A Comparative Analysis of Recombinant Bovine Somatotropin Adoption across Major U.S. Dairy Regions[1]

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Abstract:

Trends and determinants in the adoption of recombinant bovine somatotropin are examined using data from across the U.S. The core findings are: (1) moderate adoption rates and relatively small impacts on national milk production; (2) substantial disadoption, farmers who have tried the technology but stopped using it; (3) no significant differences in characteristics between adopters and disadopters; and, (4) major differences between non-adopters and farmers who have tried the technology, with the latter group having significantly higher use rates of complementary, productivity-enhancing technologies and larger herd sizes. This last result holds across states with distinctive herd size distributions.

Key Words:

agricultural biotechnology, rBST, technology adoption, dairy, profitability

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Introduction

This paper uses data from dairy farmers in seven U.S. states to examine farm-level factors influencing the adoption of recombinant bovine somatatropin (rBST), a productivity-enhancing hormone that is injected in cows. As a leading-edge agricultural biotechnology, rBST adoption has been studied extensively in the eras preceding and following its commercial release in 1994 (see Barham; and Foltz and Chang; for entry points to the rBST adoption literature). To date, most studies of rBST adoption determinants use data from a single state or a region within a state (see McBride, Short, and El Osta for an exception). Similarly, a companion literature on the profitability effects of rBST adoption (Foltz and Chang; Tauer and Knoblauch; Steffanides and Tauer; and Tauer) has only analyzed the issue using single state data. The near absence of comparative multi-state work using similar methods and data raises questions about whether findings in the rBST adoption literature are location or method-specific or whether they represent more general patterns.

This paper's contribution is to provide a comparative analysis of rBST adoption using data from five major dairy producing states, Idaho, Minnesota, New York, Texas, and Wisconsin and two minor ones, Connecticut and Utah. These data were gathered as part of a U.S.D.A.-sponsored research project on the community impacts of structural change in dairy farming.[1] Two aspects of rBST adoption are explored. One concerns measures that indicate the degree to which the technology is likely to have broader effects on the performance of the dairy sector, namely the productivity impacts of adoption and disadoption of rBST on U.S. dairy farms. The other theme examines the determinants of rBST use to identify the critical factors shaping farmer adoption decisions and hence the future trajectory of this and other similar technologies. Combined, these two themes provide the basis for a current and prospective look at the impacts and underlying logic of rBST adoption for the U.S. dairy sector.

The next section introduces the main issues, the dataset, and the econometric model deployed in the paper. Section 3 presents comparative descriptive data on rBST adoption, disadoption, and on the intensity of use on adopting farms. Section 4 provides the econometric results on rBST adoption, distinguishing among current adopters, disadopters, and non-adopters. Section 5 discusses the implications of the findings for our understanding of rBST adoption in the U.S. dairy industry.

2. Issues, Data, and Models

Prior to its commercial release, rBST was touted as a juggernaut technology. Its introduction and rapid adoption were seen as likely to transform the dairy sector through a major increase in milk output, an ensuing decline in milk prices, and strong competitive pressure on farmers, especially those running smaller-scale operations (See for example: Lesser, Magrath, and Kalter; Marion and Wills; Zepeda, 1990; and for a more nuanced view: Larson and Kuchler). So far, rBST adoption appears to have fallen well short of the levels that would have made the technology a "juggernaut" (Barham, Jackson-Smith, Moon), but recent evidence on adoption levels remains rather scarce despite the plethora of rBST papers. In academic journals, statewide adoption figures have been reported recently only for Wisconsin (17%), Connecticut (32%), and California (25%).[2]

Monsanto, the sole commercial provider of rBST (Posilac®), reports that in 1999 and 2000 the national adoption rate was about 15% of the nation's herds. They also report that these herds accounted for about 33% of the nation's cows.[3] The fact that rBST use is therefore more common nationally on larger-scale farms raises the interesting question of whether adoption is much higher in states with large farms or whether adoption is biased by farm size in all states. This issue is examined in the analysis below.

Adoption rates across farms are half of the juggernaut, or not, story. Monsanto also reports an average of 50% of cows being treated on farms currently using Posilac. This means that about 17% of the cows in the U.S. are being treated. With the 10% annual per farm productivity boost commonly associated with rBST adoption (see e.g. Foltz and Chang), then rBST use is responsible for about a 2% increase nationally in milk production per cow. This 2% estimate is much lower than *ex ante* predictions, and is equivalent to one-year worth of productivity growth at the annual growth rate in milk output per cow over the past decade.[4]

These estimates of adoption rates, adoption intensity, and production increases are useful benchmarks for the ensuing discussion. Another important measure is the rate of disadoption; that is, farmers who have tried rBST on their herds but are not currently using it. Estimates from Connecticut (Foltz and Chang), California (Butler, 1999), and Wisconsin (Barham, Jackson-Smith, and Moon; 2002) suggest that disadoption rates are substantial, ranging from 10% to 40% of farmers who used rBST, and are potentially a limit to further rBST adoption. A better understanding of the extent of disadoption and its determinants are further explored below.

