developments in DNA technology have made commercial production of BST feasible.

Controversy exists about BST's effect on cows and humans (Lesser, Magrath, and Kalter). However, the Food and Drug Administration (FDA) is likely to approve BST for commercial use. Since commercial approval of BST takes many years and because it is controversial, information about BST is widely available and has been highly publicized. Therefore, many dairy farmers have developed perceptions as to the riskiness of BST and whether they will be adopters.

BST *ex ante* adoption models have been estimated by Lesser, Magrath, and Kalter and by Hatch, Kinnucan, and Molnar for New York and the Southeast, respectively. The survey response rates were 13% and 32%. They provided respondents with information on BST from the Kalter et al. study that might be viewed as optimistic in light of more recent research: 17¢ per dose and up to a 40% increase in production. A study by Marion, Wills, and Butler uses 20¢ to 50¢ per dose and a 9% to 12% production response. Fallert et al. assume 24¢ per dose and a 13.5% production response.

In the following sections an *ex ante* model of BST adoption is estimated using survey data collected from California Grade A milk producers. The response rate was 86%. Participants were not provided with information on BST.

California is a desirable setting for assessing the impact of BST, because technology has played such a strong role in making its dairy industry the second-most productive and the second largest in the U.S. (U.S. Department of Agriculture). Previous studies addressing BST adoption have been in regions with pro-

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duction characteristics which are not comparable to those of California.

The *ex ante* adoption model estimated is used to test hypotheses on factors influencing the adoption of BST. It also is used to compare probabilities of BST adoption for different individuals and to make predictions of adoption. Categories of respondents are compared for significant differences to establish the validity of categorization. Finally, the results are used to analyze the pattern of BST adoption on the structure of the California dairy industry and to assess whether BST is a scale-increasing innovation (Mansfield 1984).

The Model

In 1982 Feder and O'Mara provided a theoretical basis for the structure of Griliches' time-dependent model of technology adoption. The model had been used for over 20 years as an ad hoc model. Although Mansfield (1961) included explanatory variables other than time in his model and others followed suit, theoretical justification for including such variables was lacking.

A general economic framework for analyzing technology adoption can be built on the work of McFadden and of Domencich and McFadden who used Thurstone's random utility formulation. With respect to adoption of BST, assume an individual attempts to maximize the expected utility of the present value of profit by choosing among m discrete technologies. The expected utility of the present value of profit of the jth technology for the ith decision maker is denoted by

$$(1) \qquad \pi_{ij} = f_j(X_i) + \epsilon_{ij},$$

where X_i is a $(1 \times q)$ vector of attributes of the ith individual[1] and ϵ_{ij} is an unobserved component of the objective function of the ith individual given the jth technology. The vector X_i reflects the ith individual's personal and production endowments which can affect the desirability of a particular technology. Assume the ϵs are random variables with a given subjective probability distribution. In this context the ith individual chooses the jth technology that maximizes the expected utility of the present value of profit. Let $y_{ij} = 1$ if the ith individual chooses the jth technology, and $y_{ij} = 0$ otherwise. It follows that

$$(2) \qquad y_{ij} = \begin{cases} 1 \text{ if } \pi_{ij} \geq \pi_{ik}, & k = 1, 2, \ldots, m \\ 0 \text{ otherwise} \end{cases}.$$

From (1), the probability of the ith individual choosing the jth technology is

$$(3) \qquad \begin{aligned} P_{ij} &= P(y_{ij} = 1) \\ &= P[\pi_{ij} \geq \pi_{ik}; k \neq j, k = 1, 2, \ldots, m] \\ &= P[\epsilon_{ik} - \epsilon_{ij} \leq f_j(X_i) - f_k(X_i)]. \end{aligned}$$

If the ϵ_{ij} in (1) are independently and identically distributed with a Weibull density function, then McFadden has shown that

$$(4) \qquad P_{ij} = P(y_{ij} = 1) = \frac{\exp f_j(X_i)}{\sum_{k=1}^{m} \exp f_k(X_i)}.$$

