Complementarities in Production Technologies:

An Empirical Analysis of the Dairy Industry

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Abstract:

In this article, we present empirical evidence to show that a commonly held belief is likely false. Specifically, we examine the claim that three widely used dairy technologies and management practices complement the use of rbST in the sense that they increase the marginal return of rbST. Using the definition described in Milgrom and Roberts (1990) that the presence of supermodular profit or total output functions is evidence of complementarity, our results show that the use of a computerized feeding system or total mixed ration feed balance system is complementary with the use of rbST, but that this complementarity only exists for when considering the effects on feed costs per cow. We are unable to detect any complementary relationships for operating margins per hundredweight of milk, operating margins per cow, or feed costs per hundredweight of milk. These results show that having a TMR feed balance system, being a member in a DHIA, or using a computerized feed system do not necessarily increase the marginal productivity or profitability of using rbST. This paper is the first to our knowledge that uses the production function approach to estimate econometrically whether complementarities among dairy technologies exist.

I. Introduction

The dairy industry has become a technology intensive sector, and the emphasis on increasing milk production per cow while reducing costs has never been greater. This article focuses on one particular dairy technology that has generated a lot of attention in the past two decades: recombinant bovine somatotropin (rbST). There are scores of articles on the adoption and profitability of rbST in the agricultural economics literature (Henriques and Butler 2002; Barham et al. 2004a, 2004b; McBride, Short and El-Osta 2004), and the findings show that the use of rbST has been declining, and that it has not had any statistically significant effect on profits. A common claim in many of these articles is that there are certain dairy technologies and management practices (henceforth referred to simply as "technologies") that complement the use of rbST. What the authors of these articles implicitly maintain, without providing explicit evidence, is that the effectiveness of rbST is enhanced when used in conjunction with these technologies. These claims are considered validated when regression results show that the use of these technologies have a positive and statistically significant effect on the adoption of rbST. However, whether or not these technologies are complementary is never actually tested. We have a simple objective in this paper: to test empirically for the presence of complementarities between rbST and several commonly used dairy technologies.

There are several approaches to test for complementarity. One popular approach to identifying complementary relationships has been to invoke the idea of revealed preferences and look for correlations among technologies, while assuming optimal behavior. In these papers (e.g., Arora and Gambardella 1990; Khanal, Gillespie, and MacDonald 2010; Yu et al. 2011), the assumption of profit maximization (or some other optimizing behavior) implies that, controlling for other relevant factors, a positive correlation between the adoption of two technologies is indicative of a complementary relationship. The idea here is that if technologies are complementary, they are more likely to be correlated. The main weakness of this approach is that it does not test actual performance.

The reduced-form approach is a second method of testing for complementarities, and is based on the use of exclusion restrictions. The intuition behind this approach is that a factor that has an effect on the use of a technology will only be correlated with the use of another technology if the technologies are complementary. Examples of this approach in the literature include Holmstrom and Milgrom (1994) and Arora (1996). The weaknesses of this approach are that it also does not test actual performance, and it is unable to deal with interactions between more than two variables (Arora 1996).

We take a third approach that explicitly tests the effect of technology use on some measure of output. That is, we do not assume that because two technologies are correlated that they improve performance. Instead, we adopt the definition described in Milgrom and Roberts (1990) that the presence of supermodular profit or total output functions is evidence of complementarity. That is, technologies *x* and *y* are complementary if the use of *x* increases the marginal productivity of *y*, and vice versa. Similarly, the presence of submodular objective functions is evidence of subadditivity. The idea of technologies being complementary to one another makes intuitive sense; it is natural to believe that profit-maximizing producers would adopt technologies that enhance the effectiveness of existing ones currently in use. However, there is little empirical evidence that complementarities, as formally defined, exist in the agricultural economics literature regarding technology. Therefore, we use Milgrom and Roberts' definition of complementarity, and the production function approach of Athey and Stern (1998) to test for complementarity. This method has been shown to be superior to estimating reduced-form adoption equations and analyzing the correlations among the residual terms (Arora 1996; Athey and Stern 1998).

Several recent papers have used the production function approach to test for complementarities, mainly in the industrial organization literature. Belderbos, Carree, and Lokshin (2006) found complementarities among different types of R&D cooperation strategies. Miravete and Pernías (2006) used the production function approach to construct a discrete choice structural model that can identify complementarity relationships in the Spanish ceramic tile industry. Mohapatra, Goodhue, and Rozelle (2008) examined incentives in rural Chinese businesses and identified complementarities in firms that used profit sharing and investment bonding activities together. More recently, Goodhue, Mohapatra and Rausser (2010) studied the complementary effects of price incentives on tomato processors.

The key advantage of the production function approach is that its criterion for complementarity is more economically intuitive than that required by the various correlation-based methods. In this approach, two technologies are considered complementary if and only if the use of one increases the marginal return of the other. If two technologies are simply adopted together often, but have no measurable impact on one another's marginal return, then these technologies are not complementary according to this definition.

This paper is the first to our knowledge that uses the production function approach and the framework of supermodular objective functions to estimate econometrically whether complementarities among dairy technologies exist. While the paper uses data from the U.S., the results have wider applicability and relevance as rbST is used in multiple countries where it has been marketed as Posilac® by Elanco for over a decade. Due to the large number of technologies currently in use, we restrict our analysis to identifying complementarities between rbST and three purportedly complementary technologies. Our empirical strategy follows a production function approach in which we directly estimate the contributions of various combinations of technology bundles to several output measures (e.g., yield, profit, and cost). The next section provides some background information about our empirical application. Section three describes the conceptual model, and section four explains the empirical model. We describe the data and present descriptive statistics in section five, and section six contains the results and discussion. The final section provides some concluding comments and suggestions for future research.