The main focus of the paper is identifying the key determinants of rBST adoption and disadoption. Recent studies (using data from California, Wisconsin, and the Northeast) have shown that both larger herd-size (or scale) and higher use of complementary (productivity-enhancing) technologies increase the likelihood that farmers will try rBST on their herds (Henriques and Butler; Steffanides and Tauer; Foltz and Chang; Barham, Foltz, Jackson-Smith, and Moon). But, the question remains whether these outcomes hold across different locales, especially in the West where dairy herd sizes are typically much larger and more farmers use the complementary technologies than in the more traditional dairy areas where rBST adoption has been examined. Traditional human capital variables, such as age and education levels, have also been found in some instances to be important in shaping rBST adoption decisions, with more educated and younger farmers being more likely to adopt rBST than less educated and older farmers (Foltz and Chang).

Data and Methods:

The data come from a collection of cross-sectional surveys of populations of dairy farmers undertaken in select communities in seven states.[5] The surveys were constructed in a manner that makes the responses readily comparable for questions regarding rBST and complementary technology use, farm structure, farm operator, and farm performance indicators. These data permit the kind of multi-state analysis of rBST adoption, disadoption, and intensity of adoption currently missing from the literature.

Two disadvantages of these data deserve mention. One is that only in Connecticut or Wisconsin are the data known to be representative of what is occurring statewide.[6] The other samples are from individual counties within states chosen because they are major dairy producing counties. In Minnesota, Stearns county dairy farms are very similar in size to the rest of the dairy farms in the state. The counties surveyed in Idaho, Utah, New York, and Texas have dairy farms with larger average herd sizes than the rest of farms in the state. Because larger farms typically are also more technologically advanced, the data from these counties are likely to show higher rates of farmers having tried rBST. A second disadvantage of these data is that although they were mostly gathered in 1999 and 2000, the range goes from 1997 in Wisconsin to 2001 in Utah and Idaho. Thus, the data do not offer a "parallel" snapshot of adoption trends. This issue is addressed again in section 4.

A multinomial logit model of rBST adoption is estimated in this paper (Zepeda; Barham) in order to identify the determinants of three distinct adoption decisions, that of current adopters, disadopters (those who have tried but no longer use the technology), and non-adopters (those that have not tried the technology).[7] Non-adopters are chosen as the benchmark category to highlight the decision of whether to try rBST (i.e. both adoption and disadoption) in comparison to those who have never used rBST. This paper presents only the full results for the models with non-adopters as a benchmark, although an analysis using current adopters as a benchmark was also run in order to explore differences between current adopters and disadopters.

One of the main challenges of using these data is how to effectively pool the data from distinctive productive environments. The strategy we pursue here is to group states into two regional groupings, Northeast (Connecticut and New York) and Upper Midwest (Minnesota and Wisconsin) and to run Utah and Idaho separately because of the major differences between them in terms of mean herd size, one of our main determinants of interest. Four regressions are executed, one for each of the regional groups and one each for Utah and Idaho, in order to be able to compare the coefficient estimates across states.[8] The Texas sample is omitted from the econometric analysis because it lacks information on rBST disadoption. As shown below, the regional groupings pair closely related states in terms of key explanatory variables.

Comparative Levels of rBST Adoption, Disadoption, and Intensity of Use

Rates of rBST adoption vary notably across the sample (see Table 1). The lowest rate is in Wisconsin, where 15 % of farmers were using rBST on their herds.[9] The highest adoption rates are 44% and 45% in the New York and Texas counties where large farms predominate.[10] The other state samples report adoption rates between 26-30%, well above that of Wisconsin and below those of New York and Texas. Except for Wisconsin, then, all of the other rBST adoption estimates are well above the 15% national figure reported by Monsanto.

Rates of rBST disadoption are high in all of the state samples. In Utah, Idaho, and Minnesota, about 34-43% of the respondents who had tried rBST were disadopters. In New York and Connecticut, disadoption rates were around 23-24%. Although the Wisconsin sample (which was taken in 1997) had the lowest disadoption rate at about 22%, a statewide sample in 2001 revealed disadoption levels closer to the 43% levels found in Minnesota. Overall, these high rates of disadoption among rBST users suggest that rBST may not have been profitable for many dairy farmers who tried it, and they provide *prima facie* evidence to support the related line of work on rBST profitability (e.g. Foltz and Chang; Stefanides and Tauer) that fails to find statistically significant impacts of rBST adoption on profitability.

The intensity of rBST use, also reported in Table 1, is measured by determining the average percent of milk cows treated on farms using rBST. Average intensity rates across the state samples vary from 41% in the Wisconsin sample to 58% in Connecticut, with the rest ranging between 50 and 55%. These intensity figures are quite close to the 50% level reported by Monsanto. Only Wisconsin's adoption intensity seems low. Barham, Jackson-Smith, and Moon provide a potential explanation; reporting that in Wisconsin a number of farmers are using the technology primarily as a means to extend lactation cycles of a few cows, rather than for productivity enhancement of their herd.

