Technology Adoption and Technical Efficiency: Organic and Conventional Dairy Farms in the United States

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Abstract
We compare productivity and technical efficiency of organic and conventional dairy farms in the United States. We address self-selection into organic farming by using propensity score matching and explicitly test the hypothesis that organic and conventional farms employ a single, homogeneous technology. Utilizing the 2005 Agricultural Resource Management Survey on Dairy Costs and Returns Report data, we reject the homogeneous technology hypothesis and find that the organic dairy technology is approximately 13 percent less productive. However, we find little difference in technical efficiency between organic and conventional farms when technical efficiency is measures against the appropriate technology.

Key words: dairy, organic, productivity, propensity score matching, stochastic frontier, technical efficiency

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Although the organic dairy sector in the United States is a niche market, it has exhibited potential for growth in the U.S. dairy sector. In 2005, certified organic dairy farms accounted for approximately 1 percent of the dairy cows in the U.S. and accounted for less than 1 percent of total U.S. milk production (McBride and Greene 2007). However, from 2003 to 2006, sales of organic dairy products nearly doubled, making organic dairy one of the fastest growing segments of organic agriculture in the United States, as well as a fast growing segment of U.S. dairy (Organic Trade Association). Growth in demand for organic dairy has been fueled by a complex mix of consumer concerns of food safety, nutrition, concern for the environment, and other factors (Klonsky 2000; Blank and Thompson 2004; Rotz *et al*. 2007). Growth in supply has been spurred in part by the promise of high returns relative to conventional dairy farming, as well as environmental concerns on the part of producers (McBride and Greene 2007). Proponents of the organic movement have held up the organic model as a potentially profitable alternative to conventional dairy production, especially for smaller operations as well as new farmers (Sato *et al*. 2005; Rotz *et al*. 2007).

Yet little is known about the production practices of the organic dairy sector, not in small part because the industry is so new. In particular, little work to date has systematically addressed the effect of organic standards on the production process. Under standards defined and enforced by the USDA's National Organic Program, organic farming systems exclude the use of synthetic chemicals, antibiotics, and hormones in crop and livestock production. Organic livestock production systems also regulate feeding practices, requiring, for example, that dairy cows have access to pasture (Greene and Kremen 2003). These standards restrict the technology of dairy farming. Not surprisingly, several studies have documented reduced yields of organic farms relative to conventional farms (Tzouvelekas, Pantzios, and Fotopoulos 2001a; Tzouvelekas, Pantzios, and Fotopoulos 2001b; Oude Lansink, Pietola, and Backman 2002; Sipilainen and Oude Lansink 2005; Kumbhakar, Tsionas, and Sipilainen 2008). Yield differences may be due to a less productive technology or lower technical efficiency in production on organic farms, or both. Measured differences in productivity and efficiency may also be influenced by self-selection in the choice of production technology, and thus not entirely attributable to organic standards.

Only two studies have compared the productivity and efficiency of organic and conventional dairy farms; both use data on Finnish farms. Sipilainen and Oude Lansink (2005) used the Heckman-type correction for selection into organic production by appending the inverse Mill's ratio as a covariate in the production technology specifications. They found technical efficiency of organic dairy farms to be on average 4.5 percentage points lower than that of conventional dairy farms. Kumbhakar, Tsionas, and Sipilainen (2008) addressed self-selection into organic production by jointly estimating the production frontiers and technology choice, where technology choice was modeled as a function of technical inefficiency and other farm characteristics. They found that on average organic farms could have produced 5.3 percent more milk had they used conventional technology. They also found that technical efficiency of organic dairy farms was on average 5 percentage points lower than that of conventional farms.

Missing from these studies is an appropriate, formal test of the homogeneous technology assumption. Kumbhakar, Tsionas, and Sipilainen (2008) estimate separate production frontiers for organic and conventional farms, without first testing whether the technologies are indeed distinct. Sipilainen and Oude Lansink (2005) tested for distinct organic and conventional production technologies by including interactions of an organic dummy variable with inputs in the production frontier, but fail to address the potential endogeneity of the organic dummy caused by self-selection.

This article highlights two important methodological issues when comparing the productivity and efficiency of organic and conventional farms: self-selection into organic farming and formal testing of the homogeneous technology assumption. We use the 2005 Agricultural Resource Management Survey–Dairy Costs and Returns Report which provides the first comprehensive data on a nationally representative sample of organic dairy farms in the United States. We address potential self-selection in the choice of dairy production system by utilizing propensity score matching (PSM) to compare organic farms to otherwise similar conventional farms. To our knowledge, this is the first study to apply PSM to address self-selection in productivity analysis. We estimate a stochastic frontier model of dairy technology and test the hypothesis that organic and similar conventional dairy farms use a homogeneous technology. To illustrate the importance of technology and self-selection, we also estimate models of dairy farm technology that assume a homogeneous technology and ignore self-selection.

Methodological Framework

In microeconomic theory, the primal transformation function, or production frontier, describes the maximum output that may be obtained given inputs and technology. Some inputs may be varied at the discretion of the decision maker, while other inputs are exogenously fixed, acting as constraints to the production process. Any deviation from the maximal output is typically considered technical inefficiency (Coelli et al. 2005; Ray 1988). A firm that operates at the production frontier has a technical efficiency of 100 percent.

A non-discretionary input of particular importance to this paper is the set of organic standards which impose constraints on the types and quantity of inputs that may be used to produce organic milk. Our objective is to test whether these production restrictions affect the production frontier, technical efficiency, or both the frontier and technical efficiency.

Stochastic Production Frontier

We adopt the stochastic frontier analysis (SFA) framework to estimate production frontiers and measure technical efficiency. This approach takes into account the stochastic nature of agricultural processes, and also allows the inclusion of categorical variables in the characterization of technology.

