The Dynamics of Agricultural Biotechnology Adoption: Lessons from rBST use in Wisconsin, 1994-2001

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Abstract:
This article exploits panel data from Wisconsin dairy farmers to examine the dynamics of rBST adoption and in the process to identify the characteristics that distinguish among non-adopters, disadopters, and early and late adopters. Panel methods are used to control for omitted variables and endogenous regressors that call into question coefficient estimates derived from cross-section adoption models. The results, however, confirm previous findings that larger farms with complementary feeding technologies are more likely to adopt rBST, non-adopters appear quite unlikely to become adopters, and rBST adoption will remain at rather moderate levels in Wisconsin.

Key Words: agricultural biotechnology, rBST, technology adoption, dairy, panel data methods

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Economists have long viewed technology adoption as a dynamic process (Griliches; Mansfield) because of the learning, coordination, and investment issues that face potential adopters (Feder and Slade). Yet, until the mid-1990s, empirical studies of adoption trends and determinants relied heavily on cross-sectional rather than panel data (Besley and Case), which meant that the underlying dynamics were rarely explored at an empirical level. Recent efforts (Foster and Rosenzweig; Conley and Udry; and Cameron) highlight the value of panel data to help uncover the subtle dynamics of learning, strategic behavior, and coordination among producers faced with decisions about whether to adopt and how to most effectively deploy new technologies.

This article shifts the focus of attention to three other ways that panel data can improve our understanding of technology adoption. First, panel data permit a move beyond the classic analysis of the determinants of adoption versus non-adoption to explicit consideration of factors that distinguish non-adopters, early adopters, later adopters, and disadopters from one another. Second, even though the conventional contribution of panel data econometrics is to control for the potential bias in regression estimations created by omitted variables (Wooldridge), very few technology adoption models have deployed these methods to probe the reliability of other estimations. Third is the use of lagged measures of key explanatory variables to address the potential endogeneity of key farm-level adoption determinants that arise when using cross-sectional data (Zepeda, 1994). This approach also provides evidence on the sequential versus simultaneous nature of some farm-level decisions regarding technology or other productive strategies.

The specific empirical analysis undertaken here is an exploration of the adoption dynamics among Wisconsin farmers of recombinant bovine somatatropin (rBST), a genetically engineered, productivity-enhancing hormone that is injected in cows. The data span the period from the commercial introduction of rBST in 1994 to 2001, and thus provide a comprehensive view of the adoption dynamics of this leading-edge (and controversial) agricultural biotechnology.

For several reasons, this study of the dynamics of rBST adoption is timely. First, the adoption dynamics of rBST are relevant to a whole class of production-oriented agricultural biotechnologies, especially as companies and farmers weigh returns and risks to future investments in agricultural biotechnology products. Unlike some farm technologies, such as silos or milking parlors for which significant sunk costs will dampen disadoption, rBST and most crop biotechnologies can be adopted and later disadopted without significant costs to the operation. While Butler, Foltz and Chang, and Barham, Jackson-Smith, and Moon have commented on the prevalence of disadoption in the case of rBST, its determinants and effects on the dynamics of rBST diffusion have not yet been explored.

Second, rBST was anticipated in the early 1990s to be a juggernaut technology, one that both opponents and proponents thought would fundamentally alter the organization and structure of U.S. dairy farming (Hallberg; Fallert et al.; and Liebhardt; see also Larson and Kuchler for a more nuanced view). Understanding the reasons why rBST has had a rather muted impact on the organization and performance of the U.S. dairy sector can be enhanced by a dynamic analysis of adoption patterns in Wisconsin, where approximately 20% of U.S. dairy farms are located. Indeed, rBST has now been commercially available for long enough that the technology is arguably mature, especially given its long pre-commercialization debate. Nationally, too, it appears that the diffusion process has flattened out, with only an incremental change in national adoption rates over the past two years: from 16 to 17% of the farms.[1]

A final motivation for examining rBST adoption is the high degree of politicization that occurred among farmers especially prior to its commercial release, and appeared to shape its initial adoption profile, at least in Wisconsin (Barham). The durability of the effects of this politicization in shaping farmer adoption choices is pertinent to current and future controversial agricultural technologies (e.g., Bt cotton, glyphosate tolerant corn). It is made more interesting by the fact that in Wisconsin the voluntary use of labeling to identify "rBST-free" fluid milk products was initially pervasive, but has largely disappeared over the past three years (except for organic products and specialty cheeses). This change means that demand-side concerns are less likely to be directly influencing current adoption decisions. Thus, if the earlier "attitudes" of farmers toward rBST continue to shape adoption outcomes, then the durability of these politicization effects would be especially noteworthy.

In the next section, the issues of dynamics, omitted variables, and endogenous regressors are reviewed in the context of previous rBST adoption studies. In the following section, we present the econometric models used in this article to analyze rBST adoption. In, the fourth section, the panel data are described, and some descriptive statistics are offered that motivate the fifth section's econometric analysis of the dynamics of adoption behavior. In the final section, we summarize the article's findings on the adoption dynamics of rBST and technology adoption in general.