II. Background

There are many studies have investigated the adoption of rbST, and its effects on production and profit (Barham, 1996; Foltz and Chang 2002; Butler 2003; Barham et al. 2004; McBride, Short, and El-Osta 2004; Gillespie et al. 2010). In general, these studies find that rbST has a statistically insignificant effect on profit even though it increases production. Regarding the adoption decision, these studies generally model the decision to adopt as a function of farm and operator characteristics and one or more technology use variables as a control. Why are some certain technologies included as explanatory variables instead of others? The main reason for inclusion is usually the belief that the included technologies complement the use of rbST (Henriques and Butler 2002). It's logical to presume then that producers who are already using a "complementary" technology are more likely to adopt rbST; or that "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" (Barham et al. 2004a, p. 63). Other studies use similar language: Foltz and Chang (2002, p. 1022,) assert that "complementary technologies...can increase the effect of rbST on milk yield and profitability."

McBride, Short, and El-Osta (2004, p. 474) argue that “complementary technologies have been [one of] the main factors found to influence of (sic) the adoption of rbST”. And Barham et al. (2004b, p. 37) write that “[p]roduction records and total mixed ration equipment are viewed as complementary productivity-enhancing technologies that should make the adoption of rBST more advantageous.”

The authors of these studies, and others, are interested in identifying which existing technologies help explain the adoption of rbST. One common finding in these rbST adoption studies is the positive effect of using a total mixed ration (TMR) feed balance system, being a member of a dairy herd improvement association (DHIA), or using a computerized feeding system on the likelihood of adopting rbST. The positive correlation between the use of these technologies and the adoption of rbST is enough evidence for most studies to conclude that these technologies are complementary with rbST. However, none of these studies formally test this assertion.

Recently, Khanal, Gillespie, and MacDonald (2010) tested for complementarities using a correlation-based approach. They analyze the adoption behavior of over a dozen common dairy technologies using 2000 and 2005 Agricultural Resource Management Survey (ARMS) data. They find high rates of adoption for many technologies in the 2005 sample, such as milkers with automatic take-offs (37.5%), genetic selection (81.5%), artificial insemination (81.4%), dairy herd improvement association (DHIA) membership (45.4%), use of a nutritionist (71.6%), grazing (64.5%), and the use of a milking parlor (49.9%). For all of the technologies except grazing and DHIA membership, adoption levels increased between 2000 and 2005. In general, they also find that larger dairy operations adopt more technologies, a finding that is consistent with Weersink and Tauer (1991) and Short (2004).

Therefore, we choose the following three dairy technologies to test: the use of a computerized feeding system, the use of TMR, and being a member of a DHIA. In the U.S. dairy industry, computerized feeding systems come in many forms and vary in their degree of technological sophistication. Some simple systems are essentially automated feed dispensers that remain open for a specified period of time. More complex systems may consist of individual electronic devices for each cow that monitor and record the length of time the cow feeds each and every time. However, these systems are extremely expensive and very rare. Unfortunately, the ARMS survey does not distinguish between the different types of computerized feeding systems. Regardless of what is actually used, the main idea behind a computerized feeding system is that it provides the producer with more control over feed, and in some cases, provides the producer with more information about the distribution of food at the herd, string, or individual cow level.

TMR is a method of providing a balanced diet by blending various feedstuffs together to ensure that each bite contains all the necessary nutritional content that a dairy cow requires. This makes it more difficult for cows to seek out specific ingredients, and provides the producer with greater control over what the animals consume. The disadvantages of TMR are that herds must be grouped by lactation stage since cows in different stages have different productions level have different nutritional requirements, and specialized machinery is required to mix the rations.

Membership in a DHIA offers numerous benefits, the most important of which are improved record keeping and access to data that can be used to make more informed management decisions. Members also receive technical support and are connected to a vast network of dairy producers at the state and federal level. However, membership costs and the growing popularity of on-farm personal computers have led to the exit of some producers (Spain and Witherspoon 1994; Higginbotham et al. 1997). Nevertheless, nearly half of all dairy operations in 2005 were members of a DHIA.

III. Conceptual model

Following Milgrom and Roberts (1990), two technologies are complementary if the use of one practice increases the marginal return of the other practice. In the case of discrete practices, two practices x_1 and x_2 are complementary in the objective function $f(\boldsymbol{x})$ if and only if $f(x_1 + 1, x_2 + 1, x_3, \dots, x_n) + f(x_1, x_2, x_3, \dots, x_n) \geq f(x_1 + 1, x_2, x_3, \dots, x_n) + f(x_1, x_2 + 1, x_3, \dots, x_n)$, with the inequality holding strictly for at least one value of $(x_1, \dots, x_n)$. The case of binary discrete practices (i.e., used or not) is a special case of the above. When practices are dichotomous, it is more convenient to write them in terms of the possible combinations of practices.