The ordering of the columns in Table 1 reflects the regional groupings used in the ensuing regression analysis, with Connecticut and New York in the Northeast and Minnesota and Wisconsin in the Upper Midwest, and the other three states handled separately. These data show strong regional differences when one compares the demographic characteristics, herd size and productivity measures, and technology use patterns across the state samples. Most notable are the differences between the rest of the states and the Minnesota-Wisconsin pair, which have sample averages for herd size numbers, levels of formal education, and use of other modern dairy production practices that while quite similar to one another are considerably lower than the average levels in the other state samples. For example, mean herd sizes in the Minnesota and Wisconsin samples are, respectively, 68 and 63, with the next closest state being Connecticut with a mean herd size of 116. Similarly, use rates of total mixed ration machinery (TMR) in the

Minnesota and Wisconsin samples are, respectively, 38% and 25%, with the next closest state samples being Utah and Connecticut with rates of around 62%.[11]

Perhaps the most interesting aspect of Table 1 is the comparison it offers in average herd size and rBST adoption levels. Note that with 537 and 718 cows per farm that the Idaho and Texas counties have much larger average herd sizes than the other state samples. Yet, it is also striking that the Utah and Minnesota counties have relatively similar rBST adoption rates to the Idaho sample, even though the average herd size in both of those states is much smaller than in the Idaho counties. Moreover, the two samples that report the highest rBST adoption rates are the New York and Texas counties, even though New York is very much in the middle of the sample in terms of average herd size. What is noteworthy about these two samples is that they were drawn from counties that represent the upper tail of the herd size distributions in those states.[12] Overall, then the descriptive data in Table 1 suggest that the size bias in rBST adoption inherent in Monsanto's national data is not driven primarily by major differences in rBST adoption across states with disparate average herd sizes but instead by differences across the herd size spectrum within states.

This inference is supported by the descriptive comparisons of current adopters, disadopters, and non-adopters that are offered in Table 2.[13] Across all of the state samples, the most distinctive difference is that non-adopters have average herd sizes that range between one-third to one-half of the size of current adopters and are also notably smaller than those of disadopters. Use rates of complementary technologies, such as herd production records and TMR, also vary notably between non-adopters and the other two categories, but they are generally quite similar across current adopters and disadopters.

Formal education levels differ most between non-adopters and the other two categories of adopters in the Northeast, but do not vary much between adoption categories in the Upper Midwest pair or in Utah.

Determinants of rBST Adoption and Disadoption

In specifying the explanatory variables used to explain adoption and disadoption in the multinomial logit, we follow the literature cited above that has to varying degrees found age, education, use of production records, use of complementary technologies such as TMR, and herd size to be significant determinants of rBST adoption.[14] Farmer education and age variables are included to capture traditional human capital attributes: younger better-educated farmers are hypothesized to be more likely to adopt rBST. Production records and total mixed ration equipment are viewed as complementary productivity-enhancing technologies that should make the adoption of rBST more advantageous. They are also "mature technologies" in the sense that they were available long before the introduction of rBST, such that their adoption is unlikely to be endogenous to the rBST decision of farmers. Herd size is included to assess whether the herd size bias of rBST adoption holds across states with widely varying average farm sizes. State binary indicators are included to pick up differences across states, where regulatory and political environments can differ, as well as differences in the years the surveys were conducted.

The results of the multinomial logit regressions are reported in Table 3. For the Northeast, the TMR variable was dropped from the specification because of a singularity problem that arose with all disadopters being TMR users. Regressions run for the other states without including the TMR variable result in very similar coefficient and standard error estimates.[15] Regressions done with current adopters as the benchmark category reveal basically no significant differences between current adopters and disadopters, and are not reported here.

The coefficient on herd size is positive and statistically significant for all of the regressions except for the case of Idaho. Comparing the herd size coefficient estimates on current adopters shows that they are very similar in the Northeast and Upper Midwest and substantially larger in those two cases than in Utah or Idaho. In the Northeast and Upper Midwest, disadopters also have positive and statistically significant coefficient estimates on herd size, with very similar coefficient estimates to those of current adopters. But, in Utah and Idaho, the herd size coefficient estimates for disadopters are notably smaller and not significant. These differences in the importance of herd size as an explanatory variable in the use of rBST are explored further below in a graph of rBST use against herd size.

In all of the regressions, the use of production records is a strong, positive, and statistically significant predictor of being a current adopter of rBST, with very similar coefficient estimates in all cases. Among disadopters, use of production records was statistically significant and of similar magnitude in two of the cases, the MN-WI pair and in Idaho. Meanwhile, use of TMR is a positive and statistically significant predictor of current adoption in MN-WI and Idaho but not in Utah, with the strongest coefficient estimate being in Idaho. Among disadopters, the TMR variable was not statistically significant in any of the cases where it was included. Recall, however, that it was excluded from the CT-NY regression because all of the disadopters used TMR and all but one of the current adopters did so as well. Thus, TMR use is certainly a critical predictor of having tried rBST in those states. Overall, then, it is clear that both larger herds and the adoption of other productivity-enhancing technologies distinguish current adopters and in some cases disadopters from non-adopters.