Expression (4) can be alternatively written as the multinomial logit model (Maddala):

$$(5a) \qquad P_{ij} = \frac{\exp f_j(X_i)}{1 + \sum_{k=1}^{m-1} \exp f_k(X_i)} \qquad j = 1, 2, \ldots m - 1$$

$$(5b) \qquad P_{im} = \frac{1}{1 + \sum_{k=1}^{m-1} \exp f_k(X_i)},$$

where the Ps are conditional probabilities of adoption given the explanatory variables (Amemiya; Nerlove and Press). This specification is appealing because it is consistent with the maximization hypothesis used in economic theory and it is empirically tractable. The conditional probabilities can be estimated by the maximum-likelihood estimation (MLE) method. In the absence of a priori information on $f_j(X_k)$, we will adopt a linear form, $f_j(X_i) = X_i\beta_j$, in the empirical work below.

In the context of technological adoption, it will be convenient to let π_{ij} in (1) represent the expected utility of the ith individual facing the jth adoption scheme, $j = 1, \ldots, m$. Allowing m to be greater than one reflects the dynamics of decision making with respect to the adoption decision. That is, milk producers can be differentiated with respect to what they know about BST and how fast they plan to use it. The conditional probabilities for these different adoption schemes are P_0, P_1, P_2, ... as defined in (5a) and (5b).[2]

[1] $f_j(X_i)$ may also contain attributes of the technology. In the case of BST, however, such attributes as profitability are unknown.

[2] Note that there is no β_0 in these equations. So while the conditional probability can be estimated, the coefficients cannot.

Since the βs enter the probabilities P_{ij} nonlinearly, these coefficients cannot be interpreted directly. However, a convenient interpretation of the coefficients can be obtained by taking the logarithm of the ratio of P_{ij}/P_{i0}:

$$(6) \qquad \ln\left(\frac{P_{ij}}{P_{i0}}\right) = X'_i\beta_{j0} \qquad j = 1, 2, 3, \ldots$$

where (6) is the odds in favor of outcome j relative to outcome 0 and β_{j0q} is the marginal effect of the qth regressor in X_i on the odds ratio.

Choice of attributes (the Xs) associated with the adoption of BST is guided by human capital theory, sociological research, and *ex post* adoption models. Nelson and Phelps; Khaldi; and Wozniak show education affects the adoption of new technology. Globerman finds firm size correlated with technology diffusion. Sociological research by Rogers and by Rogers and Stanfield associate farm productivity and size, and farmer age, education, industry involvement, and other technology use with innovation. Feder and Slade find farm size is important for pesticide adoption by Indian rice farmers. Rahm and Huffman find farm size and education are significant in explaining the adoption of reduced tillage among Iowa corn farmers.

Farm size is associated with technology diffusion because returns to adoption are often greater in an absolute sense and the risk of adoption or experimentation is often less for a large farm. Productivity of a farm is associated with technology diffusion because early adoption of technology results in high productivity. Education is a human capital measurement which reflects the ability to implement new technology. Industry involvement measures how receptive and well informed a manager is. Use of other new technologies indicates receptiveness and ability to use new technology. Age is negatively associated with technology adoption; younger farmers have a longer planning horizon and may be less risk averse than older, established farmers.

Therefore, the hypotheses to be tested are: farm size and productivity influence knowledge and potential adoption of BST. Further hypotheses are: education, industry involvement, and use of other technologies by milk producers are positively associated with knowledge of and receptiveness to BST, and age is inversely associated.

Survey Data

Data were collected from 153 (7%) randomly selected California Grade A milk producers who produce 97% of California's milk (California Department of Food and Agriculture). California is a suitable site for analysis of technology adoption because technology has been important in making its dairy industry one of the nation's largest and most productive. California also has its own marketing order for milk and sets its own price for milk, so it is somewhat self-contained.

The telephone survey was conducted between August 10 and October 23, 1987. Producers were asked structured questions about their proposed adoption plans and characteristics of themselves and their farms. Five adoption schemes were investigated. Those who had not heard of bovine somatotropin or bovine growth hormone were labeled "Haven't Heard." The rest of the categories of respondents had heard of BST. Those who said they would use BST as soon as it becomes available were "Users." Those that would wait before using it were called "Waiters." Respondents who would not use BST were "Nonusers." Undecided producers were referred to as "Don't Know."