Define $\boldsymbol{x} = (x_1, x_2, x_3, x_4)$ as a set of four technologies where two technologies x_1 and x_2 are complementary if the following four inequalities hold, with at least one of the inequalities holding strictly:

(1.a) $$f(1,1,0,0) + f(0,0,0,0) - f(1,0,0,0) - f(0,1,0,0) \geq 0$$

(1.b) $$f(1,1,1,0) + f(0,0,1,0) - f(1,0,1,0) - f(0,1,1,0) \geq 0$$

(1.c) $$f(1,1,0,1) + f(0,0,0,1) - f(1,0,0,1) - f(0,1,0,1) \geq 0$$

(1.d) $$f(1,1,1,1) + f(0,0,1,1) - f(1,0,1,1) - f(0,1,1,1) \geq 0.$$

This is known as strict supermodularity, whereas supermodularity allows for the possibility that using x_1 may have no effect on the marginal returns to using x_2. Together, equations (1.a) to (1.d) imply that the use of x_1 and x_2 lead to higher returns when the two technologies are used simultaneously than when they are used separately in at least one combination of the other technologies. If the signs are reversed to $\leq$, then using x_1 and x_2 together leads to lower returns than would occur if each technology were used on its own; this is known as subadditivity. As you can see from (1.a – 1.d), there are 2^n or 16 unique combinations possible for a set of four technologies. In addition to using operating margins as the unit of return, we also consider the effect of technology bundles on costs. Here, the objective is to minimize costs so the definition of supermodularity would require a less than or equal to sign instead of a greater than or equal to sign.

IV. Empirical model

The U.S. dairy industry is highly technological and sophisticated, with a large number of technologies and management strategies being used on the typical dairy. Using a production function approach, the curse of dimensionality quickly becomes a problem since the number of inequality restrictions that must be tested is 2^n where n is the number of technologies. This is one of the reasons we limit the set of technologies of interest to rbST and the three technologies that are most often described as being complementary to rbST: TMR feed balance system, computerized feeding system, and membership in a DHIA.

There are at least two empirical methods to test complementarity using the conceptual framework outlined earlier. The first approach involves estimating the following production function:

$$y_i = \sum_{r=0}^{1}\sum_{s=0}^{1}\sum_{t=0}^{1}\sum_{u=0}^{1} \boldsymbol{I}_{(\boldsymbol{rbST},\boldsymbol{TMR},\boldsymbol{cpufeed},\boldsymbol{DHIA})=(\boldsymbol{r},\boldsymbol{s},\boldsymbol{t},\boldsymbol{u})}{}' \boldsymbol{\alpha}_{\boldsymbol{rstu}} + \boldsymbol{Z}_i'\boldsymbol{\beta} + e_i \tag{2}$$

where y_i is the dependent variable (i.e., operating margin, or feed cost), $\boldsymbol{Z_i}$ is a vector of farm characteristics, $\boldsymbol{I}_{(\cdot)}$ is an indicator variable that represents the 15 unique combinations of dairy technologies (i.e., essentially 15 dummy variables), $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$ are vectors of estimated coefficients, and e_i is a disturbance term distributed normal with mean zero. It is necessary to estimate four versions of the model: an unconstrained model, a model that imposes equality constraints , a model that imposes greater than or equal restrictions, and a model that imposes less than or equal restrictions. Specifically, we need to place restrictions on $\boldsymbol{\alpha_{rstu}}$ as described by equations (1.a – 1.d). For example, for the test of whether rbST and TMR are complementarity, we first impose equality restrictions in equation (1.a) by setting

$$\alpha_{(r=1,s=1,t=0,u=0)} + \alpha_{(r=0,s=0,t=0,u=0)} - \alpha_{(r=1,s=0,t=0,u=0)} - \alpha_{(r=0,s=1,t=0,u=0)} = 0.$$

Simultaneously impose the equality restrictions for (1.b-1.d) in the same manner and run the equality-constrained regressions using maximum likelihood, and record the log-likelihood value. Next, run the greater-than-or-equal-to-constrained regressions, record the log-likelihood, and conduct the likelihood ratio (LR) test. To conduct the LR test for subadditivity, conduct the less-than-or-equal-to-constrained regressions. The same procedure is repeated to detect complementarities between rbST and computerized feed systems, and between rbST and membership in a DHIA. In total, the complete test requires running twelve restricted regressions in order to conduct eight LR tests.

There are several problems with this approach, however. First, it is cumbersome as you need to run regressions with inequality constraints, which not all software programs will allow. Second, and more importantly, the critical values that are used for the LR tests have a large inconclusive area in which you can neither reject nor fail to reject the null hypothesis. Carree, Lokshin and Belderbos (2011, henceforth CLB) devise a simpler testing approach that requires simple linear regressions and the standard t-test. [1]

The main insight behind CLB's testing procedure is that they make use of the observation that "a combined hypothesis is accepted if all the separate hypotheses are accepted" (CLB, pg. 265, originally from Savin 1980). In the case of four practices, we have:

$$\begin{aligned} y = \boldsymbol{Z}'\boldsymbol{\beta} &+ \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3 + \alpha_4 x_4 + \alpha_{12} x_1 x_2 + \alpha_{13} x_1 x_3 + \alpha_{14} x_1 x_4 \\ &+ \alpha_{23} x_2 x_3 + \alpha_{24} x_2 x_4 + \alpha_{34} x_3 x_4 + \alpha_{123} x_1 x_2 x_3 \\ &+ \alpha_{124} x_1 x_2 x_4 + \alpha_{134} x_1 x_3 x_4 + \alpha_{234} x_2 x_3 x_4 \\ &+ \alpha_{1234} x_1 x_2 x_3 x_4 + \varepsilon. \end{aligned} \tag{3}$$