The stochastic production frontier model is specified as

$$\ln y_i = \boldsymbol{x}_i\boldsymbol{\beta} + v_i - u_i \tag{1}$$

where y_i denotes the output for the ith farm (i = 1, ..., N), $\boldsymbol{x}_i$ is a vector of the production inputs including a column of ones, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, v_i is a two-sided stochastic term that accounts for statistical noise, and u_i is a non-negative stochastic term representing inefficiency. Standard assumptions on the stochastic terms are that $E[v_i] = 0$ for all i, $E[v_i v_j] = 0$ for all i and j ($i \neq j$), $E[v_i^2] = \sigma_v^2$, $E[u_i] > 0$, $E[u_i u_j] = 0$ for all i and j ($i \neq j$), and $E[u_i^2] = \sigma_u^2$. The stochastic terms v_i and u_i are assumed to be uncorrelated.

Much of the previous literature on comparative technical efficiency and, to our knowledge, all of the literature on technical efficiency of dairy farms assumes homoscedasticity for the statistical and inefficiency variance. Our analysis allows a double heteroscedastic error structure. We adopt the model proposed by Hadri, Guermat, and Whittaker (2003) to test for and estimate heteroscedasticity in both the statistical and inefficiency components of the error term of the production frontier. Heteroscedasticity of the statistical error term is modeled as $E[v_i^2] = \sigma_{vi}^2 = \exp(\boldsymbol{r}_i \boldsymbol{\delta})$, where $\boldsymbol{r}_i$ is a vector of variables including a column of ones and $\boldsymbol{\delta}$ is a vector of parameters to be estimated. A model with homoscedastic statistical variance results from the restriction that all the $\boldsymbol{\delta}$ parameters except the intercept are equal to zero. Similarly, heteroscedasticity of the inefficiency error term is modeled as $E[u_i^2] = \sigma_{ui}^2 = \exp(\boldsymbol{q}_i \boldsymbol{\gamma})$, where $\boldsymbol{q}_i$ is a vector of variables including a column of ones and $\boldsymbol{\gamma}$ is a vector of parameters to be estimated. A model with homoscedastic inefficiency variance results from the restriction that all the $\boldsymbol{\gamma}$ parameters except the intercept are equal to zero.

Under the further assumptions that v_i is normally distributed and u_i is half-normally distributed, the density function for $\varepsilon_i \equiv v_i - u_i = \ln y_i - \boldsymbol{x_i}\boldsymbol{\beta}$ is

(2) $$f_i(\varepsilon_i) = (2/\sigma_i)\phi(\varepsilon_i/\sigma_i)\big(1 - \Phi(\lambda_i\varepsilon_i/\sigma_i)\big), \text{ for } -\infty < \varepsilon_i < +\infty,$$

here $\sigma_i^2 = \sigma_{vi}^2 + \sigma_{ui}^2$, $\lambda_i = \sigma_{ui}/\sigma_{vi}$, ϕ is the standard normal density, and Φ is the standard normal cumulative distribution function (Hadri, Guermat, and Whittaker 2003). The log-likelihood function for the double heteroscedastic production frontier model is

(3) $$\ln L\,(\boldsymbol{\beta}, \sigma_u, \sigma_v, \boldsymbol{\delta}, \boldsymbol{\gamma}) = -N\ln\left(2/_{\pi}\right) - N\ln\sigma_i + \sum_{i=1}^{N}\{\ln\Phi[\varepsilon_i\lambda_i/\sigma_i] - 1/2\,[\varepsilon_i/\sigma_i]^2\}.$$

The output-oriented measure of firm specific technical efficiency is the ratio of observed output to the corresponding stochastic frontier output, i.e. when $u_i = 0$ (Battese and Coelli 1988). Since the output is in natural logarithmic form, technical efficiency is defined as:

(4) $$TE_i = \frac{y_i}{\exp(\boldsymbol{x}_i\boldsymbol{\beta}+v_i)} = \frac{\exp(\boldsymbol{x}_i\boldsymbol{\beta}+v_i-u_i)}{\exp\,(\boldsymbol{x}_i\boldsymbol{\beta}+v_i)} = \exp(-u_i).$$

To predict firm-specific technical efficiency we need to assess the value of u_i. After the frontier has been fit to the data, we are able to obtain an estimate of ε_i, which is then used to disentangle the inefficiency component u_i utilizing the conditional mean function $E[u_i \mid \varepsilon_i]$ as presented by Jondrow, Lovell, Materov and Schmidt (1982):

$$(5) \qquad E[u_i|\varepsilon_i] = \frac{\sigma_i\lambda_i}{1+\lambda_i^2}\left[\frac{\phi(\frac{\varepsilon_i\lambda_i}{\sigma_i})}{1-\Phi(\frac{\varepsilon_i\lambda_i}{\sigma_i})} - \frac{\varepsilon_i\lambda_i}{\sigma_i}\right].$$

Self-selection into Organic Production

As discussed in the previous section, the frontier production function may differ between organic and conventional farms because of restrictions on the production process imposed by organic standards. We wish to test for different technologies by allowing the parameters of the production function, $\boldsymbol{\beta}$, to differ for organic and conventional farms; that is, by including an organic indicator variable that interacts with the input vector $\boldsymbol{x}_i$. However, estimation of such a model is complicated by self-selection in the choice of production method. Dairy farmers self-select into organic production. The choice to produce under organic standards may be modeled as a propensity o_i* that depends on observable farm and farmer characteristics, $\boldsymbol{w}_i$:

$$(6) \qquad o_i^* = \boldsymbol{w}_i\boldsymbol{\alpha} + e_i$$

where $\boldsymbol{\alpha}$ is a vector of parameters and e_i is a random error. If any of the determinants of technology choice, $\boldsymbol{w}_i$, also affect milk production but are not included explicitly in equation (1), then the organic indicator variable in (1) is correlated with the error term ε_i. In this case, estimators of $\boldsymbol{\beta}$ that do not account for the endogeneity of the technology choice are biased.