The traditional human capital measures of age and education give the least consistent results across the 3 regional pairs. The coefficient estimate on education level was positive in all cases but only statistically significant as a predictor of current rBST adoption in the Northeast ($p<.01$). Likewise, the only case where the coefficient estimate on age was a significant predictor ($p< .05$) was among current adopters in the Northeast, where younger farmers are more likely to be rBST users. The only other significant coefficient estimate was on education in Utah, where disadopters were found to be more likely to have lower levels of education than non-adopters. Finally, in the Upper Midwest, neither of the human capital coefficients were significant predictors of current adoption or disadoption.

Perhaps the most striking finding in the econometric results is that herd size is a strong predictor of rBST adoption on dairy farms across states with very different herd size distributions. This result is illustrated in Figure 1, which uses the multinomial logit results to compare the predicted probability of having tried rBST against herd size for the Northeast, Upper Midwest, and Utah and Idaho.[16] For example, the curves for the Northeast and Upper Midwest rise from predicted probabilities of having tried rBST of 15-20% at herd size levels of 0-50 up to nearly universal adoption rates at around 250 cows. Note that especially in the Upper Midwest sample that a 250-cow farm would be considered quite large. The Utah predicted probability curve offers a stark contrast to the

Northeast and Upper Midwest curves. In the case of Utah, at 250 cows the predicted probability of having tried rBST in the Utah sample is less than 50%, while universal adoption is predicted to occur on much larger farms like those above 750 cows. Thus, the herd size bias in rBST adoption is present in states with very disparate herd size distributions. Put differently, this means that a large farm in one state which would be very likely to have tried rBST would be considered relatively small in another and would be far less likely to have tried rBST.

The results from Idaho mapped in Figure 1 can also be used to argue that the herd size bias of rBST adoption may diminish as the average herd size of a region grows to relatively large levels. Specifically, in the Idaho sample, the average herd size is over 500 cows, and the size bias of rBST adoption evident in the other states is no longer significant. However, it is not clear that this argument would necessarily hold elsewhere in regions where dairy farming has a longer history, and there is a wider range of herd size distributions than is found in Idaho. For example, in the Texas sample also included in this study, regression results on current rBST use demonstrate a strong size bias, even though the average herd size there is larger than in the case of the Idaho sample.

Discussion

This work has set out to provide a broad view of the adoption patterns of rBST across some of the major dairy producing regions of the country. Across the state samples, the lowest adoption rate was about 16%, which was comparable to the national average of 15% reported by Monsanto. In most of the state samples, adoption rates were close to twice that national average, and well above the state ranges suggested by

Monsanto. The state samples also revealed relatively high disadoption rates among dairy farmers (around 40% of farmers who have tried the technology), which is consistent with doubts raised by recent research in New York and Connecticut concerning the profitability impacts of rBST adoption.

The results of the multinomial logit estimations of rBST adoption and disadoption mostly confirm the evidence on key determinants found in individual state studies of rBST. Herd size and complementary technologies both play positive and important roles in rBST adoption. These regressions also confirm evidence found in Foltz and Chang and Barham, Jackson-Smith, and Moon (2002) that the main determinants of current adopters and disadopters are quite similar, essentially making current adopters and disadopters statistically indistinguishable from one another. Such evidence is consistent with the literature on the profitability of rBST (e.g., Stefanides and Tauer; McBride, Short, and El Osta) that finds only marginal and not statistically significant profit effects of rBST and suggests that even having tried rBST dairy farmers are indifferent as to whether to continue using it or not.

By contrast, the magnitudes of the coefficient estimates for adopters and disadopters, especially on herd size, and the significantly smaller herd sizes and adoption rates of complementary technologies among non-adopters, demonstrate that there are major differences between farms that have tried rBST and those that have not. Put differently, it would seem unlikely that most current non-adopters would be likely to become adopters without major changes occurring in farm herd sizes, their use of complementary technologies, or in key price variables, such as milk, feed, or rBST prices.

The most striking aspect of this paper's results is that herd size is such a strong predictor of rBST adoption on dairy farms across states with very different average herd sizes. Although the analysis developed above does not provide any explanations as to why the size bias in adoption should be across locales with very different herd size distributions, four possibilities are briefly considered here. One popular explanation among dairy industry professionals might be that the regressions presented here do not adequately capture management ability and that such ability is also size biased (i.e. larger herds are run by better managers who are also more likely to adopt rBST). However, the evidence from rBST disadoption and other profitability studies belie this better manager argument. First, if it were true, then we might expect the coefficient estimates on herd size to distinguish between adopters and disadopters as part of the evidence that adopters are significantly better managers than disadopters. Second, because rBST adoption has been shown to have no statistically significant impacts on dairy farm profitability (Foltz and Chang; Stefanides and Tauer), there is currently no evidence that rBST adopters earn higher profits, which would be a logical conclusion of the better manager argument.