From here, it is not difficult to derive that the conditions of complementarity are

$$\alpha_{12} = f(1,1,0,0) + f(0,0,0,0) - f(1,0,0,0) - f(0,1,0,0) \geq 0 \tag{4.a}$$

$$\alpha_{12} + \alpha_{123} = f(1,1,1,0) + f(0,0,1,0) - f(1,0,1,0) - f(0,1,1,0) \geq 0 \tag{4.b}$$

$$\alpha_{12} + \alpha_{124} = f(1,1,0,1) + f(0,0,0,1) - f(1,0,0,1) - f(0,1,0,1) \geq 0 \tag{4.c}$$

$$\alpha_{12} + \alpha_{123} + \alpha_{124} + \alpha_{1234} = f(1,1,1,1) + f(0,0,1,1) - f(1,0,1,1) - f(0,1,1,1) \geq 0, \tag{4.d}$$

with at least one of the four inequalities holding strictly. Now, re-write (3) to get:

$$\begin{aligned} y = \boldsymbol{Z}'\boldsymbol{\beta} &+ \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3 + \alpha_4 x_4 + \alpha_{12}(x_1 x_2 + x_1 x_2 x_3 x_4 - x_1 x_2 x_3 - x_1 x_2 x_4) \\ &+ \alpha_{13} x_1 x_3 + \alpha_{14} x_1 x_4 + \alpha_{23} x_2 x_3 + \alpha_{24} x_2 x_4 + \alpha_{34} x_3 x_4 \\ &+ (\alpha_{12} + \alpha_{123})(x_1 x_2 x_3 - x_1 x_2 x_3 x_4) \\ &+ (\alpha_{12} + \alpha_{124})(x_1 x_2 x_4 - x_1 x_2 x_3 x_4) + \alpha_{134} x_1 x_3 x_4 + \alpha_{234} x_2 x_3 x_4 \\ &+ (\alpha_{12} + \alpha_{123} + \alpha_{124} + \alpha_{1234}) x_1 x_2 x_3 x_4 + \varepsilon. \end{aligned} \tag{5}$$

[1] While we do not present the results here, we did follow this approach as a check against our results and, unsurprisingly, find that most of the test coefficients fall in the inconclusive area, or show no evidence of complementarity or subadditivity.

Using equation (5) and the conditions in equations (4.a-4.d), testing for complementarity requires running an ordinary least squares regression and examining the sign and significance of the coefficients of four variables: $x_1x_2 + x_1x_2x_3x_4 - x_1x_2x_3 - x_1x_2x_4$, $x_1x_2x_3 - x_1x_2x_3x_4$, $x_1x_2x_4 - x_1x_2x_3x_4$, and $x_1x_2x_3x_4$. Following the notation of CLB, denote the t-vales of the coefficients of the four variables as t_1, t_2, t_3, and t_4. There is evidence of complementarity if one of the four conditions holds: $(t_1 > t_c) \wedge (t_2 > -t_d) \wedge (t_3 > -t_d) \wedge (t_4 > -t_d)$ or $(t_1 > -t_d) \wedge (t_2 > t_c) \wedge (t_3 > -t_d) \wedge (t_4 > -t_d)$ or $(t_1 > -t_d) \wedge (t_2 > -t_d) \wedge (t_3 > t_c) \wedge (t_4 > -t_d)$ or $(t_1 > -t_d) \wedge (t_2 > -t_d) \wedge (t_3 > -t_d) \wedge (t_4 > t_c)$, where t_c and t_d are critical t-values. Since our combined hypothesis requires us to test four separate hypotheses, the probability of a type I error is greater. Therefore, we need to apply a Bonferroni correction, as described in CLB.

V. Data and descriptive statistics

The data for this study are from the National Agricultural Statistics Service's (NASS) Agricultural Resource Management Survey (ARMS) of dairy operations in 2005. The ARMS contains data on "field-level production practices, farm business accounts, and farm households" (www.ers.usda.gov). The survey's target population was dairy operations milking at least 10 cows at any time during 2005, and is designed to exclude non-commercial dairy operations. The dataset covers 24 states and has information from 1812 dairy operations, including conventional, organic, transitional and mixed dairies. We focus only on conventional dairies because operations that produce only organic milk, organic and conventional milk, or are transitioning to produce only organic milk use a different mix of technologies and follow different production technologies. Therefore, data from the three other types of operations are omitted from the analysis resulting in 1462 observations. After accounting for missing variables, our sample consists of 1445 observations.

Table 1 provides summary statistics of the variables that will be used in the econometric analyses. There is great heterogeneity among dairy operations with regards to the size of the dairy herd, average production, operating margins, and average feed costs. Of the four dairy practices, membership in the DHIA has the largest share of producers using it (45%), followed by the use of TMR (31%), the use of rbST (17%), and the use of computerized feeding systems (7%). Table 2 shows the composition of technology use. Nearly 40 percent of dairy operations did not use any of the four technologies, and only 1.36 percent used all four technologies. Only 2.28 percent of all dairy operations used rbST without adopting any of the other three practices. This means that 86.6 percent of operations that used rbST paired it with at least one of the other three technologies.[2] However, just because dairy producers are more likely to adopt rbST when they are already using one of the other technologies does not mean that complementarities exist, contrary to the claims of many studies.

Before we present the results, we need to devote some attention to the data being used and the manner in which it was collected. NASS analysts design their sampling strategy to construct a dataset where each dairy operation surveyed represents a known number of operations with comparable characteristics. Due to the complex survey sampling design, the typical formulae for variance and standard errors used by most statistical programs are invalid, which would invalidate our t-tests. While NASS recommends using the delete-a-group (DAG) jackknife variance estimator due to its performance with linear models (Dubman 2000; Kott 2001), other studies have utilized the bootstrap method (Goodwin, Mishra, and Ortalo-Magne 2003; Goodwin and Mishra 2004). We employ a probability-weighted bootstrapping method,

[2] We arrived at this number by calculating that 1-(0.0228/0.17) = 0.866.

where the probability of an observation being sampled is based on its weight in the population, and calculate 95% confidence intervals for the coefficients of interest (e.g., $x_1x_2 + x_1x_2x_3x_4 - x_1x_2x_3 - x_1x_2x_4$, $x_1x_2x_3 - x_1x_2x_3x_4$, $x_1x_2x_4 - x_1x_2x_3x_4$, and $x_1x_2x_3x_4$) from 2000 bootstrap replications.