Estimation Results

LIMDEP is the software used to fit the empirical version of equations (5a) and (5b) to the survey data. The coefficients are estimated by the MLE method, and t-statistics are calculated using the asymptotic variances of the information matrix.

The five categories of response are: Haven't Heard, User, Nonuser, Waiter, and Don't Know, P_0, P_1, P_2, P_3, and P_4, respectively. Potential adopters include Waiters and Users. The explanatory variables are: herd size (*COWS*), production per cow (*PROD*), production per cow squared (*PRODSQ*), age of respondent (*AGE*), education of respondent (*EDUC*), number of dairy industry organizations the respondent belongs to (*COWCLUB*), and use of a computer for record keeping (*PC*).[3]

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[3] Other variables of interest, such as membership in the Dairy Herd Improvement Association or three-times-a-day milking, are highly correlated with production causing multicollinearity problems when incorporated in the model.

Table 1. Predicted versus Actual Probabilities of BST Adoption

	Predicted Conditional Probabilities[a] (%)	Unconditional Probabilities from Survey (%)
Haven't Heard	20	21
User	9	8
Nonuser	29	29
Waiter	33	34
Don't Know	9	8
Total	100	100

Log Likelihood = −141.
Restricted Log Likelihood = −187.
Chi-squared = 93 with 24 degrees of freedom.
Cragg and Uhler's[b] Pseudo R^2 = .53[c].

[a] Predicted probabilities are: $\hat{P}_j = \frac{\sum_{i=1}^{n} \hat{P}_{ij}}{n}$ $j = 0, 1, 2, 3, 4$.

[b] See Maddala, p. 40.

[c] Values between .2 and .4 are considered extremely good fits (Hensher and Johnson).

The predicted probabilities of this model are listed in table 1. The model predicts each conditional probability category within one percentage point of the unconditional probability.

Hypothesis Testing

There are five categories of BST adoption and 10 sets of coefficients. The coefficients measure the marginal effect of the regressors on the logarithm of the odds of being in one adoption category versus another. P_1 through P_4 are compared to P_0, P_2 through P_4 with P_1, P_3 and P_4 with P_2, and P_3 with P_4. Coefficients for equation (6) can be estimated with a multinomial logit model, while the rest of the coefficients and standard deviations can be derived by noting that:[4]

$$(7)\quad \ln\left(\frac{P_{im}}{P_{ik}}\right) = X_i'\beta_m - X_i'\beta_k \qquad m = 2, 3, 4 \quad k = 1, 2, 3$$

$$= X_i'\beta_{mk} \qquad m > k$$

where

$$(8)\quad \beta_{mk} = \beta_m - \beta_k,$$

$$(9)\quad \operatorname{var}\beta_{mk} = \operatorname{var}(\beta_m - \beta_k) = \operatorname{var}\beta_m + \operatorname{var}\beta_k - 2\operatorname{cov}(\beta_m\beta_k).$$

[4] Note that equation (6) is a special case of equation (7) where $k = 0$ and $\beta_k = 0$.

Table 2 presents estimates of β_{mk}. The lower left triangle of estimates is omitted as it would duplicate the coefficients examined. Equations (6) and (7) provide a linear interpretation of the coefficients. A positive coefficient implies that the explanatory variable increases the probability of being in an adoption category listed across the top of table 2, relative to a category listed along the side. For example, production level significantly increases the probability of being a User or a Nonuser relative to a Haven't Heard, however, it is not a factor in explaining the differences between the probability of Nonuser versus User. The sets of significant coefficients are different for each comparison. Testing coefficients for significance explains each probability of adoption category. Therefore, the number of insignificant coefficients is indicative of differences in explanatory factors between categories.

The discussion of table 2 examines the factors explaining the probability of being a User, Nonuser, Waiter, Don't Know, or Haven't Heard relative to the probability of being in another group. In some cases, generalizations can be made with respect to all other groups.