Dynamics of rBST Adoption: Issues and Approaches

The classic literature on technology adoption views the dynamics as following an "S" shaped diffusion path in which adoption starts slowly, picks up speed, and then levels off (e.g., Rogers). In this formulation adoption dynamics depend on differences across farmers. For example, lower information costs and stronger capacity to bare risk are often argued to distinguish early adopters, who tend to be better educated and/or have larger farms, from later adopters (Feder and Slade; Feder, Just and Zilberman). One practical implication of this classical view of technology adoption is that cross-sectional estimates from early in the diffusion process may be inaccurate in predicting which types of farmers will adopt later in the diffusion process.

The dynamics of diffusion raise some questions about previous rBST studies. First, most studies have shown rBST adopters to have the characteristics typically associated with early adopters of any technology (younger, better educated, having more other new technologies, and larger farms), but these differences may be due more to the timing of the measurement than anything specific about the technology. Thus, the frequent finding of a scale bias in rBST adoption (e.g., Tauer; Foltz and Chang; Barham, Jackson-Smith, and Moon) might be a result of the moment when the analysis took place rather than to attributes of rBST.

A second dynamic issue arises from the relatively high degree of disadoption of rBST. Failure to distinguish these disadopters from non-adopters may render estimates of adoption parameters inaccurate and hence biased for making inferences about the likely adoption path of the technology. At least initially, the high degree of politicization of rBST may have exacerbated this source of bias by making some farmers for whom it is not an optimal technology more likely to adopt and others for whom it might have been an optimal technology unlikely to adopt (Barham; Klotz, Saha, and Butler). Thus, in the early adoption period, estimates that ignored this politicization effect might fit the data poorly and have parameter estimates that were inconsistent for inference on the future adoption paths. If the effects of politicization diminished over time, then one might see reversals of adoption (or non-adoption) decisions, as farmer's choices centered increasingly on economic rather than political (or emotional) criteria.

Unobserved Random Variables:

Cross-sectional estimates of rBST adoption may also suffer from an omitted variable bias. In particular, a number of unobservable farm characteristics that are uncorrelated with observable variables used as regressors may influence the profitability of rBST and hence adoption decisions. Examples of unobservable or omitted random variables likely to influence the adoption of rBST include: farmer management ability, access to family labor[2], individual farm-level milk price variations such as volume premiums, learning from previous rBST adoption, and neighborhood learning effects. These omitted variables, if they significantly influence the benefits or costs of using rBST, would lead to inconsistent estimates of parameters in an adoption equation, and might be a basis for finding, for example, that rBST adoption tends to be size-biased.

Although most of the unobservable characteristics are individual farm specific, they are likely to be relatively constant over time. Thus, repeated observations on the same unit provided by panel data can be used to control for these missing variables

(Wooldridge). The random effects modeling approach used below specify the unobservable characteristics as a random variable, and then controls for its effect.

Endogenous Regressors:

Endogeneity issues arise when one or more of the explanatory variables ($\mathbf{x}_i$'s) are also choice variables for the farmer, where a similar calculation of the expected profitability of those choices might also be part of the farmers' decision-making calculus. For adoption decisions, other complementary technologies and management practices might shape the profitability of the new technology, and thus be an endogenous part of an overarching production strategy. Often such endogenous technologies are adopted together as a "package", as is the case with conservation tillage (see e.g., Rahm and Huffman), or they may be sequenced, as for example Khanna asserts is the case for soil testing and variable rate fertilizer technology.

Panel data provide a straightforward way to resolve the endogeneity problem associated with other choice variables and their influence on the adoption of the technology in question. For example, information on the use of specific technologies from earlier waves of the panel data can be used to predict the adoption of the main technology of interest at a later point in time.   In addition to being robust to endogeneity, lagged technology use information can also provide information on the sequencing of technology adoption.

In the context of rBST adoption, studies have found that along with the traditional human capital variables, scale or farm-size and complementary feeding technologies are important in shaping farmer adoption decisions (Stefanides and Tauer; Barham, Jackson-

Smith, and Moon; Foltz and Chang). At issue is why rBST, a technology that is easy to inject, requires no fixed investments, and has minimal start-up costs, has demonstrated a very strong size-bias in adoption. One explanation focuses on the role of complementary technologies and the possibility that the full productivity enhancing effect of rBST may only be realized on farms that have a package of management practices and complementary technologies already in place (see e.g., Henriques and Butler). These practices are ones found predominantly on larger farms, and so they are the most likely to benefit from the adoption of rBST. None of the studies, however, treat in a satisfactory way the potential endogeneity between complementary technologies and rBST adoption, or between rBST and farm size. Such endogeneity could imply that the frequently reported size bias in rBST adoption is an artifact of poor econometric methodology rather than the technology itself.