VI. Results

We first present the results from four regressions (table 3) to get an overall idea of the effect of the individual technologies and technology bundles assuming four possible objectives: maximizing operating margins per cwt of milk, maximizing operating margins per head, minimizing feed costs per cwt of milk, and minimizing feed costs per head[3]. In each regression, we include ownership control dummies (e.g., individual, partnership, or corporation) and regional control dummies. In model 1, the dependent variable is the operating margin per cwt of milk. The estimated coefficients for experience (-0.034) and education (0.623) are statistically significant at the 5 percent level. Herd size (cows) is positive and significant at the 5 percent level. Of the technology use indicator variables, three are statistically significant. Since the indicator variable for the use of none of the dairy technologies is omitted to avoid problems of perfect collinearity, all estimated coefficients should be interpreted as being relative to the case in which no technology is used. Operations that only use rbST or use rbST, TMR, and computerized feeding systems have lower operating margins per cwt, while operations that use rbST and TMR have higher returns. The negative estimated coefficient on the variable indicating the use of only rbST is interesting, and lends some credence to the commonly accepted claim that the use of rbST is only profitable when used in tandem with other technologies (Henriques

[3] Operating margins are defined as the difference between the gross value of milk production and total costs. We choose feed costs instead of total costs because feed costs represent up to 75% of a dairy operation's total costs and is most directly affected by the use of rbST.

and Butler 2002). This result is also in line with numerous studies that have shown that the use of rbST is not correlated with higher profits (Foltz and Chang 2002; McBride, Short, and El-Osta 2004).

In model 2, we consider the operating margin per head. The results are qualitatively similar to those in model 1 but the overall fit is better (an adjusted R-square of 0.1176 versus 0.0555 for model 2), and more coefficients are statistically significant. Operations that only use cpufeed or TMR show statistically higher operating margins per head, as do operations that use both TMR and DHIA. Operations that use TMR and cpufeed experience lower returns, and this is significant at the 5 percent level.

In model 3, we consider the cost side by regressing feed cost per cwt of milk on the explanatory variables. We estimate this model for two reasons: first, minimizing costs is a plausible objective. Second, the main feature of rbST is that it improves the efficiency with which cows can convert feed into milk, even though most studies tout its yield-enhancing properties. In general, the results from model 3 are very similar to those of model 2, except that the signs are reversed (as expected). Operations that use rbST on its own do not seem to benefit from lower average feed costs. In fact, the only statistically significant (and negative) coefficient is on TMR. None of the technology bundles have a statistically significant effect on costs. Model 4 considers feed cost per head as the dependent variable. Of the technology variables, the use of only TMR or rbST, or being a member of a DHIA without using other technologies, all result in higher costs per head. All three results at significant at the 1 percent level. The only bundle that is statistically significant and negative is the use of rbST and TMR together.

Using the logic followed by previous studies, the results from table 3 seem to suggest that there are complementarities present. The use of rbST is most effective – from a production, profit, and cost perspective – when it is used alongside other common dairy technologies. However, as described in greater detail earlier, these results are not sufficient to show true complementarity in the sense of Milgrom and Roberts (1990). In order to show this, it is essential to compare performance in a more rigorous manner; that is, in a manner that compares all the possible situations in which two technologies are in use versus all alternative scenarios.

The key results of the regressions we run for the complementary analysis are reported in table 4.[4] In summary, we are unable to detect complementary relationships for profits but do detect complementary relationships between rbST and computerized feeding systems, as well as between rbST and TMR when the dependent variable is feed cost per head.[5] We group our results by the technology whose relationship with rbST we are testing. Comparing computerized feed systems (cpufeed) with rbST, we find no statistically significant coefficients in three of the four specifications. Recall that the test for supermodularity, or complementarity, requires that at least one of the four test coefficients be strictly greater than zero where the objective function is operating margins, while the other three may be zero or greater but not statistically significantly negative. Because the objective is to minimize feed costs, the conditions for complementarity involve reversing the sign. Therefore, the signs for the tests are reversed for models 3 and 4 where the dependent variable is feed cost. We detect evidence of complementarity between rbST and cpufeed in model 4, as the coefficient on $\alpha_{12} + \alpha_{124}$ is negative and significant, while the three other coefficients are statistically indistinguishable from zero.

We find a similar result when we test for complementarity between rbST and TMR. None of the coefficients have a statistically significant coefficient in models 1, 2, or 3 but there is a

[4] We run 12 (4x3) separate regressions to test complementarity. The full regressions results are not included here for brevity's sake but are available upon request.
[5] We also conducted tests to detect subadditivity but all tests failed to reject the null. Results are available upon request.

significant and negative coefficient on $\alpha_{12} + \alpha_{123}$ in model 4. We are unable to detect any evidence of complementarity between rbST and being a member in a DHIA. These results show that using a TMR feed balance system, being a member in a DHIA, or using a computerized feed system do not necessarily increase the marginal profitability of using rbST, but that the use of a computerized feed system or TMR can decrease the marginal cost of using rbST. This does not change the fact that dairy producers who are already using one of these technologies are more likely to adopt rbST, but claims about complementary effects are questionable.

