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Estimation of Treatment Effects of recombinant Bovine Somatotropin using Matching Samples

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Abstract

The production and profit impacts of recombinant Bovine Somatotropin (rbST) on select New York dairy farms were estimated using data over the years 1994 through 2004, by comparing matching farms which use and do not use rbST. The use of rbST increases milk production per cow and decreases the cost of production per hundredweight of milk. The cost penalty (cost reduction) is $0.39 per hundredweight for those currently using rbST to stop using rbST, while the average treatment effect is $0.73.

Keywords: Bovine Somatotropin, BST, Dairy, Matching Samples, Treatments

Introduction

Recombinant Bovine Somatotropin (rbST) has been commercially available to U.S. dairy producers since February of 1994 from the Monsanto Company under the registered trade name POSILAC. Bovine Somatotropin is a hormone produced naturally by the dairy cow that regulates milk production, but the genetic material for this compound has been isolated by genetic engineering. That genetic material has been used to produce a recombinant version of the naturally occurring compound, which can be injected into the dairy cow to augment her naturally produced levels of the natural hormone, enhancing milk production, but requiring additional feed and other inputs to achieve increased milk production.

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Because rbST has been available and used by farmers for a number of years, a number of studies have assessed its profitability on dairy farms (Tauer and Knoblauch; Stefanides and Tauer; Foltz and Chang; McBride, Short and El-Osta). The results of these studies are ambiguous. Most find a positive, but not statistically significant effect of rbST on farmers' profits, although the positive impact on milk yield per cow is unambiguous and statistically significant.

These estimates are typically based on models that entail a regression of a performance measure on a set of covariates, with farms that use and do not use rbST coded as a binary variable. Many of these studies also controlled for self selection bias. Self selection bias might occur if farmers that are more profitable even without the use of rbST may also be the farms that use rbST, or vice versa. Any comparison between rbST users and non-users then would include the inherent profitability of farmers adopting rbST without controlling for self selection.

Other statistical procedures have, however, been utilized in the treatment literature (Heckman and Hotz; Vella and Verbeek). A technique which has seen limited application in agriculture is to find matching samples for comparing treatment effects (Rubin, 1973). This technique is used in this paper to estimate treatment effects of rbST. The procedure identifies each farm that uses rbST (or does not use rbST) and then compares its performance with a similar farm which did not use rbST (or which does use rbST). These comparisons are averaged for a treatment effect estimate. The identification of similar types of farms is done by minimization of a distance metric based upon farm characteristics. Conceptually, the approach mimics random placement of farms into treatment (rbST use) and none treatment (none rbST use) groups. Although the statistical estimation technique of matching samples was only recently developed, the philosophy and approach of identifying farms who adopt some farming practice and then comparing to similar farms that do not use that specific farming practice dates to G. F. Warren (Warren).

Review of Literature

Tauer and Knoblauch were the first to estimate the impact of rbST on milk production per cow and return above variable cost per cow. Using data from the same 259 New York producers in 1993 and 1994, they found the use of rbST had a positive and statistically significant impact on the change in average production per cow between the two years, but the profit change, although positive and large, was not statistically different from zero. Using one more year of data, Stefanides and Tauer likewise found a statistically significant positive effect on milk production per cow from the use of rbST, and found the impact of rbST on profits was statistically zero. Tauer (2001a) used this same data source, but included data from 1996 and 1997. Positive profit rbST treatment coefficients were generally estimated, but the standard errors were so large that again statistically the profit impact was zero.

Foltz and Chang sampled Connecticut dairy farms for the 1998 production year and found rbST had a positive and statistically significant effect on milk production, but the impact on profits was statistically zero, although numerically negative. McBride, Short and El-Osta used a random sample of U.S dairy farms and found an increase in milk production per cow with rbST adoption, but the estimated profitability impact was not statistically different from zero. Ott and Rendelman used actual milk production experienced on rbST adopting farms, but since they did not have actual cost changes, they imputed costs and returns in a partial budget framework. They concluded that rbST would increase profits by $126 per cow, similar to previous ex ante impact studies.