Several studies have attempted to address self-selection into organic production. To compare risk attitudes of organic and non-organic farmers, Gardebroek (2006) selected in an *ad hoc* manner a subset of non-organic farms which had similar characteristics to organic farms. Sipilainen and Oude Lansink (2005) utilized a Heckman-type sample selectivity correction on stochastic production frontiers by appending the inverse Mill's ratio as a covariate in separate frontier production functions for organic and conventional farms. Kumbhakar, Tsionas, and Sipilainen (2008) addressed self-selection by jointly estimating stochastic frontiers (organic and conventional) and technology choice. These authors modeled technology choice as a function of farm characteristics and technical inefficiency. Greene (2008a) proposed the joint estimation of stochastic frontiers and the technology choice model with correlated errors. Yet the methodologies described in the three latter studies require the *a priori* assumption that technologies are different, without a formal test for differences in technology. Greene's (2008b) approach also suffers from a "common vexing occurrence" of least square residuals being skewed in the wrong direction, which makes the estimation of frontiers more complicated (p.541).

We propose a matching approach to address self-selection. In contrast to Heckman-type methods that model sample selection bias, matching models are a special case of selection models which assume that conditioning on observable variables eliminates sample selection bias (Heckman and Navarro-Lozano, 2004). In essence matching models create the conditions of an experiment in which production type (organic vs. non-organic) is randomly assigned, allowing for the identification of a causal link between organic technology and productivity.

We utilize a class of matching models called propensity score matching (PSM) to measure the effect of adopting organic production technology on productivity and technical efficiency of organic farms. The effect of organic standards on productivity is defined as $E(Y_1 - Y_0 \mid \boldsymbol{Z}, D = 1) = E(Y_1 \mid \boldsymbol{Z}, D = 1) - E(Y_0 \mid \boldsymbol{Z}, D = 1)$, where Y_0 is milk production using conventional dairy farming technology ($D = 0$), Y_1 is milk production when organic technology is adopted ($D = 1$), and $\boldsymbol{Z}$ is a vector of conditioning variables consisting of any $\boldsymbol{x}$ variables from

(1) and any $\boldsymbol{w}$ variables from (6). The mean $E(Y_1 \mid \boldsymbol{Z}, D = 1)$ can readily be identified from data of organic farms. But assumptions need to be made to identify the counterfactual mean $E(Y_0 \mid \boldsymbol{Z}, D = 1)$, i.e. milk production of organic farms had they not adopted the organic technology. Naively utilizing the outcomes of self-selected conventional farms $E(Y_0 \mid \boldsymbol{Z}, D = 0)$ to approximate $E(Y_0 \mid \boldsymbol{Z}, D = 1)$ results in selection bias. The resulting selection bias from making such an approximation is defined as $B(\boldsymbol{Z}) = E(Y_0 \mid \boldsymbol{Z}, D = 1) - E(Y_0 \mid \boldsymbol{Z}, D = 0)$.

Matching methods find a substitute for $E(Y_0 \mid \boldsymbol{Z}, D = 1)$ based on the statistical independence of (Y_0, Y_1) and D conditional on $\boldsymbol{Z}$, i.e. technology is exogenous after conditioning on $\boldsymbol{Z}$. This condition is also referred to as “selection on observables” (Imbens 2004). Rosenbaum and Rubin (1983) show that the independence condition also holds when conditioning on a propensity score $P(\boldsymbol{Z})$, hence the name propensity score matching. PSM reduces the dimensionality of having to match on $\boldsymbol{Z}$. If the assumptions of this method hold, then $E(Y_0 \mid P(\boldsymbol{Z}), D = 1) = E(Y_0 \mid P(\boldsymbol{Z}), D = 0) = E(Y_0 \mid P(\boldsymbol{Z}))$, allowing unbiased estimates of $E(Y_1 - Y_0 \mid \boldsymbol{Z}, D = 1)$.

Propensity score matching is a three step procedure. In the first step, a probability model for adoption of organic production standards is estimated and used to calculate the probability or propensity score of being organic for each observation. In the second step, each organic farm is then matched to a conventional farm with a similar propensity score. For this analysis we consider single-nearest-neighbor matching, where each organic farm is paired with the conventional farm that has the closest propensity score. All other conventional farms are discarded for the analysis (Dehejia and Wahba 2002). In the third step we estimate the stochastic frontier model on the sub-sample of organic farms and matched conventional farms, and test the hypothesis that these farms employ a homogeneous technology.

A limitation of the PSM approach (and, incidentally of the approach proposed by Kumbhakar, Tsionas, and Sipilainen, 2008) is that unobservable variables that may affect both the choice of production technology and technology are not accounted for directly. We assume that the distributions of such unobservables are the same for organic and conventional farms. Imbens (2004) argues for the validity of a matching approach on the basis that the unobservable factors that affect the optimizing behavior of agents, i.e. adoption of organic technology, are independent of outcomes of interest to that analyst, i.e. milk output. In fact, Imbens (2004) elaborates on an example akin to this study, i.e. the effect of adopting a new technology on a firm's output. In this example, whether a farmer adopts a technology is dependent on firm-specific marginal costs, and not output per se.

Imbens (2004) further states that the assumption that the distributions of unobserved variables are similar for treated and untreated agents is ultimately an empirical question. To provide some empirical evidence that the PSM approach is in fact eliminating the selection bias, we conduct formal tests of the endogeneity of the organic dummy variable in the production frontier.

Empirical Models and Data

We assume a Cobb-Douglas functional form for $f(x)$ in (1), estimating the model:

(7) $$y_i = \boldsymbol{x}_i'\boldsymbol{\vartheta} + I\boldsymbol{x}_i'\boldsymbol{\tau} + \boldsymbol{z}_i'\boldsymbol{\gamma} + \boldsymbol{\varepsilon_i}$$

where y_i is the natural log of farm milk output, $\boldsymbol{x}_i$ is a vector of discretionary production inputs (also in natural logs) and a column of ones, I is an indicator variable for organic farms, $\boldsymbol{z}_i$ is a vector of non-discretionary inputs of farm and operator characteristics, and $\boldsymbol{\vartheta}$, $\boldsymbol{\tau}$, and $\boldsymbol{\gamma}$ are parameters to be estimated.[1]

We estimate the following probit specification of (6) to obtain propensity scores:

(8) $\Pr(o_i = 1) = \boldsymbol{w}_i'\boldsymbol{\alpha} + e_i$

where $\boldsymbol{w}_i$ is a vector of farm and farmer characteristics and $\boldsymbol{\alpha}$ is a vector of parameters to be estimated. The propensity score for each farm is the estimated probability of being organic.