In order to see what the results of a correlation-based approach might look like, we follow the correlation approach described by Yu et al. (2011) in table 3[6]. Yu et al. (2011) address the dimensionality problem by proposing a method that allows one to test a large number of technologies (they test eight). They conclude that "[c]ombinations of technologies that occur with greater frequency than would occur under independence are complementary technologies". We use their empirical strategy and test for complementarities among a set of nine common dairy technologies: rbST, computerized feed systems, computerized milking systems, genetic breeding, milking three times per day or more, keeping individual cow records, on farm computers, TMR, and membership in a DHIA. In table 5(a), we summarize the number of subadditive, complementary and independent technology bundles in our sample. Of the 512 possible technology bundles, 178 of them exist in our sample. 93 of the bundles (52%) are complementary; that is, they are more prevalent than expected under the assumption of independence. 43 of the bundles (24%) are subadditive, or are less prevalent than expected. We are unable to reject the null hypothesis of independence for the remaining 78 technology bundles (44%).

[6] For a more detailed description of the procedure, please refer to the appendix.

Next, we focus our attention on bundles that contain rbST (table 5(b)). The first thing to note is that of the 8 possible 2-technology bundles containing rbST, we find that the only pair that is complementary is *rbST* and *cpufeed*. We do not identify any other single technology that is complementary with rbST that is not part a larger technology bundle. However, there are three 2-technology bundles that have a subadditive relationship: *rbST-dhia*, *rbST-indivcowrec*, and *rbST-genbreed*. Of the 28 possible 3-technology bundles, we find that only one bundle (*rbST-cpumlksys-milk3plus*) is complementary. Again, we find more 3-technology bundles that are subadditive. In this case, there are five such bundles. Once the bundles consist of four or more technologies, we see many more instances of complementarity and fewer instances of subadditive relationships using a correlation-based definition.

These results suggest several things. First, adding technologies is more likely to make a bundle complementary; there are few instances of 2- and 3-technology bundles that are complementary. Second, smaller technology bundles are more likely to show a subadditive relationship. Lastly, the two technologies that are most often cited as being complementary to rbST (TMR and being a member of a DHIA) actually show a subadditive relationship when other technologies are not being used. Overall, these results suggest that dairy farmers are using multiple technologies simultaneously at a frequency that is greater than would be expected under the assumption of independence. However, these results do not say anything about whether or not the use of multiple technologies actually leads to greater output.

VII. Conclusion

In this article, we have presented empirical evidence to show that a commonly held belief is likely false. Specifically, we examine the claim that three widely used dairy technologies and management practices – total mixed ration feed balance system, computerized feeding systems, and membership in a dairy herd improvement association – complement the use of rbST in the sense that they increase the marginal return of rbST. Using a correlation-based definition of complementarity, we detect many instances of complementary technology bundles. The complementary bundles generally consist of many technologies, with only one technology – computerized feeding system – being complementary with rbST on its own. Adopting a production function approach and the definition of supermodularity, we show that none of the three technologies we test are complementary to rbST when the objective function is operating margins. We do find evidence of complementarity when the objective function is feed cost per head.

While we believe that our results are robust, there are weaknesses. The main weakness is that we only consider a subset of four dairy technologies in our production function approach. That is, we do not analyze all technologies that could be complements to rbST. We choose the three technologies that are most often cited in the rbST adoption literature as being complementary. Some examples of other potentially complementary technologies include the use of genetics or artificial insemination, the practice of milking cows three times per day, and the use of other forms of computer record keeping. However, adding additional technologies would require testing additional hypotheses, quickly leading to a curse of dimensionality problem. We attempt to address this by adopting the framework of Yu et al. (2011), but their method only detects correlations amongst multiple technologies, and does not actually test for the existence of complementarities as we have defined it.

Second, there is a potential endogeneity problem if there is an underlying and unobserved (to the econometrician) factor that is correlated with a specific technology bundle being adopted.

That is, there is the possibility that operations that use rbST are low quality and therefore not likely to benefit much from the complementary effects of other technologies. However, if this were true, then producers that do not use rbST but use other technologies would see higher returns, and our tests would detect substitutability. This is not the case. In this particular instance, the likelihood of endogeneity due to an omitted variable being a serious problem is limited due to the large number of farms and technology bundles. Unlike studies (e.g. Mohapatra, Goodhue, and Rozelle 2008) that only look at two practices (and four bundles) in total, our study examines four technologies and 16 bundles. As long as a reasonable share of the farms is using non-optimal combinations of technologies, it is unlikely that self-selection problems are the main driver of our results (Carree, Lokshin, and Belderbos 2011). The curse of dimensionality and the nature of the empirical tests make the testing of more than four or five technologies difficult. It is possible that there are dairy technologies that complement the use of rbST, but there are no technologies outside of the ones we have chosen that *a priori* should be chosen instead of others.

Our analysis can be extended in several directions. First, a study to examine the complementary effects of different technology packages over time would be of great interest. A panel data set would allow the economist to account for fixed (or random) effects, as well as address certain endogeneity issues. In addition, panel data would allow for an analysis of dynamic complementarities if we believe that the sequence in which technologies are adopted have an effect (Miravete and Pernías 2006). Second, we only consider technologies that are adopted in a discrete manner. This analysis could be extended to technologies in which the intensity of adoption is continuous (e.g., share of herd treated with rbST).