Most of these studies estimated rbST profitability impacts that were numerically positive, but due to large standard errors on these estimates, the impacts were statistically not different from zero. Yet, many farmers continue to use the product. It is challenging to quantify and estimate the determining factors of farm level profitability. Profits across farms and years are extremely variable, subject to weather, pests, and other stochastic and difficult to measure determinants. Most previous rbST impact assessment only used several hundred observations, and typically from only one production year. Additional years of rbST use data are now available and more farm observations over more years may permit a clearer picture of the impact of rbST. Thus, this article revisits the profitability impact of rbST, but uses data from year 1994, the first year of rbST use, through the year 2004. Moreover, a matching sample approach is used to obtain estimates of treatment effects.

Method of Matching Samples

The method commonly used in the agricultural literature to determine the impact of a treatment is to estimate a regression equation where the dependent variable is a performance variable, with the treatment entered as a dummy independent variable along with other covariates. If treatment self-selection bias is a concern, then the treatment variable may be estimated with instrument variables, or a control function is estimated to construct an inverse mills ratio to control for endogeneity (Fuglie and Bosch). These are the estimation techniques used in previous rbST impact studies.

As an alternative, the concept of measuring treatment effects by matching samples was pioneered in the medical field by Cochran; Billewicz; and further developed by many including Rubin (1974), and Heckman, Ichimura and Todd (1997). The process entails finding matching samples to those that were subject and not subject to a treatment and comparing differences in performance. The assumptions necessary for effective evaluation are that there is overlap of the characteristics of both groups after sorting, and that these characteristics control for any self selection bias. This is discussed by Imbens who names these two assumptions overlap and unconfoundedness, respectively. The overlap is necessary to mimic random placement into treatment and control groups. If the characteristics do not control for self selection bias, then the impact measurement may be biased. These requirements are further discussed in Heckman and Navarro-Lozano, who compare various treatment estimation techniques.

The estimation procedure of matched sample we use is specified in Abadie, Drukker, Herr and Imbens, and implemented in the STATA software command "nnmatch". Let the observed measured performance from rbST be denoted by Y_i, so that:

$$Y_i = Y_i(W_i) = \begin{cases} Y_i(0) & \text{if } W_i = 0, \\ Y_i(1) & \text{if } W_i = 1, \end{cases}$$

Where $W_i = 1$ if rbST is used and $W_i = 0$ if rbST is not used on the farm.

The average treatment effect for all farms in the use of rbST is then:

$AT = \frac{1}{N} \sum_{i=1}^{N} (Y_i(1) - Y_i(0))$, where each farm is compared to a matching farm that either uses rbST if the farm i does not use rbST, or the matched farm does not use rbST if the farm i uses rbST, with N the total number of farms.

The average treatment effect for those farms that have used rbST is:

$$\text{ATT (Treated)} = \frac{1}{N_1} \sum_{i|W_{i=1}} (Y_i(1) - Y_i(0)),$$ where for each farm i that uses rbST a matching farm is identified that does not use rbST, and $N_1 = \Sigma_i W_i$ count the number of farms that use rbST.

The average treatment effect for those farms that have not used rbST is:

$$\text{ATC (Non-Treated)} = \frac{1}{N_0} \sum_{i|W_{i=0}} (Y_i(1) - Y_i(0)),$$ where for each farm i that does not use rbST, a matching farm is identified that does use rbST, and $N_0 = \Sigma_i (1 - W_i)$ count the number of farms that did not use rbST.

The task is to find matched farms in the sample such that a farm using rbST is almost identical to a farm not using rbST and vice versa. That matching is done based upon a set of variables. Given that more than one variable is used to match farms, a weighting matrix is needed to find closest matches. The weighting index used is the k by k diagonal matrix of the inverse sample standard errors of the k variables in the matching list. That process is discussed more fully in the appendix.

Even with nearest neighbor matches, farms may still be dissimilar, which may introduce bias into a treatment estimate. An adjustment is possible based on the estimate of two regression functions using covariates, dependent upon whether rbST is used or not used on the farm.

$$\mu_w(x) = E\{Y(w)|X = x\} \text{ for } w = 0 \text{ or } 1.$$

Following Rubin (1979) and Abadie and Imbens, we approximate these regression functions by linear functions and estimate them using least squares on the matched observations. The details are discussed in the appendix.