We use data on U.S. dairy farms from the 2005 Agricultural Resource Management Survey (ARMS) Dairy Costs and Returns Report. These data were collected through a survey conducted by USDA in 24 major dairy states: Illinois, Indiana, Iowa, Missouri, Ohio (Cornbelt region), Michigan, Minnesota, Wisconsin (Upper Midwest region), Maine, New York, Pennsylvania, Vermont (East region), California, Idaho, Oregon, Washington (West Region), Arizona, New Mexico, Texas (Southwest region) , Florida, Georgia, Kentucky, Tennessee, and Virginia (Southeast region). The sample is a multi-frame, probability-based survey in which farms are randomly selected from groups of dairy farms stratified by value of sales. Each sampled farm represents a number of farms that are of similar value of sales; this number represents the survey expansion factor, or weight. Weighting is recommended for descriptive and econometric analyses when inferences are made of the population of interest (Dubman 2000). Data are collected on farm and operator characteristics, revenue and costs of production, marketing practices, production technology, and management practices. The usable sample with complete observations for all variables used in our analysis consists of 288 organic dairy farms and 1,194 conventional dairy farms.[2] After we apply the respective weights, the weighted sample represents approximately 693 organic dairy farms and 44,744 conventional dairy farms in the United States. The sample of organic farms represents approximately 1.5 percent of the number of conventional farms.

The discretionary inputs in the production frontier include milking cows, feed, labor, capital, and other costs. Our feed variable is an aggregate measure of feed mixes, grains, and forage quantities used by the farm. Feed items included in the aggregated measure include high moisture corn, low moisture corn, barley, high moisture sorghum/milo, low moisture sorghum/milo, wheat, soybeans, oats, other feed grains, milk replacer/calf starter, alfalfa hay, other hay, straw, corn silage, sorghum/milo silage, other silage or haylage, and green chop. Each feed item is converted to total digestible nutrients (TDN), which is directly related to the feed's nutrient content, as reported in the Directory of Feeds and Feed Ingredients (McGregor 1989). We consider the use of TDN content to be appropriate because it is a quantity measure that is not influenced by the higher weight of certain feed items. Capital includes the ownership costs (depreciation and interest) of the investment on buildings and machinery devoted to dairy production. Our 'other inputs' category includes expenditures on agricultural chemicals, marketing containers, livestock purchases of heifers, bedding and litter, medical supplies, fuel, electricity, repairs/maintenance of machinery and buildings, contract labor, custom work, renting of machinery, and fees paid for professional services.

The non-discretionary inputs in $\boldsymbol{z}_i$ include farm and operator characteristics. Farm characteristics include: use of rbST, type of milking facility, average weight of milking cows that are retired from the farm (which we use as a proxy for breed differences), region, percent of land rented, whether the farm supplies more than 25 percent of forage needs from pasture during pasture months, percent of replacement heifers raised in the farm, percent of feed items produced in the farm, and years that the dairy farm has existed. Operator characteristics include college education, age, years that the farmer has participated in the dairy industry, and hours of off-farm work. Heteroscedasticity of the statistical and inefficiency variances are concurrently specified as a function of herd size, i.e. number of milking cows in logarithmic form.

We specify selection into organic production, equation (8), as a function of farm and farmer characteristics, as well management practices. For farm characteristics hypothesized to influence propensity to choose organic include region, use of a parlor, use of automatic takeoffs on parlors, herd size, pasture usage per cow, average weight of culled cows, percent of land rented, percent of feed items produced in the farm, and years that the farm has operated. Operator characteristics include college education of the main operator, age, years that the operator has participated in the dairy industry, and the operator's expectation that the farm will continue to produce milk for more than 11 years. The management practices include participation in the Dairy Herd Improvement Association (DHIA), use of a nutritionist, use of veterinarian services, and seasonally drying off cows. For both the frontier and probit models we use the natural log transformations of all continuous variables. Continuous variables with a zero value were further transformed by adding one prior to the log transformation.

Summary statistics and statistical significance of tests on equality of means for continuous variables and equality of proportions for binary variables of organic and conventional farms are presented in table 1. On average, organic dairy farms milk smaller dairy herds. The average herd size is 81 cows for organic farms and 140 cows for conventional farms. To control for size differences, table 1 presents output and other input quantities on a per cow basis.[3] Milk production per cow is 28 percent lower on organic dairy farms than on conventional farms. Organic farms provide approximately 25 percent fewer pounds of TDN of feed than conventional farms, and have lower expenses on other inputs. On the other hand, organic farms allocate approximately 2.7 times more pasture acres per cow than conventional dairies. Organic farms are on average more labor intensive, although the difference is not statistically significant. There are no significant differences in terms of average capital invested per cow.

There are significant differences in farm characteristics. Most of the organic dairies are located in the Upper Midwest (44%) and the East (41%), followed by the Cornbelt (9%) and West (6%) regions. There are no organic dairies in the Southwest or Southeast in our sample. Most of the conventional dairies are also in the Upper Midwest (41%) followed by the East (27%), Cornbelt (15%), West (11%), Southeast (6%) and Southwest (2%). Samples of both types of farms have diverse types of milking facilities: 40 percent of organic farms and 49 percent of conventional farms have a milking parlor. Conventional dairies are more likely to have parlors with automatic takeoff units. On average, both types of farms have been part of the dairy industry for more than twenty years. Most of the organic dairies switched from conventional production and have been producing organic milk for approximately five years. There is no information regarding specific breed differences between organic and conventional dairies, yet from the weight of cows retired from the dairy it is evident that larger breeds predominate in conventional dairies. On average a retired milking cow from a conventional dairy weighs 1,295 pounds whereas a retired milking cow from an organic dairy weighs on average 1,177 pounds. A higher proportion of organic farms provide more than 25 percent of forage needs from pasture during pasture months.