Our results contribute to the literature in two ways. First, we extend the application of the production function approach of testing complementarity by applying it to technology use in the

U.S. dairy industry. Other studies that have examined this issue have used more common, but limited, correlation-based methods. Second, we show empirically that a commonly held belief in the agricultural economics literature regarding dairy technologies is not true. While it has been repeatedly shown that dairy producers who are use TMR, computerized feeding systems, and DHIA services are more likely to adopt rbST, the use of these technologies does not necessarily increase the marginal productivity of rbST.

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Table 1: Descriptive statistics

Variable	Mean	Standard Deviation
Age (years)	51.26	66.48
Experience (years)	23.40	76.93
Education (share with college degree)	0.16	2.18
Milkcows (number)	156.16	2286.73
Operating margin ($/cwt of milk)	4.92	28.92
Operating margin ($/head of cow)	876.76	4833.76
Average cost of feed ($/cwt of milk)	9.02	22.07
Average cost of feed ($/head of cow)	1452.27	3469.10
Individual ownership (share)	0.81	2.31
Partnership (share)	0.13	1.98
Corporation (share)	0.02	0.87
Technology use and management practices (share)		
Recombinant bovine somatotropin (rbST)	0.17	2.22
Dairy Herd Improvement Association (DHIA)	0.45	2.95
Total mixed ration (TMR)	0.31	2.75
Computerized feeding system (cpufeed)	0.07	1.53
N=1445		

Note: the results presented here calculated using the NASS sampling weights.

Table 2: Composition of technology use

Technology bundle	Share
No technology	39.88%
DHIA only	18.42%
Cpufeed only	1.03%
TMR only	9.42%
rbST only	2.28%
Cpufeed & DHIA	0.91%
TMR & DHIA	11.82%
rbST & DHIA	4.43%
TMR & cpufeed	0.30%
rbST& TMR	0.78%
rbST& cpufeed	0.45%
TMR, cpufeed, DHIA	1.36%
rbST, TMR, cpufeed	0.48%
rbST, cpufeed, DHIA	1.28%
rbST, TMR, DHIA	5.81%
rbST, TMR, cpufeed, DHIA	1.36%

Table 3: Regression results

	(1) Operating margin per cwt of milk	(2) Operating margin per head	(3) Feed cost per cwt of milk	(4) Feed cost per head
Constant	5.787***	1114.485***	8.758***	1392.538***
	(0.749)	(117.274)	(0.569)	(86.347)
Age	0.007	-3.559	0.002	-4.945**
	(0.016)	(2.688)	(0.013)	(1.9260)
Experience	-0.034**	-5.128**	0.013	2.645*
	(0.014)	(2.309)	(0.010)	(1.558)
Education	0.623**	114.895*	-0.569**	-62.594*
	(0.301)	(57.229)	(0.233)	(37.868)
Cows	0.002**	0.574***	-0.001*	0.007
	(9.02E-04)	(0.183)	(6.82E-04)	(0.107)
Cows Squared	-2.05E-07	-8.72E-05**	1.26E-07**	-7.19E-06
	(3.53E-07)	(7.13E-05)	(2.61E-07)	(3.00E-05)
Technology bundles				
DHIA	-0.151	58.941	-0.355	233.847***
	(0.363)	(56.189)	(0.271)	(40.583)
Cpufeed	1.464	380.224*	-1.739*	202.676
	(1.338)	(230.696)	(0.871)	(194.916)
TMR	0.608	246.137***	-1.282***	151.666***
	(0.410)	(71.586)	(0.280)	(41.7518)
rbST	-2.465***	-147.244	0.329	687.251***
	(0.948)	(173.596)	(0.887)	(142.384)
Cpufeed, DHIA	-0.486	-86.613	1.198	-19.126
	(1.754)	(337.773)	(1.069)	(248.726)
TMR, DHIA	0.764	187.671*	0.390	-64.462
	(0.548)	(104.637)	(0.394)	(65.091)
rbST, DHIA	1.510	174.533	0.343	-185.133
	(1.203)	(229.279)	(1.095)	(192.259)
TMR, cpufeed	-5.628*	-1125.180**	3.709	28.871
	(3.341)	(555.184)	(2.301)	(406.137)
rbST, TMR	3.313*	418.102	-0.772	-583.352*
	(1.762)	(372.682)	(1.512)	(309.860)
rbST, cpufeed	-0.789	-266.890	1.336	-241.874
	(2.237)	(443.166)	(1.486)	(312.198)
TMR, cpufeed, DHIA	3.155	452.930	-2.674	-228.253
	(3.573)	(620.933)	(2.396)	(437.132)
rbST, TMR, cpufeed	3.093	687.561	-2.663	137.712
	(4.587)	(833.305)	(3.256)	(612.358)
rbST, cpufeed, DHIA	1.567	419.693	-2.843	-371.340
	(2.703)	(552.024)	(1.815)	(381.939)
rbST, TMR, DHIA	-3.515*	-599.215	-0.556	152.862
	(1.990)	(418.040)	(1.681)	(341.874)
rbST, TMR, cpufeed, DHIA	-2.370	511.399	4.339	734.294
	(4.955)	(925.838)	(3.483)	(664.89)
Ownership controls	Yes	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.0555	0.1176	0.0648	0.1540
Number of obs.	1445	1445	1445	1445

Notes: *, **, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Numbers in parentheses represent bootstrapped standard errors.