Data

Data are from the New York Dairy Farm Business Summary (DFBS) for the years 1994 through 2004 (Knoblauch, Putnam and Karszes). This is the same data source used by Tauer and Knoblauch; Stefanides and Tauer; and Tauer (2001a) to assess the impact of rbST, although they used fewer years of data and different estimators. This is a voluntary farm record project primarily meant to assist dairy farmers in managing their operations. It represents a sample from a population of farmers that actively participate in agricultural extension and research programs. The farms in this population are on average larger than New York dairy farms and they experience higher levels of production per cow. To be included in this data set, milk receipts must constitute at least 90 percent of total farm receipts, and thus farms are strictly dairy operations with miscellaneous sales representing the by-product sales of cull cows, calves, and periodically excess grown feed. All farms that participated in the DFBS during the eleven year period are used in the analysis.

Variable specification is consistent with the annual Dairy Farm Business Summary Report and is shown in Table 2. A limited number of exogenous variables are collected including age, education, number of cows, type of milking system, and barn type. These variables are used to match farms. Separate performance variables used are milk production per cow, total cost of producing milk per hundredweight, and labor and management income per operator per cow. Production per cow is milk sold per cow in pounds. The total cost of production includes opportunity cost of operator and family labor and equity capital, and thus includes opportunity cost for all unpaid factors of production. This cost was extracted directly from the DFBS data set, which uses a whole farm method of computing this cost, where the value of miscellaneous sales of crops and other outputs are subtracted from costs. This assumes that the costs of producing crops are equal to the revenue value. It is important to realize that these are full time dairy farms, and any crop sales are incidental to the dairy operation. Labor and management income is the income to the operators after deducting as expenses all other paid and unpaid expenses. It is normalized on an operator and cow basis to adjust for farm size.

The DFBS surveys for each year asked farmers to indicate their use of rbST in one of five categories as follows: (0) not used at all; (1) stopped using it during the year; (2) used on less than 25 percent of the herd; (3) used on 25-75 percent of the herd; or (4) used on more than 75 percent of the herd. These groups pertain to the percentage of cows that were treated during lactation. Only beginning in 2003 was a definite use percentage collected, precluding use of that statistic in the analysis. For those farms that used rbST in 2004, the average use was on 43 percent of the cows. Most responses were in categories 0 and 3. Very few farms indicated they used it on more than 75 percent of the herd. Likewise, few farms used it on less than 25 percent of the herd. The usage categories are not concisely defined, so farms were simply sorted as rbST users if they checked categories 2, 3, or 4 and non-users if they checked categories 0 or 1. Given this coding, slightly more than half of the DFBS farms used rbST in any year as shown in table 1.

Results

The variables used to match farms are the number of cows, the milking system used on the farm, type of housing, operator age, and operator education. In various rbST adoption studies these variables have typically explained rbST adoption (Barham, Foltz, Jackson-Smith and Moon; Stefanides and Tauer). Farms which adopt rbST have tended to be larger, use milking parlors and freestall housing, are younger but have more formal education. The intent is to match farmers who use and who do not use rbST by these characteristic variables. In addition, only farm data from the identical year were matched, since year to year randomness impacts the performance variables.

Since more than one variable was used for matching farms, a weighting matrix was used to find the nearest four farms in any given year. The weighting matrix used was the k x k diagonal matrix of the inverse sample standard errors of the k variables in the matching list. This allows weighting by normalization of each variable by it's standard deviation. Abadie and Imbens found four matches performed well in terms of mean-squared error, so we located the four closest matching farms to any particular farm in a given year

Three treatment effects were estimated: 1) Average Treatment Effect, 2) Average Treatment Effect for the Treated (rbST use) and 3) Average Treatment Effect for the Control (no rbST use). The average treatment effect measures the impact of rbST using all farms. The average treatment effect for the treated measures the impact of rbST for the farms that used rbST, while the average treatment effect for the control indicates what non-rbST users would have experienced if they had used rbST. In the analysis, four farms are matched with each farm successively, and the average results from the four farms are compared to the comparison farm.

Matching of farms will not be identical because of non-overlap of farm characteristics. A larger percentage of smaller farms do not use rbST and many large farms do use rbST (figure 1). This discrepancy will cause a bias in the estimate. This bias was corrected with the regression procedure developed by Abadie and Imbens and explained in the appendix section of this paper.