The same critique can be levied on attitudinal variables used in studies of rBST adoption (e.g. Barham). For example, a farmer who has tried rBST, and finds it useful, may be more likely to have a favorable attitude toward the technology than one who has not yet adopted it. Thus, in cross-section data, attitudinal variables may also be compromised by problems of endogeneity.

A typical solution to this potential problem of endogeneity in regressors is to find instrumental variables plausibly correlated with the adoption decision but uncorrelated with the current error term. A lagged measure of the relevant technology, farm-size, or attitudinal variable fits that description, and thus can help to address the endogeneity issue that otherwise plagues cross-sectional adoption analyses.

Estimation Strategy:

This work presents three models of rBST adoption. Each deals with a different set of estimation issues. The first uses a multinomial logit that separates individual farms into four distinct adoption categories in order to explore the factors that distinguish among these adoption categories. A second estimation uses the panel structure of our data to control for unobserved variables in a random effects logit model as a means of testing the reliability of many of the standard results in rBST adoption analyses, including those obtained from the multinomial logit. Finally, the random effects logit panel model is re-specified using lagged regressors as instruments to control for endogeneity.

Following the standard index model (e.g., Wooldridge), let the decision of whether to adopt a new technology be described by the relative costs and benefits of the new technology compared to the standard technology.[3] One can model this marginal benefit, which will be different for each farm in each time period, as an unobservable latent variable, y_{it}^{*} , such that

(1) $$y_{it}^{*} = \boldsymbol{\beta}'\mathbf{x}_{it} + \varepsilon_{it},$$

where $\mathbf{x_{it}}$ are observed explanatory variables, $\boldsymbol{\beta}$ is a vector of parameters to be estimated which potentially take on different values by time period, and $\varepsilon_{\mathbf{it}}$ is an error term, which may have both individual farm specific and idiosyncratic elements. Since we only observe whether the farmer adopts the new technology, not the actual marginal value of the technology one can define the adoption as an index function:

$$y_{it} = 1 \;\; if \;\; y_{it}^{*} > 0$$
$$y_{it} = 0 \;\; if \;\; y_{it}^{*} \le 0.$$

In general one is interested in describing the probability of adoption as a function of the observed explanatory variables:

(2) $$\Pr(y_{it}^{*} > 0) = \Pr(y_{it} = 1) = G(\boldsymbol{\beta}'\mathbf{x}_{it}),$$

where $G(\boldsymbol{\beta}'\mathbf{x}_{it})$ is a function normally chosen to be either logistic or normal. The logistic function is chosen for this exercise in order to make consistent assumptions across the different estimations described below.

Multinomial Logit:

An issue that arises in studying the adoption of new technologies is that over time there are more than just adopters and non-adopters of a technology. At a minimum, there are four important categories of adoption behavior: early adopters, late adopters, non-adopters, and one that is often overlooked, disadopters. Knowledge of the relative frequencies of these behaviors, and the fundamental differences among farms in each category, reveals more about the dynamics of the diffusion process than a simple binary analysis of adoption allows. A multinomial logit estimation strategy using the panel data structure can capture the unique determinants of these distinctive categories of dynamic adoption behavior. Specifically, the determinants associated with each category can be contrasted with those in a benchmark category (McFadden; Zepeda, 1990; Barham).

Using the formulation above one can describe the different unordered outcomes by the notation $j = 0, 1, \ldots, J$. Letting time $t=0, 1, \ldots T$, then the categories j can be defined as:

$$
\begin{array}{ll}
j = 0 \;\; if \;\; y_{it}^{*} \le 0 \quad \forall t, & Non-adoption \\
j = 1 \;\; if \;\; y_{it}^{*} > 0 \quad \forall t, & Early-adoption \\
j = 2 \;\; if \;\; y_{it}^{*} \le 0 \;\; for \; t = 0, but \; y_{it}^{*} > 0 \; for \; t = T, & Late-adoption \\
j = 3 \;\; if \;\; y_{it}^{*} > 0 \;\; for \, t = s, but \;\; y_{it}^{*} \le 0 \;\; for \; t = T, & Dis-adoption.
\end{array}
$$

While this formulation is dynamic, if the characteristics that determine in which category a farmer falls can be adequately described in the first period, $\mathbf{x}_{\mathbf{it}=0}$, the problem reduces to a single period estimation. Dropping time subscripts and using the notation above, the standard approach to a multinomial logit relies on the Weibull distribution for the various disturbance terms. Then, the J+1 unordered outcomes occur with a probability determined by the following equation:

(3) $$\Pr(y_i = j) = \frac{e^{\boldsymbol{\beta}_\mathbf{j}' \mathbf{x}_\mathbf{i}}}{\sum_{k=0}^{J} e^{\boldsymbol{\beta}_k' \mathbf{x}_\mathbf{i}}}, \;\; j = 0, 1, ...J.$$