Table 4: Results of the complementary tests

	Dependent variable			
	(1) Operating margin per cwt	(2) Operating margin per head	(3) Feed cost per cwt	(4) Feed cost per head
cpufeed				
α_{12}	-0.828	-278.532	1.363	-238.796
	[-5.087,3.482]	[-1124.97, 612.27]	[-1.445,4.265]	[-846.73,349.64]
$\alpha_{12} + \alpha_{123}$	2.599	479.815	-1.442	-111.172
	[-4.029,11.356]	[-881.53,1882.26]	[-7.687,3.492]	[-1217.67,723.41]
$\alpha_{12} + \alpha_{124}$	0.794	152.051	-1.510	-615.445**
	[-2.399,3.757]	[-514.92,804.26]	[-3.682,0.497]	[-1095.0,-148.43]
$\alpha_{12} + \alpha_{123} + \alpha_{124} + \alpha_{1234}$	1.664	602.462	0.071	242.373
	[-0.549,3.717]	[112.57,1036.17]	[-1.436,1.909]	[-76.15,625.04]
tmr				
α_{12}	2.981	366.630	-0.634	-557.078
	[-0.713,6.027]	[-426.78,997.14]	[-3.165,2.864]	[-1028.03,225.39]
$\alpha_{12} + \alpha_{123}$	-0.296	-205.666	-1.250	-418.737**
	[-2.036,1.529]	[-564.43,167.07]	[-2.730,0.186]	[-687.60,-149.08]
$\alpha_{12} + \alpha_{124}$	6.408	1124.977	-3.439	-429.454
	[-0.975,15.920]	[-385.99,2638.99]	[-9.787,1.527]	[-1476.85,470.21]
$\alpha_{12} + \alpha_{123} + \alpha_{124} + \alpha_{1234}$	0.575	244.746	0.331	439.081
	[-2.714,3.822]	[-493.55,963.06]	[-1.643,2.678]	[-17.13,970.24]
dhia				
α_{12}	1.291	137.938	0.431	-169.736
	[-1.059,3.709]	[-320.55,586.17]	[-1.754,2.509]	[-563.50,187.82]
$\alpha_{12} + \alpha_{123}$	2.912	568.521	-2.442	-546.384
	[-1.433,7.530]	[-365.80,1545.21]	[-5.237,0.354]	[-1172.58,107.86]
$\alpha_{12} + \alpha_{124}$	-1.987	-434.358	-0.185	-31.394
	[-4.591,1.439]	[-1032.63,329.98]	[-3.269,1.583]	[-751.02,321.14]
$\alpha_{12} + \alpha_{123} + \alpha_{124} + \alpha_{1234}$	-2.921	-311.710	1.328	322.151
	[-11.317,3.399]	[-1631.39,980.32]	[-3.281,7.211]	[-442.15,1260.73]

Notes: ** indicates statistical significance at the 5% level.

Numbers in brackets represent 95% confidence intervals from a bootstrapped sample (# of replicates = 2000).

Table 5(a): Summary of technology bundles by type

Relations	Number
Do not exist in sample	78
Subadditives	43
Independents	42
Complements	93

Table 5(b): Complementary and subadditive technology bundles

Bundle size	Complementary technologies	Subadditive technologies
2 technologies	cpufeed	genbreed, indivcowrec dhia
3 technologies	cpumlksys, milk3plus	indivcowrec, tmr indivcowrec, onfarmcpu genbreed, tmr genbreed, onfarmcpu genbreed, indivcowrec
4 technologies	cpumlksys, tmr, dhia mlk3plus, indivcowrec, onfarmcpu cpufeed, indivcowrec, dhia cpufeed, indivcowrec, tmr cpufeed, genbreed, tmr	Indivcowrec, onfarmcpu, dhia genbreed, tmr, dhia genbreed, indivcowrec, tmr genbreed, indivcowrec, onfarmcpu
5 technologies	genbreed, indivcowrec, tmr, dhia genbreed, indivcowrec, onfarmcpu, dhia genbreed, milk3plus, onfarmcpu, dhia genbreed, milk3plus, indivcowrec, onfarmcpu cpumlksys, genbreed, tmr, dhia cpumlksys, genbreed, indivcowrec, onfarmcpu cpufeed, indivcowrec, onfarmcpu, dhia cpufeed, genbreed, onfarmcpu, tmr cpufeed, genbreed, indivcowrec, dhia cpufeed, genbreed, indivcowrec, onfarmcpu cpufeed, genbreed, milk3plus, indivcowrec	genbreed, indivcowrec, onfarmcpu, tmr
6 technologies	17 unique bundles	-
7 technologies	12 unique bundles	-
8 technologies	5 unique bundles	-
9 technologies	1 bundle	-

Note: All results are based on 2000 bootstrapped samples.

Appendix

The exact method is described in great detail in Yu et al. (2011) but the basic idea is to compare the frequency of technology bundle q_j assuming independence, $\hat{q}_j^0$, with the actual frequency $\widehat{q_J}$. The difficulty lies in testing the null hypothesis that $\hat{q}_j^0 = \hat{q}_j$ because the sample variances are difficult to calculate, and the sampling distributions are unknown so the standard t-tests would be invalid. Following Yu et al. (2011), we use percentile bootstrapping (in our case, 2000 bootstrap replicates) and order the vector of differences $\boldsymbol{C}$, where $\boldsymbol{C} = (C_1, C_2, \dots, C_M)$ is "the ordered vector of adoption differences $\hat{q}_j - \hat{q}_j^0$". We then calculate the 95% confidence $[C^L, C^H]$ interval by selecting the 2.5th and 97.5th percentiles. We cannot reject the null hypothesis of independence, or $\hat{q}_j^0 = \hat{q}_j$, if zero is within the confidence interval. If $C^L > 0$, then we reject the null hypothesis of independence, but cannot reject the alternative hypothesis that there is a complementary relationship. If $C^H < 0$, then we reject the null hypothesis of independence, but cannot reject the alternative hypothesis that there is a subadditive relationship.