Similar to previous estimates, it is clear that the use of rbST increases milk production per cow as shown in table 3. Over the 11 year data period, the impact of the average treatment effect was 2,505 pounds per cow, a 14 percent increase over non-rbST using farms, indicating that the use of rbST substantially increased milk production per cow. This compares to an estimate by Tauer (2001a) of 3,015 pounds over the first 4 years of rbST availability on these DFBS farms (1994-1998), using regression and controlling for self selection bias. McBride, Short and El-Osta estimated a milk production increase from rbST on U.S. farms of 2,666 pounds with sample selection correction.

The average impact on production per cow for the average treatment effect for the treated was 2,060 pounds per cow, and the average treatment effect for those that did not use rbST (control) would have been 2,943 pounds. All of these estimates are statistically significant. It is interesting that the potential impact is greater for those that did not use rbST than the impact on those farms that did use rbST (compared to comparable farms). What this implies is that farms that did not use rbST would experience a larger increase in production per cow than the increase experienced by those farms that elected to use rbST. As will be seen, this disparity carries over to cost and net return from the use of rbST and will be further discussed later.

Average treatment effect of the use of rbST numerically reduces the cost of producing a hundredweight of milk by $0.73, and this is statistically different from zero. McBride, Short and El-Osta estimated a difference in operating margin on U.S. farms from the use of rbST to be similar at $0.74, but their estimate was not statistically different from zero, possibly from the fact that they only had data on 820 farms from the year 2000. Tauer (2006), using an econometric approach to estimate the cost reduction on these New York farms over the years 1994 through 2002, as compared to the current data from 1994 through 2004, estimated the cost reduction from rbST use was from $0.23 to $0.52 depending upon model specification.

An advantage of using a match treatment approach is the generation of estimates of benefits for those that did use rBST compared to those that did not use rBST, and vice versa. The average effect for the treated was much lower at a cost reduction of $0.39. It is interesting that the use of rbST appears to have had little impact on costs for those that used it over the period compared to their costs if these farms had not used rbST.

In contrast, even more interesting is the finding that those that did not use rbST would have benefited even more from using rbST. The average cost reduction they would have experienced over the 11 year period was $1.07. One explanation for the significant impact for the control is that the non-rbST users may have been matched to only a few rbST users that were exceptional managers, but that does not appear to be the case. A check of the index of the matching farms produced a very large set of farms being matched to the non-rbST users. Heckman, Ichimura, Smith and Todd further show that if matching variables do not overlap, the matching estimator may not accurately identify the treatment effect. Figure 1 shows that the farmers that use rbST do tend to be larger, but there is significant overlap by size. In addition, the regression adjustment corrects for non-overlap bias. Without controlling for bias with regression, the three treatment estimates were almost identical, with ATE estimate at -1.08, ATT at -0.97, and ATC at -1.19, all highly statistically significant.

What is possibly occurring is that the matching variables may not be correlated with the managerial ability of farms, and the ability to successfully use rbST. Thus, treatment bias may be present in the results. Tauer (2006) using fewer years of this data source found no prevalence of self selection bias, but the variables he used may not have successfully measured self selection bias, since adoption of rbST was not perfectly explained. Tauer (2001b) using this data source discovered the typical small farm was more cost inefficient than the typical large farm, although many small farms were almost as cost efficient as the cost efficient large farms. Those farms not using rbST tend to be smaller, and those that are successful using rbST may have lower costs even if they did not use rbST. This implies that self selection bias may still be prevalent in the results. This, however, occurs also in self selection models if the variables used do not explain selection based upon potential performance (Heckman and Navarro-Lozano).

Average profit per cow averaged $69.73 for the average treatment effect, a much smaller $29.03 for the average treatment effect for the treated, which was not statistically different from zero, and $110 for the average treatment effect for the control. Tauer (2001a) previously estimated a profit impact of $64.25 per cow using regression with a dummy treatment variable and controlling for self selection bias.

Conclusions

A technique to estimate the impact of treatments is to find matching samples and compare differences in performance. This allows estimating an average treatment effect for the sample, an average treatment effect for the treated only, and an average treatment effect for the control (not treated). That technique is used in this paper to estimate treatment effects of rbST using a sample of New York dairy farm data from the year 1994, the first year of rbST commercial use, through the year 2004. This procedure identifies each farm that uses rbST (or does not use rbST) and then compares the performance of that farm with identical four farms from the same year which did not use rbST (or which does use rbST). The identification of similar types of farms is done by minimization of a distance metric based upon farm characteristics. Although the statistical estimation technique of matching samples is recent, the philosophy and approach of identifying farms who adopt some farming practice and then comparing those farms that do not use that specific farming practice dates back to at least 75 years.