A second possible explanation for the size bias issue is also related to management strategy, but does not rely on rBST adopters being more profitable. It could be that farms that have specialized their labor tasks are more likely to adopt rBST, because such specialization may be critical for managing the herd in a way that makes rBST use profitable. Then, if the herd size at which such specialization is likely to occur varies across regions according to the range of tasks normally taken on by dairy farms, then average herd sizes of farms with and without specialization could vary within regions yet be distinct across regions. For example, it may be that due to less effort being spent on cropping, nutrient management, and certain types of animal care, a non-specialized family labor farm in Texas would have, on average, 400 cows while in Wisconsin a fully integrated, non-specialized livestock and crop cultivation operation might have 75 cows. By contrast, operations that specialized over the different ranges of tasks across those two states might have, on average, 800 and 150 cows, respectively. Testing this explanation would require more information on management practices and labor allocation than we have in these studies, though Barham, Jackson-Smith, and Moon (1999) find some evidence to support this claim in Wisconsin.

The third and fourth possibilities relate to the information costs and attitudes associated with the adoption of new technologies. In the case of information, larger farm operations might be more able to make the fixed cost investment of learning about the new technology and hence be more likely to adopt, especially early in a technology's diffusion process. This hypothesis seems plausible but less likely for rBST given the extended controversy that preceded its commercialization and, in effect, made information on the technology widely available from the outset. Also, this hypothesis does not explain the size-bias finding across disparate regions. Finally, a last possibility is that attitudes toward rBST and/or new technologies in general might be positively correlated with herd size in all of the locales. This explanation, while plausible, begs the question of why these attitudes would be sustained as the diffusion process of technologies matured.

Overall, the paper identifies two intriguing avenues for future research, one related to the lack of discernible differences between adopters and disadopters of rBST and the other related to the consistent herd size bias in rBST adoption across states with very disparate herd size distributions. In both cases, research efforts will likely benefit from further comparative work across multiple states with sufficient information on farm management strategies and attitudes toward new technologies to explore contending explanations more carefully.

References:

Barham, B. "Adoption of a Politicized Technology: bST and Wisconsin Dairy Farmers," *Amer. J. Ag. Eco.* 78 (November 1996):1056-1063.

Barham, B., D. Jackson-Smith, and S. Moon. "The Adoption of rBST on Wisconsin Dairy Farms," *AgBioForum*, 3 (2-3) (2000). http://www.agbioforum.org.

Barham, B., D. Jackson-Smith, and S. Moon. "The Dynamics of Agricultural Biotechnology Adoption: Lessons from rBST Use in Wisconsin, 1994-2001," under review at *AJAE*.

Butler, L. "The profitability of rBST on U.S. dairy farms." *AgBioForum*, 2, 2, (Spring 1999). Available on the World Wide Web: http://www.agbioforum.org.

Foltz, J.D. and H.H. Chang. "The Adoption and Profitability of rBST on Connecticut Dairy Farms." *Amer. J. Ag. Econ.* 84(4), (November 2002): 1021-1032.

Greene, W. *Econometric Analysis, 3rd Edition.* Upper Saddle River, New Jersey: Prentice Hall. 1997.

Henriques, I. and L.J. Butler. "The Importance of Feed Management Technologies in the Decision to Adopt Bovine Somatotropin (bst): An Application to California Dairy Producers," in *Market Development for Genetically Modified Foods*, ed. Santaniello, V., R.E. Evenson, and D. Zilberman, CABI (2002).

Larson, B. and F. Kuchler. "The Simple Analytics of Technology Adoption: Bovine Growth Hormone and the Dairy Industry." *Nor. Cent. J. Ag Econ*. 12, 1 (January, 1990): 109-123.

Lesser, W., W. Magrath, and R. Kalter. "Projecting Adoption Rates: Application of an Ex Ante Procedure to Biotechnology Products, *Nor. Cent. J. Ag Econ*. 8, 1 (1986): 159-174.

Marion, B. and R. Wills. "A Prospective Assessment of the Impacts of Bovine Somatotropin: A Case Study of Wisconsin," *Amer. J. Ag. Econ.* 72, 2 (May 1990): 326-36.

McBride, W., S. Short, and H. El Osta. "Production and Financial Impacts of the Adoption of Bovine Somatotropin on U.S. Dairy Farms." Selected Paper 2002 AAEA Meetings, Long Beach CA. 2002.

Saha, A., H. Love, and R. Schwart. "Adoption of Emerging Technologies Under Output Uncertainties." Amer. J. Ag. Econ. 76 (November 1994): 836-46.

Stefanides, Z. and L. Tauer. “The Empirical Impact of Bovine Somatotropin on a Group of New York Dairy Farms.” *Amer. J. Ag. Econ*. 81 (February 1999): 95-102.

Tauer, L. “The Estimated Profit Impact of Recombinant Bovine Somatotropin for the Years 1994-1997.” *AgBioForum*, 4, 2 (2001). Available on the World Wide Web: http://www.agbioforum.org.

Tauer L. and W. Knoblauch. “The Empirical Impact of Bovine Somatotropin on New York Dairy Farms.” *J. Dairy Sci*. 80 (1997): 1092-1097.