Herd size increases and age decreases the probability of being an immediate adopter of BST (User) relative to all other categories. Industry involvement and PC use significantly increase the probability of being a User relative to the Nonuser or Haven't Heard categories.

The probability of Nonuser versus User decreases with herd size, but the probability of Nonuser versus the other groups is not significantly affected by herd size. The probability of nonuse increases with age relative to the User and Don't Know categories. Computer use decreases the probability of nonuse relative to use or waiting. Education increases the probability of nonuse relative to the Haven't Heard and Don't Know categories.

Herd size decreases the probability of Waiter relative to User. Age increases the probability of Waiter versus User and undecided respondents. Education increases the probability of the Waiter versus the Haven't Heard and Don't Know categories. Club membership, or industry involvement, increases the probability of the Waiter category over the Nonuser and Haven't Heard categories. Computer use significantly increases the probability of waiting relative to the Haven't Heard, Nonuser, and Don't Know categories.

Table 2. β_{mk} Coefficients, Equation (8): Characteristics Affecting BST Adoption

		Users, $k = 1$	Nonusers, $k = 2$	Waiters, $k = 3$	Don't Know, $k = 4$
Haven't Heard, $m = 0$	*COWS*	2.89E−03**	−9.13E−04	−6.44E−04	−4.40E−04
	PROD	−9.45E−04**	−1.02E−03**	−1.26E−03**	−5.11E−04*
	PRODSQ	3.16E−08**	4.18E−08**	5.27E−08**	2.49E−08*
	AGE	−5.90E−02*	1.98E−02	8.39E−03	−5.68E−02**
	EDUC	3.00E−01**	2.74E−01**	2.83E−01**	1.18E−01
	COWCLUB	1.84E+00**	1.21E+00**	1.57E+00**	1.31E+00**
	PC	2.54E+00**	4.05E−01	2.60E+00**	7.30E−01
User $m = 1$	*COWS*		−3.80E−03**	−3.53E−03**	−3.33E−03**
	PROD		−7.41E−05	−3.13E−04	4.33E−04
	PRODSQ		1.02E−08	2.11E−08*	−6.65E−09
	AGE		7.89E−02**	6.74E−02**	2.23E−03
	EDUC		−2.60E−02	−1.70E−02	−1.83E−01
	COWCLUB		−6.31E−01*	−2.66E−01	−5.32E−01
	PC		−2.13E+00**	5.98E−02	−1.81E+00*
Nonuser $m = 2$	*COWS*			2.68E−04	4.73E−04
	PROD			−2.39E−04	5.08E−04*
	PRODSQ			1.09E−08*	−1.69E−08
	AGE			−1.15E−02	−7.66E−02**
	EDUC			8.96E−03	−1.57E−01*
	COWCLUB			3.65E−01*	9.86E−02
	PC			2.19E+00**	3.24E−01
Waiter $m = 3$	*COWS*				2.05E−04
	PROD				7.46E−04**
	PRODSQ				−2.78E−08**
	AGE				−6.52E−02**
	EDUC				−1.66E−01*
	COWCLUB				−2.66E−01
	PC				−1.87E+00*

Note: Single asterisk indicates significant at .1 level; double asterisk indicates significant at .05 level or better. Variables: *COWS*, herd size; *PROD*, production per cow; *PRODSQ*, production per cow squared; *AGE*, age of respondent, *EDUC*, education of respondent; *COWCLUB*, number of dairy industry organizations the respondent belongs to; *PC*, use of a computer for record keeping.

The probability of not having heard of BST (Haven't Heard) decreases with industry involvement and education. Relative to the probability of being a User, the probability of not having heard of BST decreases with herd size and increases with age.[5]

The results indicate there are significant differences between all categories. This verifies the importance of including more than two adoption categories in the *ex ante* model. Ignoring respondents who are unaware or undecided about BST is likely to misstate the probabilities of adoption. It is appropriate to preserve response categories as given and to test whether there are significant differences between them. Aggregating response categories would produce a misspecified model.