Results show that rbST clearly increases milk production per cow. The use of rbST also decreases cost of production per hundredweight of milk. The reduction on cost of production translated into a higher profit per operator per cow, except for the treatment effect for the treated. Most surprising is the result that the greatest estimated impact of rbST was not for those that used rbST over the period, but rather for those that elected not to use rbST. If non-rbST users had elected to use rbST (the average treatment effect for the control), their cost of production would have been lower on average by $1.07 per hundredweight of milk. In contrast, the average treatment effect was only a cost reduction of $0.73, and the cost reduction for the treated was only $0.39.

These results imply that farmers who are offered a premium for producing non-rbST milk should receive $0.39 to $1.07 per hundredweight more for milk. Although the high end of this estimate is for farmers who might gain that cost advantage by using rBST when they currently are not, and thus could be considered an opportunity cost for not using rBST, that estimate may be biased upward. The cost of $0.39 would be the real cost for those farmers who stop using rbST, and they would not terminate using rbST without an offer of at least this amount. Stephenson recently collected information from select New York DFBS farms on price premiums they were receiving for rbST free milk, and found a range from about $0.05 to $0.50 per hundredweight, with 75 percent receiving a rbST premium between $0.15 and $0.30 per hundredweight. Interesting, however, is that dairy cooperative collecting milk from these farms have been receiving an average premium from processing plants for rbST free milk of $0.75. Part of that larger amount goes to cover the cost of less efficient collection routes, but to the extent that collection costs and rbST premium payments to farmers are less or greater than the $0.75, some may go back to all producers as cooperative earnings or losses.

Appendix

Finding Matching Farms

For matching farms the vector norm $\|x\|v = (x'Vx)^{1/2}$ is used, with the positive definite variance matrix V serving as the weights. This weighting matrix allows weighting by normalization of each variable by its standard deviation. Define $\|z - x\|v$ to be the distance between the vectors x and z, where z represents the covariate values for a potential match for observation i.

Applying this weighting index to all observations determines the nearest matches for each observation by the following index indicator: Let $J_M(i)$ denote the set of indices for the matches for unit i that are at least as close as the Mth match:

$$J_M(i) = \{t = 1,\ldots, N \mid W_t = 1 - W_i, \|X_t - X_i\|v \leq d_M(i)\}$$

Also let $K_M(i)$ denote the number of times i is used as a match for all observations t of the opposite treatment group, each time weighted by the total number of matches for observation t.

A straightforward estimator is the simple matching estimator, which uses the following approach to estimate the pair of potential outcomes:

$$\hat{Y}_i(0) = \begin{cases} Yi & \text{if } W_i = 0 \\ \dfrac{1}{\#J_M(i)} \sum\limits_{t \in J_M(i)} Y_t & \text{if } W_i = 1 \end{cases}$$

and $$\hat{Y}_i(1) = \begin{cases} \frac{1}{\#J_M(i)} \sum_{t \in J_M(i)} Y_t & \text{if } W_i = 0 \\ Y_i & \text{if } W_i = 1 \end{cases}$$

Given that only one potential outcome is observed for each observation i, the observed outcome $Y_i = Y_i(0)$, or $Y_i = Y_i(1)$ represents one potential outcome. The unobserved outcome is estimated by averaging the observed outcomes for the observations t of the opposite treatment group that are chosen as matches for i. We used four matching farms.