Zepeda, L. “Predicting Bovine Somatotropin Use by California Dairy Farmers.” *W. J. Agr. Econ.* 15 (July 1990): 55-62.

Zepeda, L. “Simultaneity of Technology Adoption and Productivity.” *J. Ag. Res. Econ.* 19, 1 (1994): 46-57.

Table 1. National Wide Characteristics by State Sample

Characteristics	Overall	CT	NY	MN	WI	UT	ID	TX
Number of observations in sample	929	123	50	227	252	87	143	47
Year of Survey		1999	1998	2000	1997	2001	2001	2000
rBST Adoption Rate								
Currently Use rBST on Any Milking Cows (Percent of all dairy farms)	25.9	30.1	44.0	26.0	15.5	28.7	26.6	44.7
Have tried but no longer use rBST: Disadopter (Percent of all dairy farms)	11.7	8.9	14.0	19.4	4.4	14.9	16.1	N/A
Disadopter (Percent of those who have tried rBST)	31.6	22.8	24.1	42.7	22.1	34.2	37.7	
Percent of Milk Cows treated with rBST on adopting farms *	51.5	57.7	50.1	52.6	40.7	55.1	49.9	N/A
Operator Demographics								
Mean age of operator	48.5	53.3	49.5	46.2	47.7	51.4	48.5	44.2
Operator Education Level (percent)								
- Less than High School	10.1	8.0	10.0	8.4	17.7	2.3	6.3	8.7
- High School Diploma	43.5	44.2	38.0	63.3	49.6	20.9	25.4	15.2
- Some College or Trade school	31.0	30.1	28.0	23.0	27.0	45.3	41.5	37.0
- BA Degree or Higher	15.5	17.7	24.0	5.3	5.6	31.4	26.8	39.1
Herd Size and Productivity								
Mean Herd Size (cows)	200.1	115.7	200.8	67.5	63.2	238.6	537.0	718.5
Standard Deviation of Herd size estimate	546.3	106.6	198.9	50.5	51.1	567.7	1073.3	967.4
Median Herd Size (cows)	71.5	90.0	127.5	56.0	50.0	105.0	200.0	401.0
State Average Herd Size in Year 1997 (cows) **	68.7	85.7	77.7	54.2	55.7	101.1	194.3	108.0
Rolling Herd Average (lbs/cow/year)	19,815	19,824	21,994	20,040	18,720	19,984	20,035	20,108
Technology Use								
Keep Any Type of Production Record (%)	65.2	65.5	86.0	78.8	72.5	47.1	33.8	74.5
Use of TMR (Total mixed Ration machinery) (%)	48.1	63.6	82.0	37.6	25.1	59.3	67.1	68.1

* Conditional on Current rBST User

** Source: USDA Final Estimates of Milk Cows and Milk Production by State in Year 1997 (number of milk cows 1/number of operations)

Table 2. Descriptive Statistics by Sub Groups

Characteristics	Overall	CT-NY	MN-WI	UT	ID	Texas
Non-adopter						
Number of Observation	579	96	326	49	82	26
Operator Age	50.0	54.3	48.3	52.5	49.3	46.6
Use of TMR (%)	33.3	47.3	19.1	49.0	58.5	50.0
Keep Production Records (%)	55.3	59.1	67.3	33.3	19.8	65.4
Herd Size (cows)	129.9	85.6	53.9	120.8	399.3	411.4
Operator Education - Less than High School (%)	13.6	12.5	17.4	2.1	7.3	11.5
- High School Diploma (%)	46.2	52.3	54.2	22.9	29.3	23.1
- Some College or Trade school (%)	28.7	25.0	23.7	43.8	40.2	38.5
- BA Degree or Higher (%)	11.5	10.2	4.7	31.3	23.2	26.9
Current Adopter						
Number of Observation	241	59	98	25	38	21
Operator Age	46.1	49.1	44.5	50.3	45.3	41.1
Use of TMR (%)	77.5	94.8	60.2	80.0	86.8	90.5
Keep Production Records (%)	83.8	87.9	94.2	76.0	57.9	85.7
Herd Size (cows)	376.2	222.7	91.3	517.6	878.5	1084.0
Operator Education - Less than High School (%)	4.6	5.2	5.1	0.0	5.4	5.0
- High School Diploma (%)	36.6	25.9	63.3	12.0	16.2	5.0
- Some College or Trade school (%)	31.1	34.5	23.5	44.0	35.1	35.0
- BA Degree or Higher (%)	27.7	34.5	8.2	44.0	43.2	55.0
Dis-Adopter						
Number of Observation	109	18	55	13	23	N/A
Operator Age	47.2	51.2	44.0	49.8	50.6	N/A
Use of TMR (%)	61.7	100.0	49.1	58.3	65.2	N/A
Keep Production Records (%)	74.1	83.3	90.9	41.7	43.5	N/A
Herd Size (cows)	188.0	159.9	85.4	146.2	478.7	N/A
Operator Education - Less than High School (%)	3.7	0.0	3.6	7.7	4.3	N/A
- High School Diploma (%)	44.4	47.1	54.5	30.8	26.1	N/A
- Some College or Trade school (%)	42.6	35.3	36.4	53.8	56.5	N/A
- BA Degree or Higher (%)	9.3	17.6	5.5	7.7	13.0	N/A