[5] A factor relevant to not having heard of BST, but not asked in the survey, is native tongue. Many of those who had not heard of BST spoke Portuguese as their first or only language. This also may indicate why so many in the Haven't Heard category do not participate in industry organizations.

Forecasting

Equations (6) and (7) are used to derive a linear interpretation of the coefficients estimated by equations (5a) and (5b) and to test for significant differences between all categories. Given that the adoption categorization is validated by significant differences, how do the explanatory variables affect the probability of being in a category? Table 3 contains predicted probabilities derived from equations (5a) and (5b) for different levels of explanatory variables. Only one variable is changed at a time. For comparison, the unconditional probability of each adoption category derived from survey data is listed in the first line of table 3, and the predicted conditional probability for mean values of the explanatory variables are listed on line two. The mean values of the explanatory variables are: 46-years old (*AGE*), high school education (*EDUC*), two dairy industry organizations (*COWCLUB*), 17% use of personal computers (*PC*), herd size of 508 cows

Table 3. Probability of Being in Each Adoption Category Given Different Levels of Explanatory Variables[a]

	User	Non-user	Waiter	Don't Know	Haven't Heard
Unconditional Survey Values:	.08	.29	.34	.08	.21
Conditional:					
Mean values	.05	.38	.39	.09	.09
100 Cows	.01	.43	.39	.09	.08
300 Cows	.03	.40	.39	.09	.09
600 Cows	.07	.36	.38	.09	.10
1,000 Cows	.24	.26	.31	.08	.11
15,000 lbs.	.09	.32	.21	.10	.28
20,000 lbs.	.02	.36	.50	.08	.04
30-yrs old	.11	.26	.31	.23	.09
65-yrs old	.01	.48	.40	.03	.08
Jr. High	.037	.33	.328	.127	.178
College	.06	.42	.44	.05	.03
No Clubs	.01	.252	.133	.052	.553
Three Clubs	.081	.316	.497	.087	.019
No *PC*	.03	.44	.31	.10	.12
PC	.08	.12	.74	.04	.02

[a] Unless otherwise indicated, the probabilities are evaluated at sample mean values.

(*COWS*), and a rolling herd average of 17,900 pounds of milk per year (*PROD*).

Herd size has little effect on the probability of being in the Don't Know or Haven't Heard categories. The probability of being a Waiter or a Nonuser decreases between a 100- and a 1,000-cow herd. However, the probability of being an immediate adopter increases by more than 20 times between a herd of 100 and 1,000 milking cows.

The probability of adoption changes little for the Nonuser or Don't Know categories between production levels of 15,000 and 20,000 pounds of milk per cow per year. The probability of being a User or a Haven't Heard falls while that of being a Waiter more than doubles between 15,000 and 20,000 pounds average production.

The impact of age on the probability of BST adoption is significant. A 30-year-old dairy farmer is 11 times more likely to adopt BST right away than a 65-year old. A 65-year old is nearly twice as likely to not use BST as a 30-year old. Thirty-year old dairy operators are less decisive; they are over seven times more likely to be undecided about BST than 65-year old farmers.

Education is a factor in the potential adoption of BST. College graduates are nearly twice as likely as junior high graduates to want to adopt BST immediately. Junior high graduates are six times more likely to not have heard of BST and two and a half times more likely to be undecided than college graduates.

Industry involvement is another important explanatory variable. A producer belonging to three industry organizations is eight times more likely to be a User than a farmer who belongs to none. A member of three organizations is nearly four times more likely to use BST sometime after it is released than a farmer belonging to no organizations. A farmer who doesn't belong to any organization is 29 times more likely to not have heard of BST than an operator belonging to three.

A producer with a personal computer for record keeping is more than twice as likely to use BST right away, or to wait before using it, as one who does not have a computer.

Elasticities

Elasticities were calculated to measure the marginal change in the probability of being in an adoption category for a change in each explanatory variable. They are listed in table 4. As an example, a 1% increase in herd size increases the probability of immediate adoption by 1.4%, whereas a 1% increase in age decreases the probability of immediate adoption by 1.6%. The value of the *PC* variable indicates aggregate usage of personal computers, e.g., a 1% increase in PC use implies a .5% increase in the probability of immediate BST use.