Although not statistically significant, operators of organic dairies tend to be younger, and thus have devoted less time to dairy farming. Organic operators are also more likely to have a college degree. There are no significant differences in off-farm work measured in hours per year. On average, the operator of an organic dairy works outside the farm for about 130 hours a year and a conventional operator for 143 hours. When dairy operators were asked “How many more years do you expect this operation will be producing milk?" 66 percent of the organic operators responded a longer planning horizon of "11 or more" years compared to 48 percent of the conventional operators.

In terms of management practices, there are some clear differences between production systems. As expected, rbST is not used in organic dairies. In conventional farms, about 8 percent of the milking herd is using rbST. Conventional farms also invest more in veterinarian and nutritional management of the herd. Approximately 70 percent of conventional dairies report the use of regularly scheduled veterinary services, whereas only 39 percent of organic dairies do so. Approximately 73 percent of conventional dairies use a nutritionist to design mixes or purchase feed, whereas 45 percent of organic dairies do so. A larger share of conventional dairy farms appears to have a seasonal dry-off period for the dairy herd. There are no statistically significant differences in DHIA participation, proportion of farm raised herd, proportion of farm raise feed, and rented land.

Results and Discussion

As a starting point in the analysis, we first evaluate whether there is reason to be concerned with self-selection into organic farming. To do so, we conduct a Durbin-Wu-Hausman test of the endogeneity of the organic dummy variable included in (7) (Davidson and Mackinnon 1993). We conduct the test by estimating equation (8) as a linear probability model, where pasture acres per cow, dummy variables for various management practices (DHIA participation, use of veterinary services, use of nutritionist, seasonal dry-off), and planning horizon are instruments excluded from equation (4). The resulting chi-squared statistic from a Wald test is 2.75 with 1 degree of freedom (p-value = 0.097). We reject the null hypothesis that the organic dummy is exogenous at the 10 percent level.[4]

PSM Analysis

The probit estimates of the organic propensity equation are presented in table 2. The probit model has a McFadden pseudo R^2 value of 0.42 and correctly predicts 96 percent of conventional dairies and 57 percent of organic dairies. Several variables are statistically significantly associated with producing organic milk. Farms located in the East and West are more likely to be organic than farms in the Upper Midwest. On the other hand, farms in the Cornbelt region are less likely than farms in the Upper Midwest to be organic. As expected, farms that allocate more pasture acres per cow are more likely to be organic. A higher proportion of feed raised on the farm, and a higher proportion of rented land are also associated with organic production. On the other hand, larger cows, and use of a milking parlor are negatively associated with organic production. The only management practice that is associated with organic production is farmer participation in DHIA. The use of veterinarian and nutritionist services and seasonal drying off of cows are not strongly associated with organic farming. Younger farmers are more likely to farm organically, as are farmers that have a longer planning horizon. College education is not strongly associated with the choice of production method.

We use the probit estimates to generate a propensity score—i.e., the predicted probability of being organic—for each dairy farm. We then create a sub-sample of conventional farms that we match to organic farms by selecting for each organic farm the conventional farm with a propensity score closest to that of the organic farm.[5] Figure 1 shows kernel density estimates of the distribution of propensity scores for organic farms, all conventional farms, and the sub-sample of matched conventional farms. As expected, the distribution of propensity scores for all conventional farms is skewed towards zero. By design, the distribution of the sub-sample of matched conventional farms more closely resembles that of organic dairy farms.

The resulting sub-sample of matched conventional farms consists of 137 dairies, which after applying the respective weights represent approximately 10,979 conventional dairy farms in the United States. These farms are on average approximately half the size of the original conventional dairy sample and even smaller than an average organic dairy (table 1). Compared to the organic farms, the matched conventional dairies are still different in some farm and operator characteristics. For example, the matched dairies still have a statistically significantly higher yield and feed use. Operators have less college education and a shorter planning horizon. The matched farms are less likely to have a parlor and participate in the DHIA. The matched farms are more likely to use veterinary and nutritionist services, and dry-off their cows. But compared to the original sample of conventional dairy farms, the sub-sample better resembles the organic farms. Yield, use of feed items, and other variable input expenses are lower than the average conventional farms. Average pasture per cow in the PSM sub-sample is almost double that for all conventional farms, and no longer statistically different from organic farms. Compared to the full sample of conventional farms, the matched conventional dairies have operators that have less college education and who work fewer hours off-farm. Fewer of the matched farms use a milking parlor or automatic takeoffs; and the matched farms make less use of rbST, veterinary, and nutritionist services, and participate less in the DHIA program.

By design, and as shown in figure 2, compared to the full sample of conventional farms, the matched sub-sample of conventional farms more closely resemble organic farms in terms of propensity to adopt organic production. We conduct the DWH test for exogeneity of the organic dummy variable when equation (7) is estimated over the PSM sub-sample. The resulting chi-squared statistic from a likelihood ratio test is 0.24 with 1 degree of freedom (p-value = 0.624). We cannot reject the null hypothesis that the organic dummy is exogenous. Thus by selecting on farm and operator characteristics, the PSM approach appears to have generated a sub-sample of farms for which organic is randomly assigned.

Stochastic Frontier Analysis

Results from the stochastic frontier models estimated on the PSM sub-sample of dairy farms are presented in table 3. We estimate two different models. In the first we assume that both organic and conventional dairy farms have the same production technology. The specification for the second model allows the organic and conventional production technologies to differ. Using the model that allows for different technologies, we test the restrictions that the organic intercept and slope shifters are jointly equal to zero. The resulting chi-squared statistic from a Wald test is 14.25 with 6 degrees of freedom (p-value = 0.027). Thus we reject the null hypothesis that the organic intercept and slope shifters are jointly equal to zero at conventional significance levels. That is, we reject the hypothesis of a homogeneous technology for organic and conventional dairy farms.

We find both discretionary and nondiscretionary inputs that statistically significantly affect productivity. For conventional production, the input elasticities for cows, feed and other costs are positive and statistically significant. Cows have the largest marginal effect on milk production, followed by feed, and other costs. For organic production, we find the intercept shifter to be negative and statistically significant, indicative of lower productivity in organic production. We also find the input elasticity of cows to be lower in organic production, and the input elasticity of capital higher in organic production, although the differences are not statistically significant.