Using these estimates of the potential outcomes, the simple matching estimator is

$$\hat{\tau}_M^{sm,} = \frac{1}{N}\sum_{i=1}^{N}\left\{\hat{Y}_i(1) - \hat{Y}_i(0)\right\} = \frac{1}{N}\sum_{i=1}^{N}(2W_i - 1)\{1 + K_M(i)\}Y_i$$

This estimator can be modified to estimate the average treatment effect for the treated

$$\tau_M^{sm,t,} = \frac{1}{N_1}\sum_{i;W_i=1}\left\{Y_i(1) - \hat{Y}_i(0)\right\} = \frac{1}{N_1}\sum_{i=1}^{N}\{W_i - (1-W_i)K_M(i)\}Y_i$$

or the average treatment effect for the controls

$$\tau_M^{sm,c,} = \frac{1}{N_0}\sum_{i;W_i=0}^{N}\left\{\hat{Y}_i(1) - Y_i\right\} = \frac{1}{N_0}\sum_{i=1}^{N}\{W_i\, K_M(i) - (1-W_i)\}Y_i$$

<u>Adjusting for non-perfect matches with regression</u>

For the average treatment effect, the regression functions use only the data in the matched sample

$$\hat{u}_w(x) = \hat{\beta}_{w0} + \hat{\beta}_{w1}^{'}x$$

for w = 0,1 where

$$(\hat{\beta}_{w0}, \hat{\beta}_{w1}) = \operatorname*{argmin}_{i:W_{i=w}} \sum K_M(i)(Y_i - \beta_{w0} - \beta_{w1}^{'}X_i)^2$$

Given the estimated regression functions, for the bias-corrected matching estimator, we predict the missing potential outcomes as

$$\tilde{Y}_i(0) = \begin{cases} Y_i & \text{if } W_i = 0 \\ \dfrac{1}{\#J_M(i)} \displaystyle\sum_{t \in J_M(i)} \{Y_t + \hat{\mu}_0(X_i) - \hat{\mu}_0(X_t)\} & \text{if } W_i = 1 \end{cases}$$

and $$\tilde{Y}_i(1) = \begin{cases} \dfrac{1}{\#J_M(i)} \displaystyle\sum_{t \in J_M(i)} \{Y_t + \hat{\mu}_1(X_i) - \hat{\mu}_1(X_t)\} & \text{if } W_i = 0 \\ Y_i & \text{if } W_i = 1 \end{cases}$$

with the corresponding estimator for the ATE

$$\hat{\tau}_M^{bcm} = \frac{1}{N} \sum_{i=1}^{N} \{\tilde{Y}_i(1) - \tilde{Y}_i(0)\}$$

The bias-adjusted matching estimators for the ATT and ATC are then

$$\hat{\tau}_M^{bcm,t} = \frac{1}{N_1} \sum_{i:W_{i=1}} \{Y_i - \tilde{Y}_i(0)\} \text{ and } \hat{\tau}_M^{bcm,c} = \frac{1}{N_0} \sum_{i:W_{i=0}} \{\tilde{Y}_i(1) - Y_i\}$$

References

Abadie, A. and G.. Imbens. "Simple and Bias-corrected Matching Estimators for Average Treatment Effects." National Bureau of Economic Research, Technical Working Paper 283. 2002.

Abadie, A., D. Drukker, J. L. Herr and G. W. Imbens. "Implementing Matching Estimators for Average Treatment Effects in Stata." *The Stata Journal* 4 (No. 3, 2004):290-311.

Barham, B. L., J. D. Foltz, D. Jackson-Smith, and S. Moon. "The Dynamics of Agricultural Biotechnology Adoption: Lessons from Series of rBST use in Wisconsin, 1994-2001." *American Journal of Agricultural Economics* 86 (Feb. 2004):61-2.

Billewicz, W. Z. "Matched samples in medical investigation." *British Journal of Preventive and Social Medicine* 18 (Oct. 1964):167-173.

Cochran, W. G. "Matching in Analytical Studies." *American Journal of Public Health* 43 (June 1953):684-691.

Foltz, J. and H. H. Chang. "The Adoption and Profitability of rbST on Connecticut Dairy Farms." *American Journal of Agricultural Economics* 84 (Nov. 2002):1021-1032.

Fuglie, K.O. and D. J. Bosch. "Economic and Environmental Implications of Soil Nitrogen Testing: A Switching-regression Analysis." *American Journal of Agricultural Economics* 77 (Nov. 1995): 891-900.

Heckman, J. J. and V. J. Hotz. "Choosing Among Alternative Nonexperimental Methods for Estimating the Impact of Social Programs: The Case of Manpower Training." *Journal of the American Statistical Association* 84 (Dec.1989):862- 874.