Implications and Conclusions

The first contribution of this research is to provide an economic rationale for inclusion of human capital and sociological characteristics in the commonly used logit technology-adoption model. Another contribution is to justify the inclusion of separate categories for undecided, unaware, and cautious respondents in an *ex ante* adoption model. Results from this multinomial model indicate significant differences between all five categories of respondents. Aggregating or ignoring respondents such that a binomial model can be estimated would

Table 4. Elasticities: Percent Change in Probability for One Percent Change in Exogenous Variable (Sample Enumeration Method)[a]

	COWS	*PROD*	*AGE*	*EDUC*	*COWCLUB*	*PC*
*P*0: Haven't Heard[b]	0.0269	−3.4589	−0.0472	−1.3454	−0.8779	−0.0650
*P*1: User	1.4198	2.5040	−1.5822	2.6699	2.6217	0.5455
*P*2: Nonuser	−0.2421	5.6101	0.5993	2.0515	1.3628	0.0193
*P*3: Waiter	−0.1553	6.6826	0.1994	1.7978	1.6181	0.2536
*P*4: Don't Know	−0.1697	5.9668	−1.8978	1.1594	2.0852	0.0613

[a] Hensher and Johnson.
[b] $E^{\bar{P}_0}_{0s}$ is zero by definition since X_{0s} is not used to determine P_0, therefore $E^{\bar{P}_0}_{s}$ is calculated instead, where s = *COWS, PROD*, etc. Please note that the elasticities for P_0 are not comparable to those for P_1 through P_4 but are added for completeness.

misspecify the model, over- or understating BST adoption.

A third implication of this research is prediction of BST adoption by California milk producers. The importance of the California dairy industry as a technological leader and as the second-largest producer of milk in the U.S. is critical in determining the impact BST will have on milk production and the structure of the dairy industry. Potential adoption of BST by California milk producers, based on the Waiter and User categories, is about 44%. That this adoption rate is lower than in studies of other regions may reflect Romeo's finding that diffusion rates of highly concentrated industries are lower than less concentrated industries.

A fourth contribution of this research is to test hypotheses on producer characteristics which affect the adoption of BST. Factors which significantly increase the probability of early adoption of BST are: increases in herd size, education, industry involvement, and computer use, and decreases in the age of the dairy operator. These are consistent with *ex post* research. Production level is not significantly associated with early adoption of BST. The exception is that production does increase the probability of early adoption relative to not having heard of BST.

Three explanations are presented for the lack of association between production level and anticipated BST use. First, this is an *ex ante* study and herds with lower production may be looking for technologies to increase production. Second, herd size of early adopters is almost twice as large as other groups, and they may find it easier to spread the risk of new technologies over their larger herd. Finally, producers with lower herd averages have less downside risk.

Factors that significantly increase the probability of a cautious but receptive attitude towards BST, the Waiter category, are similar to those of the Users. However, age and production increase the probability of being a Waiter relative to a User, while herd size decreases the probability. These characteristics are consistent with being more risk averse than early adopters.

The probability of not using BST (Nonuser) increases with age and education and decreases with herd size and computer use. These characteristics indicate greater risk aversion and less interest in new technology, which is consistent with lack of receptiveness to BST.

A final contribution of this research can be derived from the implications of adoption characteristics on the structure of the dairy industry in California. Since early adopters gain most from new technologies, if BST is profitable, it would improve the profitability of large dairies with young operators who are most likely to adopt. Small dairies run by older farmers would lose the most, given that they are more cautious or reluctant to adopt. If adopters do not reduce their herd size, their share of milk production would increase with BST use. If regulation allows a decrease in milk prices to accompany this rise in production, the absolute income and profitability of small farms would fall.

These changes in the profitability of small versus large farms would exacerbate the structural trends in the California dairy industry towards larger and fewer dairies. So, although there is nothing inherent in the technology of BST that would imply economies of size, its impact on the California dairy industry would be to accelerate the trend towards larger and fewer dairy farms.

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