Adding up the coefficients on discretionary inputs to measure economies of scale, we find statistically significant increasing returns to scale in both organic and conventional production. The chi-squared statistic for a Wald test of the null hypothesis that the sum of the 5 input elasticity coefficients for conventional production are equal to one is 18.21 with 1 degree of freedom (p-value = 0.00002). We reject the hypothesis that the sum of marginal elasticity coefficients for conventional production is equal to one. The chi-squared statistic for a Wald test of the null hypothesis that the sum of the 10 input elasticity coefficients for organic production are equal to one is 8.77 with 1 degree of freedom (p-value = 0.003). We reject the hypothesis that the sum of marginal elasticity coefficients for organic production is equal to one. Increasing all inputs by 1 percent would cause a 1.33-percent increase in milk output on an organic farm, and a 1.21-percent increase in milk output on conventional farms. Previous research has found economies of scale for conventional farms in the U.S. dairy industry (Mosheim and Knox Lovell 2009; Tauer and Mishra 2006). To our knowledge, our research is the first to show that economies of scale also exist in organic dairy production. Although organic farms appear to benefit more from increasing returns to scale than conventional farms, the difference is not statistically significant. The chi-squared statistic for a Wald test of the null hypothesis that the input elasticity coefficients of conventional production are equal to the coefficients of organic production is 3.53 with 5 degrees of freedom (p-value = 0.619). We fail to reject the hypothesis that the marginal elasticity coefficients of conventional and organic production are equal. Yet the organic and conventional technologies as a whole are different. In particular, the organic technology is less productive than the conventional technology all else equal, as shown by the negative, statistically significant coefficient on the organic dummy intercept shifter.

We find that compared to the Upper Midwest, the technology used by farms in the Southeast is more productive. Farms with cows of higher weight also produce more milk. This agrees with previous research which has documented more milk production by heavier cows, especially Holsteins (White et al. 2002; Sehested, Kristensen, and Søegaard 2003; Sato et al. 2005). In terms of management practices we find that farms that tend to rent more of their land for either crop production or pasture are less productive. Intuitively, a renter does not have the same incentive as a land owner to invest in the productivity of the land. Farms that raise more of their own feed seem to be less productive. This may be an indication of decreasing returns to fixed management stock (Alvarez and Arias 2004). Operator age is associated with lower productivity. Variability in the production frontier due to technical inefficiency is approximately 1.6 times that of the variability due to the stochastic nature of milk production. Using a Wald test with a chi-square value of 11.59 and 2 degrees of freedom, we reject the null hypothesis that both variances are homoscedastic. Herd size has a statistically significant effect on the statistical and inefficiency variances. As herd size increases, statistical variance decreases while inefficiency variance increases.

To assess productivity differences between organic and conventional dairy farms we evaluate the stochastic frontiers at the means of discretionary inputs for all farms. When we allow technologies to be different, we find that the organic technology is 13 percent less productive than the technology used by conventional farms. This means that the best practice organic farms are not able to produce as much as a conventional dairy farm operating at the production frontier.

Next we estimate technical efficiency for each farm based on the estimated frontiers, and compare technical efficiency of organic and conventional dairy farms. The means and standard errors of the technical efficiencies measured under different methodological assumptions are presented in table 4. Measured against the appropriate frontier, we find that average technical efficiency is 81.73 percent on organic farms and 83.60 percent on conventional farms. A Kruskal-Wallis test suggests the difference in mean technical efficiency is not statistically significant. When we correct for self-selection but assume a homogeneous technology, we find the technical efficiency of organic farms to be 78.11 percent, which is 5 percentage points lower than for conventional farms. The difference between average technical efficiency on organic and conventional dairy farms is statistically significant at the 0.01 level, and is larger in magnitude under the homogeneous technology assumption than otherwise. Thus, a false assumption of a homogeneous technology causes a downward bias in the estimate of technical efficiency on organic farms relative to that on conventional farms. This finding echoes Stigler (1976), who argued that the measurement of inefficiency is but the lack of accounting for differences in technology between firms.

Our productivity and efficiency results suggest that observed differences between productivity of organic and conventional dairy farms are due primarily to differences in technology, with inefficiency playing a negligible role. This result differs from findings of Kumbhakar, Tsionas, and Sipilainen (2008) and Sipilainen and Oude Lansink (2005), each of whom find an important role for inefficiency.

To highlight the importance of addressing selection, we also estimate similar stochastic frontier models on the sample of all dairy farms (i.e., ignoring potential self-selection into organic). Results are presented in Mayen, Balagtas, and Alexander (2009). Input elasticities are mostly similar to those estimated on the sub-sample (table 3). But inference on productivity and inefficiency is quite different. In particular, when we ignore selection into organic we find a bigger effect of organic on productivity; the organic frontier is 16 percent less productive than the conventional frontier, compared to a 13 percent difference when we use PSM to control for selection. Moreover, when we further assume that the technology is the same, average technical efficiency is 11 percentage points lower on organic farms than on conventional farms. Again, assuming a homogeneous technology leads to an overstatement of the inefficiency of organic farms.

Conclusion

This article contributes to the literature on organic versus conventional agricultural production and efficiency in two important ways. First, we use propensity score matching (PSM) to address potential self-selection in production method. Second, we explicitly test the hypothesis that organic and conventional farms employ a single, homogeneous technology. Our application employs the 2005 ARMS data that provides for the first time comprehensive, farm-level information for a nationally representative sample of organic dairy farms in the United States. After rejecting the homogeneous technology hypothesis, we estimate separate technologies for organic and conventional farms and generate technology-appropriate measures of technical efficiency. We find that the organic dairy technology is 13 percent less productive than that used by conventional farms matched to the organic farms on farm and operator characteristics. However, we find little difference in technical efficiency across these two groups of farms when technical efficiency is measured relative to the appropriate technology.

These findings differ dramatically from inference drawn from analyses that assume homogeneous technology and/or ignore self-selection in the choice of production technology. When PSM is used to control for self-selection, but a homogeneous technology is assumed, we find organic farms are, on average, 5 percentage points less efficient than conventional farms. Thus, imposing a homogeneous technology on all farms results in a downward bias in the estimated efficiency of organic farms. When we ignore self-selection and assume homogeneous technology we find that organic farms are, on average, 11 percentage points less efficient than conventional farms. Thus, failure to correct for self-selection also results in a downward bias in the estimated efficiency of organic dairy farms.