In order to identify the J+1 possible unordered outcomes in this model, and the model's parameters, a standard normalization is to assign a benchmark outcome to have the parameter matrix $\beta_0 = 0$. This technique allows the rest of the coefficients in the estimation of the different technology choices to be identified relative to the benchmark outcome. Once this is done, the probabilities of falling into a specific category become:

(4) $$\Pr(y_i = j) = \frac{e^{\boldsymbol{\beta}_\mathbf{j}' \mathbf{x}_\mathbf{i}}}{1 + \sum_{k=0}^{J} e^{\boldsymbol{\beta}_k' \mathbf{x}_\mathbf{i}}}, \;\; j = 1, 2, \; .... \;\; J$$

(5) $$\Pr(y_i = 0) = \frac{1}{1 + \sum_{k=0}^{J} e^{\boldsymbol{\beta}_k' \mathbf{x}_\mathbf{i}}}.$$

The multinomial logit model, as specified, also partially addresses the endogeneity issue by using explanatory variables from the baseline to describe the adoption process from the baseline to the current period (1994-2001). While it does not remove potential endogeneity from the estimates for early adopters, the baseline farm and farmer characteristics are plausibly exogenous for all other categories of farmers who made adoption decisions later. This solution to the endogeneity issue comes at a cost, which is that the model describes adoption decisions made in 2001 as being a function of farm and farmer characteristics fixed at 1994/1995 values. The random effects logit model described below relaxes this stricture.

Random Effects Logit:

We specify a random effects logit panel data model to account for omitted variables and the possible endogeneity of some regressors. Following the discussion in Guilkey and Murphy, one can describe the latent variable, y_{it}^* as a function of a vector of exogenous variables, x_{it}, an unobserved random variable μ_i, and an error term ε_{it}, as follows:

(6) $$y_{it}^* = x_{it}\beta + \mu_i + \varepsilon_{it},$$

where μ_i is distributed normally with mean zero and variance, σ_μ^2, and ε_{it} has a logistic distribution with mean zero and variance σ_ε^2.

Although y^* is unobserved, one does observe the indicator variable defined as follows:

$$y_{it} = \begin{cases} 0 & if\ y_{it}^* \leq 0 \quad Not\ Adopt \\ 1 & if\ y_{it}^* > 0 \quad Adopt \end{cases} .$$

Imposing the normalizations $\sigma^2 = \sigma_\mu^2 + \sigma_\varepsilon^2 = 1$ and $\rho = \sigma_\mu^2 / (\sigma_\mu^2 + 1)$. Then the probability of the observed sequence of the indicator variable $Y_i = [Y_{i1}, Y_{i2} \ldots . Y_{iT}]$ can be described as:

(7) $$\Pr(y_i \mid x_i) = \int_{-\infty}^{\infty} \frac{e^{-\mu_i^2/2\sigma_\mu^2}}{\sqrt{2\pi\sigma_\mu}} \left\{ \prod_{t=1}^{n_i} F(x_{it}\beta + \mu_i) \right\} d\mu_i ,$$

where

$$F(x_{it}\beta + \mu_i) = \begin{cases} \dfrac{1}{1+\exp(x_{it}\beta + \mu_i)} & \textit{if } y_{it} \neq 0 \\ 1 - \dfrac{1}{1+\exp(x_{it}\beta + \mu_i)} & \textit{otherwise.} \end{cases}$$

Consistent and asymptotically efficient estimators can be obtained by maximizing the likelihood function:

(8) $$L = \prod_{i=1}^{N} \Pr(y_i \mid x_i) .$$

The likelihood function is maximized using a gauss-hermite quadrature procedure that approximates and evaluates the integrals. The quadrature procedure requires that the integrated function is well approximated by a polynomial, which is the case when T is not too large, typically under 50.

Endogeneity:

If a subset of variables z_{it} of the independent variables x_{it} are endogenously determined with the dependent variable y_{it}^*, the independent variables will be correlated with the error term ε_{it} , violating one of the model's basic assumptions. In the context of a panel data model lagged independent variables make very strong instruments in that they are likely to be exogenous to the dependent variable, but correlated with the contemporaneous dependent variable of interest. If one partitions x_{it} into a set of exogenous variables, $\hat{x}_{it}$, and potentially endogenous variables z_{it}, one can estimate the following model with lagged endogenous variables.

(9) $y_{it}^{*} = \hat{x}_{it\,t}\beta + z_{it-1}\,\delta + \mu_i + \varepsilon_{it}$.

The procedure for estimating this model is that of the random effects logit described above with the replacement of potentially endogenous variables with their lagged counter parts.