Heckman, J. and S. Navarro-Lozano. "Using Matching, Instrumental Variables, and Control Functions to Estimate Economics Choice Models" *The Review of Economics and Statistics* 86 (Feb. 2004):30-57

Heckman, J. J., H. Ichimura, J. Smith, and P. Todd. "Sources of Selection Bias in Evaluating Social Programs: An Interpretation of Conventional Measures and Evidence on the Effectiveness of Matching as a Program Evaluation Method." *Proceedings of the National Academy of Sciences* 93 (Nov 1996):13416- 3420.

Heckman, J. J., H. Ichimura and P. Todd. "Matching as an Econometric Evaluation Estimator." *Review of Economic Studies* 65 (Oct. 1997):261-294.

Imbens, G. W. "Nonparametric estimation of Average Treatment Effects under Exogeneity: A Review" *The Review of Economics and Statistics* 86 (Feb. 2004):4-29.

Knoblauch, W. A., L. D. Putnam and J. Karszes. “Dairy Farm Management Business Summary New York State 2004.” Dept. Appl. Econ. & Mgt. Research Bulletin 2005-03, Cornell University, Ithaca, NY, 2005.

McBride, W.D., S. Short, and H. El-Osta. “The Adoption and Impact of Bovine Somatotropin on U.S Dairy Farms.” *Review of Agricultural Economics* 26 (Win. 2004): 472-488.

Ott, S. L. and C. M. Rendelman . “Economic Impacts Associated with Bovine Somatotropin (BST) Use Based on Survey of US Dairy Herds.” *AgBioForum* 3 (No. 2&3 2000):173-180.

Rubin, D. B. “The Use of Matched Sampling and Regression Adjustments to Remove Bias in Observational Studies.” *Biometrics* 29 (March 1973):185–203.

Rubin, D. B. “Estimating Casual Effects of Treatments in Randomized and Nonrandomized Studies.” *Journal of Education Psychology* 66(1974): 688-701.

Rubin, D. B. “Using Multivariate Matched Sampling and Regression Adjustment to Control Bias in Observational Studies.” *Journal of the American Statistical Association* 74 (June 1979):318-328.

Stefanides, Z. and L. W. Tauer. “The Empirical Impact of Bovine Somatotropin on a Group of New York Dairy Farms.” *American Journal of Agricultural Economics* 81 (Feb. 1999):95- 02.

Stephenson, M. “The Thing about Milk Checks….” *Northeast Dairy Business Magazine*, Feb 2008.

Tauer, L. “The Estimated Profit Impact of Recombinant Bovine Somatotropin on New York Dairy Farms for the Years 1994 through 1997.” *AgBioForum* 4 (No.2 2001a):115-123.

Tauer, L. W. “Efficiency and Competitiveness of the Small New York Dairy Farm” *J. Dairy Science* 84 (2001b):2573-2576

Tauer, L. “Impact of Recombinant Bovine Somatotropin on Dairy Farm Cost of Production. Evidence from Multiyear Data.: *AgBioForum* 9 (No. 2, 2006):79-83

Tauer, L.W. and W.A. Knoblauch. “The Empirical Impact of bST on New York Dairy Farms.” *Journal of Dairy Science* 80 (June 1997):1092-1097.

Vella, F. and M. Verbeek. “Estimating and Interpreting Models with Endogenous Treatment Effects.” *Journal of Business and Economic Statistics* 17 (Oct. 1999): 473-478.

Warren, G. F. “The Origin and Development of Farm Economics in the United States.” *Journal of Farm Economics* 14 (Jan. 1932):2-9.

Table 1. Number of New York DFBS farms and number of farms using rbST, by year

Year	Number of Farms	Number of rbST Users	Percent of rbST Users
1994	324	135	42
1995	329	152	46
1996	307	145	47
1997	280	130	46
1998	324	169	52
1999	314	166	53
2000	294	155	53
2001	228	117	51
2002	219	113	52
2003	205	118	58
2004	199	103	52

Table 2. Summary of variables for matching samples and bias correction

Variable	Mean	Std. Dev.	Min.	Max.
Cost of production per cwt.	15.92	3.07	8.73	42.10
Number of cows	222	292	19	3605
Milking system (1=parlor)	0.59	0.49	0	1
Housing (1=freestall)	0.56	0.50	0	1
Operator age in years (principal operator)	48	10	23	85
Operator formal education in years (principal operator)	13.6	1.9	6	20
Number of observations	3023			

Table 3. Impact of rbST on New York farms. Treatment comparisons with four matching farms. Bias correction using regression.