Further, when we control for self-selection and estimate separate production frontiers for organic and (matched) conventional farms, the disparity in technical efficiency all but disappears. In this case we find mean efficiencies for organic and conventional farms statistically indistinguishable.

Given previous findings that unit costs are higher on organic farms (McBride and Greene, 2007), our finding that the organic technology is less productive suggests that profit-maximizing dairy farms will continue to require a premium over conventional milk in order to stay in the organic market. The results also suggest that public policies aimed at enhancing viability of organic farms should support innovations that increase productivity of the organic technology, for example, R&D to increase the productivity of dairy technology given the organic standards. There is also room to increase efficiency of organic farms, but inefficiency does not appear to be a disadvantage for organic farms relative to conventional farms.

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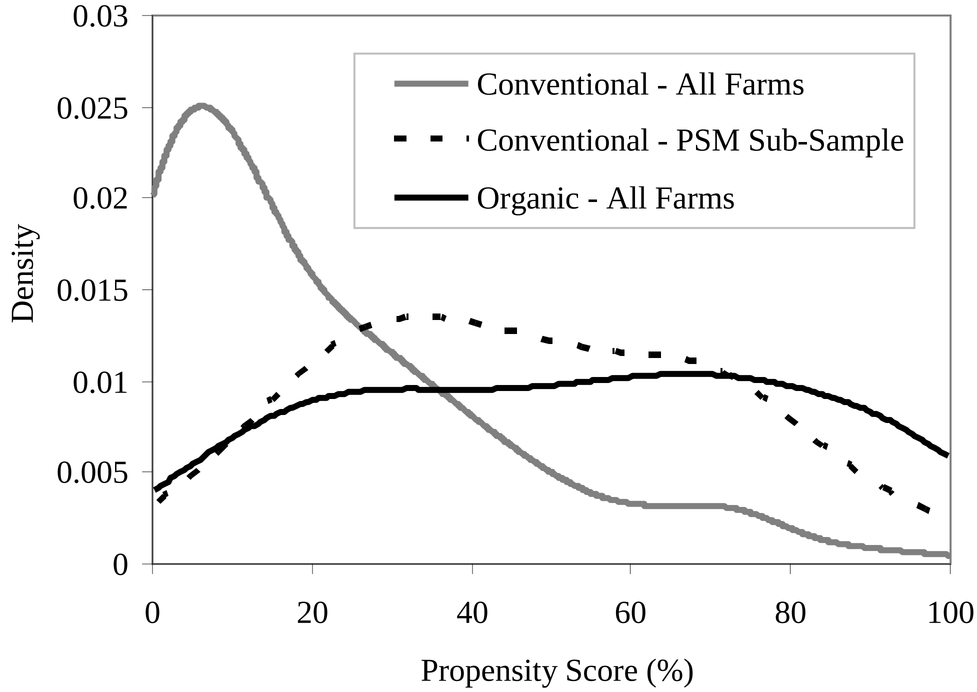

Figure 1. Kernel densities for propensity scores by production system

Table 1. Description, Units and Statistics for Variables Included in the Study

	Organic (N=288)		Conventional (N=1,194)		Matched Conventional[a] (N=137)	
<u>Inputs and Output per Cow</u>	Mean	*SE*	Mean	*SE*	Mean	*SE*
Herd Size (Cows)	81.1	*12.7*	140.1	*8.7*	65.3	*5.6*
Milk Production (Lbs/Year)	12,333	*225*	17,076	*153****	14,816	*422****
Feed (Lbs/Year)	11,457	*414*	15,169	*242***	14,144	*633***
Labor (Hrs/Year)	93.9	*3.2*	81.1	*1.5*	102.5	*4.5*
Capital Costs ($/Year)	305	*8*	300	*3*	297	*8*
Other Inputs ($/Year)	428	*20*	578	*11**	500	*23*
Pasture Acres (Acres)	1.62	*0.07*	0.61	*0.03***	1.22	*0.12*
<u>Operator and Farm Characteristics</u>						
Upper Midwest (1/0)	0.44	*0.03*	0.41	*0.01***	0.44	*0.04*
East (1/0)	0.41	*0.03*	0.27	*0.01***	0.40	*0.04*
Cornbelt (1/0)	0.09	*0.02*	0.15	*0.01***	0.05	*0.02***
West (1/0)	0.06	*0.01*	0.11	*0.01***	0.06	*0.02*
Southwest (1/0)	0	*0*	0.02	*0.01***	0.01	*0.01**
Southeast (1/0)	0	*0*	0.06	*0.01***	0.04	*0.02***
Parlor (1/0)	0.40	*0.03*	0.49	*0.01***	0.19	*0.03***
Automatic Takeoffs (1/0)	0.23	*0.02*	0.37	*0.01***	0.19	*0.03*
Years in Dairy Production	20.8	*0.7*	23.4	*0.4*	25.0	*1.1*
Years in Organic Production	5.1	*0.2*	0	*0*	0	*0*
Cow Weight (Lbs)	1,177	*11*	1,295	*6****	1,239	*16**
Pasture Based (1/0)	0.88	*0.02*	0.30	*0.01***	0.44	*0.04***
Age (Years)	48.4	*0.6*	51.2	*0.3*	52.1	*0.9*
Years in Industry	23.0	*0.7*	25.9	*0.4*	28.0	*1.0*
College Education (1/0)	0.19	*0.02*	0.16	*0.01***	0.12	*0.03***
Off-Farm Work (Hrs/Year)	130	*28*	143	*14*	134	*32*
Planning Horizon (1/0)	0.66	*0.03*	0.48	*0.01***	0.46	*0.04***
<u>Management practices</u>						
Use of rbST (%)	0	*0*	8.0	*0.6**	2.0	*1.0*
Veterinary (1/0)	0.39	*0.03*	0.70	*0.01***	0.41	*0.04***
Nutritionist (1/0)	0.45	*0.03*	0.73	*0.01***	0.51	*0.04***
DHIA Participation (1/0)	0.48	*0.03*	0.47	*0.01*	0.29	*0.04***
Seasonal Dry-off (1/0)	0.12	*0.02*	0.21	*0.01***	0.26	*0.04***
Farm Raised Herd (%)	96.7	*0.9*	92.7	*0.7*	92.9	*1.9*
Farm Raised Feed (%)	68.1	*1.7*	66.1	*0.8*	70.3	*2.2*
Rented Land (%)	33.1	*1.9*	30.3	*0.9*	31.7	*2.3*

[a] The sub-sample of conventional farms matched to organic farms on the basis of the estimated likelihood, or propensity, to produce organic milk. Note: Asterisks denote a statistically significant difference with the organic mean at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.