Data and Descriptive Statistics

Baseline surveys were conducted of two random samples of farmers selected from the Wisconsin Dairy Producer List, a population list of commercially licensed dairy farms maintained by the Wisconsin Department of Agriculture, Trade, and Consumer Protection. The first baseline survey was done in the fall 1994, the second in the spring of 1995. The 399 respondents from the spring of 1995 were then re-surveyed in 1997 and 2001 creating a useable panel of 216 observations, although only 172 contained all three years of complete data. In addition, the 441 respondents in 1994 were re-surveyed in 2001, eliciting 188 useable responses. This creates a panel data set of 404 observations on continuing farmers spanning 1994-2001, the seven years since rBST's commercial introduction.[4] Because we are interested in the dynamics of the adoption process, the analysis only uses data from continuing farmers.[5]

Data for multinomial logit analysis

For the multinomial logit analysis, we merge the two baseline responses (1994 and 1995) into one initial period. This consolidation seems reasonable given that both were drawn from random samples of producers, the surveys were done within 6 months of each other, and there were relatively small differences evident across the two periods. For example, rBST adoption rates in the fall of 1994 sample were 5.4%, compared to 6.6% in the spring of 1995. In addition, comparison of the two baseline samples across other observable variables reveals almost identical values (i.e., average herd size of 56 in 1994 and 58 in 1995, and total mixed ration, TMR, equipment use 25% versus 27%).

Data for random effects logit analysis

The random effects logit analysis uses the 1995 panel data with three observations, 1995, 1997, and 2001, on 172 farms. The 1994 baseline is dropped because there are only two observations for that group, 1994 and 2001, and the panel methods exploit the three observations for each respondent to generate estimates that control for unobserved variables and potential endogeneity. Specifically, the lagged variables used in the second random effects regression as instruments to control for endogeneity refer to either the baseline observation of 1995 or the 1997 observation depending on whether the dependent variable is from 1997 or 2001, respectively.

Descriptive Statistics

The baseline data used in the regressions are shown in table 1. The table is divided into the four adoption categories based on rBST use over time. "Non-Adopters" are the dominant category, accounting for 74% of the panel data sample. They are farmers who report never having used rBST on their farms. "Disadopters", the next category in the table, account for about 10% of the panel respondents. They are farmers who were not using rBST on their herds in 2001 but had used it sometime prior to 2001 (but not necessarily at the time of their baseline response).[6] "Later Adopters" account for 11% of the sample, and are currently using rBST on their herds. They were *not* using it at the time of the baseline surveys (most of them began use in the 1996-99 period). Finally, "Early Adopters," account for about 5% of the sample. They adopted rBST at the beginning of the panel study period 1994 or 1995 and are still using it in 2001. Combining the disadopters with the two other adopter categories allows the observation that while more than a quarter of the respondents tried rBST, about 40% of farmers who have tried rBST are currently not using it.

Table 1 also provides a profile of the farm characteristics in 1994/1995 of the different adoption categories. These statistics conform to previous findings that show non-adopters, on average, to be distinct from adopters in terms of size and complementary technology use (Barham; Zepeda, 1990; Foltz and Chang; Barham, Jackson-Smith, and Moon). They also show that the differences among the three "adopter" categories (including disadopters) are much smaller, although early adopters have larger herds and are more likely to use complementary technologies.

The table also provides information on milk productivity levels among the different adoption categories. What is striking is that even though rBST users have higher productivity levels overall, the non-adopters had the largest growth in productivity (13%), followed by later adopters (11%) whose productivity increase includes rBST adoption, while disadopters had the lowest increase (5%). This suggests that in terms of productivity increases among Wisconsin dairy farmers, rBST adoption represents only a small portion of the action.

The explanatory variables ($\mathbf{x}_i$'s) used in the regressions, shown in table 1, represent farm and farmer characteristics. Consistent with previous studies, we focus on the influence of age, education, herd size, use of a complementary feeding technology TMR, and the attitudes of farmers to predict adoption behavior. These latter two variables require a bit more discussion.

Total mixed ration machinery (TMR) is used to improve the management of the feed mix supplied to cows. Although most studies cited above find its use a significant predictor of rBST adoption, Henriques and Butler find that in California feed buffers have a more significant impact on adoption that TMR. If that were also the case in these data, the random effects specification should help to account for this missing variable. It is also noteworthy that use of dairy herd production records, another productivity enhancing technology, had to be dropped as an independent variable from the regressions because 100% of the early adopters used that technology in the baseline period.

The attitudinal measure was constructed as follows. In the 1994 and 1995 surveys, dairy farmers were asked how Wisconsin dairy farmers would be affected by FDA approval of rBST. For those who gave a somewhat negative or strongly negative response, they were assigned a value of 1. If they responded with a neutral or positive response, they were assigned a value of 0. The more nuanced attitudinal measures used in Barham were only available for the 1994 respondents. Results using those measures were similar to those reported below for the attitudinal measure that was common to both the 1994 and 1995 surveys.