	Average Treatment Effect	Average Treatment Effect for the Treated*	Average Treatment Effect for the Control**
	Change in production per cow for rbST use (pounds)		
Estimate	2505	2062	2943
Standard Error	134.19	160.03	144.80
z Score	18.67	12.89	20.33
Prob.	0.000	0.000	0.000
	Change in cost of production per hundredweight of milk produced ($)		
Estimate***	-0.73	-0.39	-1.07
Standard Error	0.11	0.12	0.14
z Score	-6.44	-3.21	-7.81
Prob.	0.000	0.001	0.000
	Change in labor and management income per operator per cow ($)		
Estimate	69.73	29.03	110.00
Standard Error	25.66	26.14	32.19
z Score	2.72	1.11	3.42
Prob.	0.007	0.267	0.001

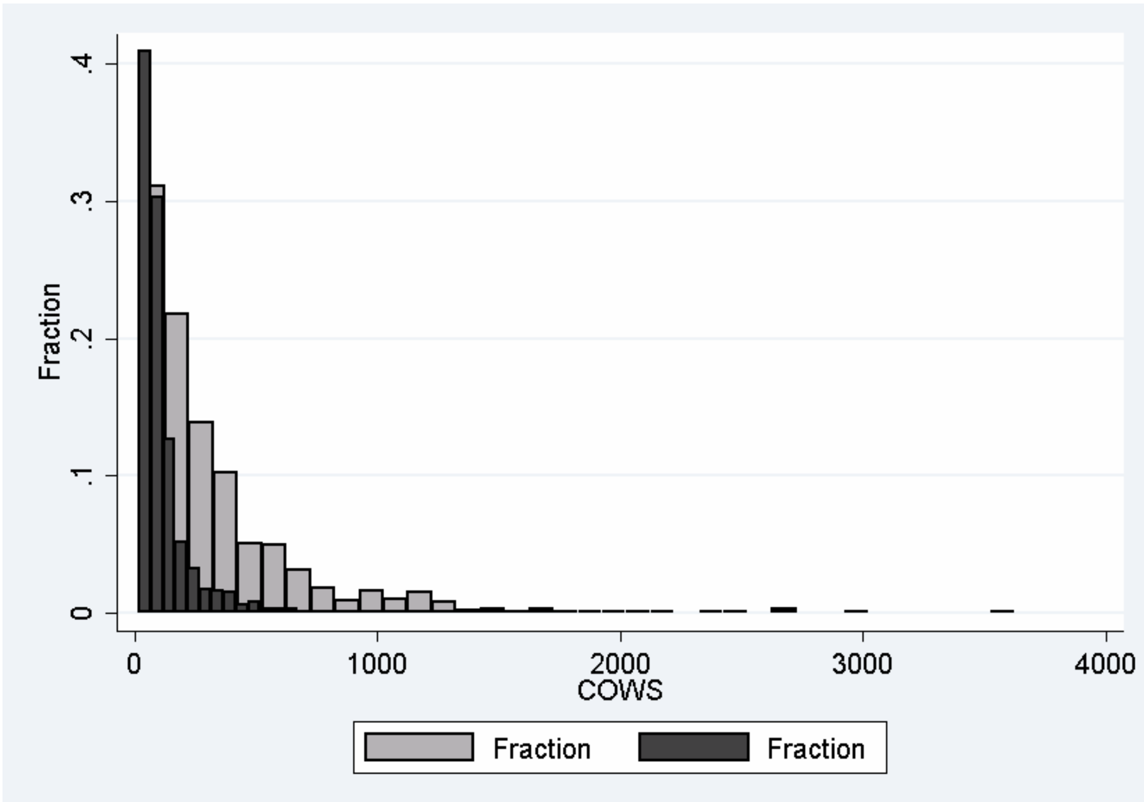
N=3023 farms over 1994 through 2004

* Treated farms that used rbST

** Control farms that did not use rbST

*** Without controlling for bias with regression, the ATE estimate was -1.08, ATT was -0.97, and ATC was -1.19, all highly statistically significant.

Figure 1. Histogram of rbST users (grey) and non-users (black); Fraction of observations by number of cows



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