Table 2. Probit Estimates of the Propensity to Produce Organic Milk

	Coefficient	*S.E.*
Constant	13.146	*2.419****
East	0.231	*0.117***
West	0.459	*0.172****
Cornbelt	–0.499	*0.165****
Pasture Acres per Cow	0.345	*0.044****
Cows	–0.371	*0.079****
Farm Raised Feed	0.128	*0.052***
Rented Land	0.073	*0.031***
Cow Weight	–1.407	*0.292****
Parlor	–0.419	*0.132****
Automatic Takeoffs	–0.025	*0.131*
Years in Dairy Production	0.063	*0.127*
DHIA Participation	0.272	*0.109***
Veterinary Services	–0.524	*0.111****
Nutritionist	–0.458	*0.117****
Seasonal Dry-off	–0.939	*0.139****
Age	–0.753	*0.339***
Planning Horizon	0.493	*0.109****
College Education	0.129	*0.126*
McFadden Pseudo R - Squared		0.419
Conventional Dairy Farms Correctly Predicted		96 %
Organic Dairy Farms Correctly Predicted		57 %

Note: Asterisks denote statistical significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.

Table 3. Stochastic Production Frontier Estimates, PSM Sub-Sample[a]

	Same Technology		Different Technology	
Technology Model	Coefficient	*S.E.*	Coefficient	*S.E.*
Constant	4.463	*0.992****	4.699	*1.031****
Cows	0.893	*0.065****	0.946	*0.072****
Feed	0.153	*0.035****	0.136	*0.038****
Labor	0.027	*0.033*	0.025	*0.036*
Capital Costs	–0.008	*0.060*	–0.013	*0.063*
Other Inputs	0.124	*0.022****	0.115	*0.023****
Organic			–1.969	*1.162**
Organic x Cows			–0.119	*0.151*
Organic x Feed			0.010	*0.078*
Organic x Labor			0.044	*0.087*
Organic x Capital Costs			0.158	*0.126*
Organic x Other Inputs			0.028	*0.075*
West	0.025	*0.070*	0.022	*0.071*
Southwest	0.229	*0.190*	0.204	*0.192*
Southeast	0.399	*0.093****	0.391	*0.099****
Cornbelt	–0.057	*0.059*	–0.062	*0.060*
East	0.059	*0.035**	0.053	*0.037*
Use of rbST	0.023	*0.025*	0.024	*0.026*
Cow Weight	0.597	*0.095****	0.586	*0.099****
Parlor	–0.013	*0.048*	–0.019	*0.049*
Years in Dairy Production	0.041	*0.047*	0.036	*0.049*
Pasture Based	0.023	*0.032*	0.043	*0.034*
Farm Raised Herd	0.020	*0.037*	0.017	*0.035*
Farm Raised Feed	–0.067	*0.027***	–0.067	*0.027***
Rented Land	–0.043	*0.009****	–0.041	*0.009****
College Education	–0.016	*0.047*	–0.018	*0.047*
Years in Industry	0.163	*0.166*	0.199	*0.168*
Years in Industry Squared	–0.034	*0.029*	–0.041	*0.029*
Age	–0.518	*0.121****	–0.518	*0.121****
Off-Farm Work	0.026	*0.008****	0.026	*0.008****
Variance of *v*				
Intercept	–0.936	*0.746*	–1.009	*0.753*
Cows	–0.623	*0.206****	–0.603	*0.215****
Variance of *u*				
Intercept	–5.311	*1.710****	–5.998	*1.997****
Cows	0.633	*0.364**	0.784	*0.425**
Log Likelihood	0.808		5.459	

Note: Asterisks denote statistical significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels. [a] The PSM sub-sample comprises all organic farms and matched conventional farms.

Table 4. Means and Standard Deviations of Technical Efficiency

	Organic		Conventional		Difference
	Mean	SE	Mean	SE	in Means
PSM Sub-Sample					
Different Technology	81.73	*6.25*	83.60	*6.70*	–1.87
Same Technology	78.11	*6.48*	83.20	*6.62*	–5.09***
All Farms					
Different Technology	77.06	*7.53*	79.42	*3.25*	–2.36***
Same Technology	68.41	*8.13*	79.45	*3.23*	–11.04***

Note: Asterisks denote statistical significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.

Footnotes

[1] Estimation of a translog production frontier is complicated by strong multicollinearity between inputs and interaction terms.

[2] The original data set has nine dairy farms that produce both organic and conventional milk. We are not able to identify the quantity of inputs allocated to each type of production. Thus we drop these farms from our analysis.

[3] We normalize input use by dividing input quantities by the average number of milked cows (not including average amount of dried off cows).

[4] The null hypothesis of the standard Durbin-Wu-Hausman test is that OLS is consistent; rejection of the null is typically used as justification for instrumental variables (Davidson and Mackinnon, 1993). We estimate the frontier not by OLS but by maximum likelihood. Also, we do not adopt the instrumental variables approach, but rather we interpret rejection of the null hypothesis as evidence that organic is endogenous.

[5] We also conduct our analyses on a sub-sample of farms created by choosing the two nearest conventional farms. The resulting sub-sample of matched conventional farms is larger (203 farms as opposed to 137 farms), however inference on differences in productivity and technical efficiency are qualitatively and quantitatively similar.