Finally, a regional dummy variable is also included to identify farmers located in the three Eastern agricultural statistics districts of the state (there are nine districts overall). A combination of factors including flatter and larger farm plots, higher land prices (via urban pressure), and proximity to the state's main corridor of industrial and manufacturing activity distinguish this region from the rest of the state, and appear to create a distinctive economic and cultural environment for farming. This difference is reflected in previous experience that farmers in this region of Wisconsin are often considered to be more "progressive" or aggressive in their adoption of emerging technologies. This variable also partially controls for neighborhood effects in which farmers in an area with higher average adoption rates will have lower information costs than those in regions with low adoption rates. The regression results reported below are not sensitive to the inclusion of this variable.

Econometric Results

Multinomial Logit

The multinomial logit regression results are reported in table 2. The model places 75% of the sample in the correct adoption categories, although, due to its similarity to other adoption categories, disadoption is poorly predicted (5.4% correct). The most significant differences are between the three adopter-groups on the one hand and the non-adopter group on the other. In terms of farmer characteristics, non-adopters have significantly lower education levels than later adopters ($p < .1$) and are significantly older than the early ($p<.05$) and later adopters ($p<.01$). The other coefficient estimates on education and age have similar signs and magnitudes to the significant results but are insignificant at common confidence levels.

Adoption of the complementary feed-balancing technology, TMR, in the baseline period is a very strong predictor of being among those who have tried the technology, both adopter and disadopter. All three estimates are significant at the $p<.01$ level. The same holds true for operations with larger herd sizes. Farms with larger herds are more likely to have tried rBST, and interestingly the coefficient estimates across early, late, and dis-adopter are virtually identical. Thus, as suggested by the descriptive data and previous studies, both complementary technology **and** herd size are important predictors of rBST adoption. In addition along the technology and herd size dimensions no differences are evident between those who currently use the technology (early and later adopters) and those who no longer use the technology (disadopters).

The coefficient estimate on the attitudinal variable only distinguishes non-adopters from the early adopters, with the early adopters being more likely to have a positive view of the technology than the other categories. Indeed, the coefficient estimate on the attitudinal variable in the early adopter category is significantly different from the estimates for both disadopters and later adopters at a 90% confidence interval. This result suggests that negative views of the technology had significant impacts on the initial adoption choices of farmers, but that the importance of attitudes and beliefs has diminished over time. Similarly, the regional dummy variable distinguishes the early adopters from the non-adopters at a significant level ($p<.05$). Thus, both attitudes and location seem to be explicitly linked to early adoption outcomes, while farm size and complementary technology do not distinguish early adopters from later adopters and disadopters.

Put differently, farm size and complementary technology use appear to be robust explanatory factors for distinguishing between non-adopters, on the one hand, and the three categories of adopters, on the other hand. This outcome suggests that these standard findings are not related to the timing of adoption in a fundamental way but to the distinctive characteristics of farm operations and management approaches. These findings also underscore the suggestion made in Foltz and Chang that disadopters are very much like adopters.

Random Effects Logits:

Table 3 presents in the first column the results of a random effects logit estimation of the probability a farmer adopts rBST in each year (1995, 1997, 2001) as a function of that farm and farmer's characteristics in that year. The exception is that, in order to avoid an endogeneity problem, the anti-biotech dummy variable is for the farmer's initial opinions and does not change in subsequent years. As shown in table 3, the estimates of the unobserved random variable represented by rho are significantly different from zero, supporting the use of a random effects formulation and attention to unobserved variables in the adoption estimation. The strength of this effect is somewhat surprising given that disadoption is so prevalent, and should potentially mute the correlation in adoption outcomes across time periods.

Despite the significance of the random effect estimate, the remaining parameter estimates are mostly consistent with those in the multinomial logit as well as those reported elsewhere in the literature. Adoption of rBST is again significantly decreasing in age and increasing in herd size and use of complementary feeding technologies (TMR) as well as being lower for those who have anti-biotech attitudes. In contrast to the multinomial logit results, which had the measure of neighborhood effects in the eastern region of the state significantly positive for early adopters but insignificant for later adopters, these results suggest that being in a region of higher adoption continues to have an influence even after controlling for unobserved farm-specific factors. This outcome suggests that the distinguishing feature of the Eastern region of the state is more than just information, but may include other factors (higher land prices, attitudes, or land characteristics) that promote adoption of technologies that are oriented toward enhancing the productivity of cows. Finally, while the multinomial logit results showed some evidence of a relationship between operator education and being either an early adopter or a disadopter, no such effects are evident in the random effects logit.

Table 3's second column presents the results of the random-effects logit estimation with two potentially endogenous variables, herd size and TMR, lagged one period. In this case only two years of adoption data are used, 1997 and 2001, along with the lagged variables for 1995 and 1997. The results are again quite similar to the previous regression that uses only contemporaneous independent variables. Overall, the consistency of these core results suggest that the finding of larger herd size and use of complementary feeding technologies as significant determinants of rBST adoption are robust and are not an artifact of correlated endogenous adoption patterns. In this manner, the two random-effects panel models buttress the findings of the multinomial logit regression regarding the key role of complementary technology, farm size, and attitudes in shaping the dynamics of adoption. The endogeneity corrected regressions also show that rBST has been adopted sequentially after TMR adoption and decisions about herd size increases were already made, or at least well underway, rather than being either simultaneous to them or even a cause of them.