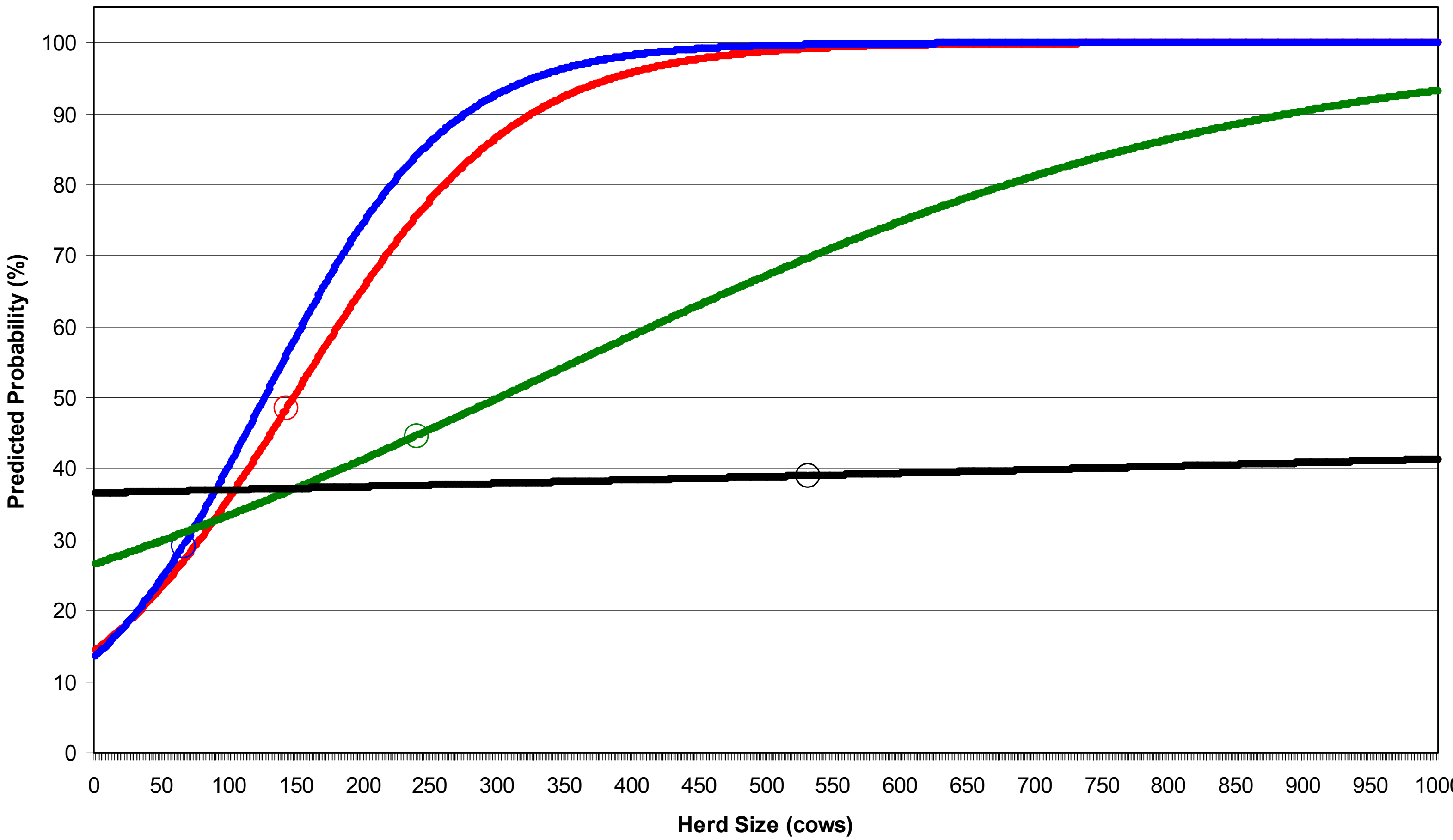
Table 3. Multinomial Logit Regression Analysis (Non Adopter - Comparison Group)