Conclusion

This article used panel data from Wisconsin dairy farmers to explore the dynamics of rBST adoption. Initially, the panel data are used to move beyond the classic comparison of adopters and non-adopters, to a more nuanced multinomial logit analysis of non-adopters, early adopters, later adopters, and disadopters. The multinomial logit shows significant differences between non-adopters and those who have tried the technology, but few differences between adopters and disadopters. The panel data were next used to estimate two random effects logit models that control for omitted variables and endogenous regressors. The results show significant effects of omitted variables and confirm the robustness of the standard finding in the literature that larger farms with complementary feeding technologies are more likely to adopt rBST. These results are also shown to be robust with respect to potential endogeneity of these two farm characteristics.

Overall, the empirical analysis of adoption leads us to the following conclusions about the future adoption process of rBST in Wisconsin. First, the non-adopters looked and continue to look very distinct from the other categories of adopters in terms of their characteristics. They have much smaller operations, much lower use of complementary technologies, and hold negative views of the technology, at least relative to the early adopters. Looking ahead, current non-adopters seem very unlikely to adopt rBST, and sensitivity analyses show that they would have to make major changes in their operations in order to be "predicted" as rBST users. Moreover, 75% of the non-adopters reported in 2001 that they will definitely not use rBST over the next three years, a response that proved to be 95% reliable in the 1994 baseline survey compared with 2001 outcomes. Of the remaining non-adopters, 23% say they are not very likely to start using rBST, a response that proved to be 75% reliable in the 1994 baseline compared with 2001 outcomes (and 90% reliable if disadopters are included in a non-adoption category). The upshot of both of these findings is that a very small proportion of non-adopters seem likely to become adopters of rBST.

Second, the regression analysis did not reveal many distinguishing characteristics among early adopters, late adopters, and disadopters. Attitudes and to a much lesser extent use of complementary technologies were the only significant distinguishing characteristics. Yet, the current use rate of these complementary technologies is actually quite high among the disadopters (68% using TMR for example), which suggests that while they may be critical conditioning factors for rBST adoption that they by no means guarantee that rBST use will be attractive. Thus, changes in the use rates of these technologies do not appear likely to make much of a difference in terms of moving disadopters back into the adopter category.

Clearly the diffusion of rBST in Wisconsin, as in the U.S. overall, has hit a plateau in recent years. While adoption rates rose from 15% to 16% between 1999 and 2001, the actual number of users of rBST in Wisconsin fell for the first time. The empirical analysis offered above suggests that this plateau is not likely to change much in the near future. Adoption rates may rise, because rBST adopters may be more likely to survive than non-adopters, but there does not appear to be a significant proportion of new (or return) adopters waiting in the wings. Most Wisconsin dairy farms would have to change many other characteristics of their operations before the adoption of rBST would become a likely prospect.

Further work on rBST adoption could usefully explore the potential sensitivity of adoption rates to price-cost environment changes, especially reductions in the price of Posilac^{TM}, the only commercially available rBST product. Such an undertaking could also explore the potential impacts of monopoly pricing of the technology on its diffusion path. It may be that the high rates of disadoption, the large proportion of farmers who have never tried the technology, and hence the lower diffusion than was once anticipated are directly related to the pricing of the technology. Use of panel data combined with more detailed farm financial information could allow this type of analysis.

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Table 1. Mean and Standard Deviations of Regressors by rBST Adoption Category

	Overall	Non-adopter	Dis-adopter	Later-adopter	Early-adopter
Percent (Number) of Sample	(404)	73.5 (297)	9.7 (39)	11.4 (46)	5.4 (22)
Operator Education Level (1-4)*	2.35	2.24	2.64	2.63	2.73
	(0.84)	(0.85)	(0.63)	(0.80)	(0.77)
Operator Mean Age (years)	45.61	46.51	44.61	41.96	42.95
	(10.87)	(11.06)	(10.48)	(9.84)	(9.31)
Use of TMR (1 or 0)	0.26	0.14	0.50	0.55	0.76
	(0.44)	(0.35)	(0.51)	(0.50)	(0.44)
Mean Herd Size (cows)	57.23	48.35	81.62	77.15	92.09
	(41.84)	(27.73)	(37.64)	(76.49)	(57.32)
Anti-Bio Tech Attitude (1 or 0)**	0.49	0.53	0.41	0.50	0.09
	(0.50)	(0.50)	(0.50)	(0.51)	(0.29)
Eastern Region (1 or 0)***	0.27	0.25	0.23	0.26	0.64
	(0.44)	(0.43)	(0.43)	(0.44)	(0.49)
1994/95 Rolling Herd Average (lbs/cow/year)	18,015	16,913	19,443	20,258	22,105
2001 Rolling Herd Average (lbs/cow/year)	20,333	19,115	20,442	22,481	23,795
Percent increase in milk productivity 1994-2001	12.9	13.0	5.1	11.0	7.6

Note: Standard deviations are in parentheses;
* Education Level: 1=Less than High School, 2=High School Diploma, 3=Some College or Trade School, 4= BA Degree or Higher.
** Anti-Bio Tech Attitude: 1=Biotechnology will not bring improved levels of living for most farm families (1994) or FDA approval of rBGH will negatively effect respondents dairy operation (1995), 0 = Otherwise.
*** Eastern Region: 1=East (North East, Central East, and South East Wisconsin Agricultural Statistics Districts), 0=Otherwise.

Table 2
Multinomial Logit Analysis of rBST Adoption

(Categories in 2001 based on 1994/95 Characteristics, Non-adopter as Comparison Group)

Regressors	**Dis-adopter**	**Late-adopter**	**Early-adopter**
Constant	-3.01 ***	-2.25 **	-3.37 **
	(1.07)	(1.02)	(1.50)
Operator Education	0.38	0.41 *	0.49
	(0.23)	(0.22)	(0.35)
Operator Age	-0.03	-0.05 ***	-0.06 **
	(0.02)	(0.02)	(0.03)
Use of TMR	1.30 ***	1.54 ***	2.19 ***
	(0.40)	(0.38)	(0.60)
Herd size	0.02 ***	0.02 ***	0.02 ***
	(0.005)	(0.005)	(0.006)
Anti-Bio Tech Attitude	-0.33	0.05	-3.06 ***
	(0.38)	(0.36)	(1.07)
Eastern Region	-0.22	-0.220	1.34 **
	(0.44)	(0.42)	(0.55)
Log Likelihood	-259.24		
Pseudo R squared	0.21		
LR Chi Squared	138.38		

Note: Standard errors are in the parentheses; Single asterisk indicates significance at the 10% level; double asterisk at the 5% level, and triple asterisk at the 1% level.

Table 3
Random Effect Logit Analysis of rBST Adoption

	Model 1	Model 2
Constant	-2.53	-1.97
	(1.56)	(1.69)
Operator Education	0.31	0.32
	(0.36)	(0.37)
Operator Age	-0.05 **	-0.07 **
	(0.03)	(0.03)
Use of TMR	1.65 ***	
	(0.56)	
Use of TMR in Previous Period		1.52 **
		(0.65)
Herd size	0.016 ***	
	(0.005)	
Herd Size in Previous Period		0.022 ***
		(0.008)
Anti-Bio Tech Attitude	-2.31 ***	-1.83 ***
	(0.63)	(0.65)
Eastern Region	1.06 *	1.39 **
	(0.62)	(0.65)
$\rho = \sigma v^2/(\sigma v^2+1)$	0.50 ***	0.46 ***
	(0.04)	(0.05)
Number of observations	493	330
Number of groups	169	166
Log Likelihood	-118.80	-89.61
Wald Chi Squared (d.f.=6)	39.47	25.04

Note: Standard errors are in the parentheses; Single asterisk indicates significance at the 10% level; double asterisk at the 5% level, and triple asterisk at the 1% level.
$\rho = \sigma v^2/(\sigma v^2+1)$ which is the proportion of the total variance contributed by the panel-level variance component. When rho is zero, the panel-level variance component is unimportant and the panel estimator is not different from the pooled estimator.

Endnotes:

[1] Data source: Personal email communication with Steve Bierschenk who is the Posilac Marketing Lead at the Monsanto Corporation August 29, 2002.
[2] We thank an anonymous reviewer for pointing out the potential relationship between access to family labor and success in using rBST. While family size is observable, actual access to the labor in the family is more difficult to observe or proxy and rarely included in estimates reported in the literature.
[3] An alternative formulation, the random utility model, has a slightly different motivation because it is based on a utility structure rather than direct costs and benefits, but leads to the same set of econometric models to be estimated. The index formulation is preferred as a way to minimize the extraneous notation.
[4] Of the 840 farmers who responded to the original 1994 and 1995 surveys, 404 responded in 2001. Among the non-respondents, 217 (26%) were identified either by returned surveys or subsequent inquiries as exiters from the dairy industry, while 219 (26%) did not respond or returned blank surveys . The 26% exit rate compares to a statewide exit rate of 34% from 1994 to 2001, suggesting that at least a quarter of the non-responses are likely to be exits.
[5] Analysis of our sample suggests that sample attrition was reasonably close to random. Estimates of sample attrition probabilities had pseudo r-squares of 0.02 and had age as the only determinant significant at a 5% level or better. They showed no significant effect of rbst use on sample attrition (t-statistic of 0.69).
[6] The predominant reason for disadopters to stop using the technology seems to be economic. When asked their reason for discontinuing use of rBST, 82% said that "rBST was not cost effective" for them, and that this was the most important reason for them to stop using the technology.