Variables		CT-NY	MN-WI	UT	ID
		Coefficient estimates (std. errors)			
Current Adopter	Constant	-3.367 ***	-2.906 ***	-4.186 *	-3.169 **
		(1.291)	(1.010)	(2.181)	(1.504)
	Operator Education	0.926 ***	0.170	0.361	0.473
		(0.257)	(0.201)	(0.425)	(0.290)
	Operator Age	-0.044 **	-0.016	0.006	-0.016
		(0.019)	(0.014)	(0.026)	(0.020)
	Keep Production Record	1.314 **	1.495 ***	1.671 ***	1.437 ***
		(0.586)	(0.507)	(0.617)	(0.477)
	Herd Size	0.0131 ***	0.0144 ***	0.0041 *	0.0003
		(0.0028)	(0.0038)	(0.0025)	(0.0002)
	Use of TMR		0.985 ***	0.732	1.315 **
			(0.302)	(0.699)	(0.580)
	Regional Dummy [1]	-0.094	-1.082 ***		
		(0.486)	(0.296)		
Dis-adopter	Constant	-4.172 **	-2.908 ***	1.842	-1.985
		(1.743)	(1.112)	(2.022)	(1.593)
	Operator Education	0.497	0.380	-1.021 **	-0.110
		(0.323)	(0.235)	(0.467)	(0.299)
	Operator Age	-0.013	-0.021	-0.019	0.009
		(0.025)	(0.017)	(0.028)	(0.020)
	Keep Production Record	0.857	1.096 **	0.265	1.192 **
		(0.725)	(0.520)	(0.719)	(0.527)
	Herd Size	0.0102 ***	0.0151 ***	0.0020	0.00005
		(0.0031)	(0.0041)	(0.0034)	(0.0003)
	Use of TMR		0.527	0.392	0.308
			(0.357)	(0.784)	(0.536)
	Regional Dummy [1]	0.388	-1.756 ***		
		(0.604)	(0.384)		
	Log Likelihood	-114.28	-292.95	-64.76	-118.85
	Number of Observation	159	408	84	140

[1] Regional Dummies in the first two sub-groups are New York and Wisconsin respectively.

Note: single asterisk indicates significance at the 0.1level; double asterisk at the 0.05 level; and triple asterisk at the 0.01 level.

Figure 1. Predicted Probability of Having Tried rBST by States



Note: Circled lines represent the predicted probabilties given the mean herd size in each sample.

Endnotes:

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[1] Northeast Regional project number 177 examines the impacts of structural change in dairying on local communities or regions where dairy farming is an important activity in the local economy.
[2] Adoption figures for Wisconsin in 2001 are reported in Barham, Foltz, Moon, and Jackson-Smith. Adoption figures for Connectic[illegible] MN & WI [illegible]rted in Foltz and Chang. Adoption figures for California in 1997 are reported in Butler.
[3] Thanks to Steven Bierschenk, the Posilac Marketing L[illegible] CT & NY [illegible] these estimates.
[4] Figures for the past decade were taken from USDA's National Agricultural Statistics Service report on cow productivity numbers for the leading 20 dairy producing states. The annual growth rate of milk production per cow between 1991 and 2001 was 2%.
[5] The locales are: Stearns County in Minnesota, Ontario County in New York, Cache County in Utah, Utah Franklin, Twin Falls, Jerome, and Gooding Counties in Idaho, Erath County in Texas, and three towns with lots of dairy farms in distinctive regions of Wisconsin (Athens, Chilton, and Richland Center). The Connecticut data come from a statewide survey of all dairy farms, but with only 250 dairy farmers in the state they are comparable to a minor dairy-farming county in some of the major dairy production states.
[6] In Wisconsin, the data for the three communities provide comparable adoption levels to statewide averages from a survey undertaken at the same time, while in Connecticut the sample is based Idaho statewide survey of all dairy farmers.

[7] The probabilities for the multinomial logit model are: $\Pr(Y_i = j) = \dfrac{e^{\beta_j' x_i}}{1+\sum_{k=1}^{J} e^{\beta_k' x_i}}$ *for j=1,2,…J* and

$\Pr(Y_i = 1) = \dfrac{1}{1+\sum_{k=1}^{J} e^{\beta_k' x_i}}$ (Greene). The log likelihood function that is maximized is developed from them.
[8] We also estimated the models with corrections for heteroskedasticity using the multinomial logit version of the Huber-White robust variance technique. These results produced the same inference on the models reported. Since it is not clear that this particular correction is the correct one, we prefer to report the uncorrected standard errors. Results are available from the authors upon request.
[9] A comparison of the Wisconsin sample with a statewide survey from the same year (1997) reveals that the adoption rate for this Wisconsin sample was slightly higher than the statewide figure of 12% (Barham, Jackson-Smith, and Moon), and the same as the 15% figure that was recorded in a 1999 statewide survey. Thus, the lower adoption rate in the Wisconsin sample is not an artifact of the earlier date of this survey.
[10] The New York and Texas data come from counties where farms are much larger than the state averages. Specifically, the statewide herd-size averages in New York in 1997 and in Texas in 1999 were, 80 cows and 123 cows, respectively, while the sample counties had average herd sizes of 201 and 718 cows.
[11] Total mixed ration machinery (TMR) allows farmers the ability to mix optimal quantities of different feedstuffs. This helps improve the nutrition of the cows, which is important both to overall productivity and to the cow's ability to respond to rBST.
[12] Ibid.
[13] For Texas, the comparisons are only available for adopters and non-adopters, since a disadoption question was not included in that survey.
[14] Henriques and Butler argue that use of feed buffers rather than TMR is of more importance to rBST adoption in California, but these data do not allow us to examine the role of that particular technology.
[15] The main difference is a reduction in the standard error for the herd size coefficient estimate and thus a higher level of statistical significance when TMR is omitted.

[16] Having tried rBST combines adopters and disadopters into a category, and contrasts them with non-adopters.