FIRM-LEVEL DETERMINANTS OF PRODUCT CONVERSION: ORGANIC MILK PRODUCTION

Tristan D. Skolrud

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Tristan D. Skolrud*

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Abstract

We investigate the role of technology in the decision of dairy farmers to convert to organic production methods. Using data from the U.S. Department of Agriculture’s Agricultural Resource Management Survey, we estimate an input distance function using stochastic frontier analysis to measure several characteristics of the production technology, including technical efficiency, returns to scale, and elasticities of substitution. We use a new functional form that allows for a global approximation to the unknown distance function without comprising approximation at the data boundaries. Using a linear random utility model, we then estimate the impact of these characteristics on the probability of converting from conventional to organic milk production between 2005 and 2010. Conventional dairies with lower technical efficiency, higher returns to scale, and those with the ability to easily substitute between key inputs have considerably higher likelihood of converting to organic production. Empirical findings suggest that the removal of sources of diseconomies of scale and subsidization of substitutes for restricted inputs may incentivize organic adoption. Furthermore, this research suggests further consolidation in the conventional industry as the low-end firms exit for the organic industry. This study contributes to the literature by identifying a new set of factors that play a major role in organic conversion.

Keywords: Organic, stochastic frontier analysis, dairy, technology adoption

* Tristan Skolrud is a Ph.D. Research Assistant, School of Economic Sciences, Washington State University.

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1. Introduction

Over the past fifteen years, the demand for organic food has risen substantially in the United States. Organic milk products have been a large component of this shift in demand, representing approximately four percent of total milk products consumed in the U.S. in 2013 and fifteen percent of total organic food sales (USDA 2014a, 2014b). To accommodate this demand shift, some conventional dairies are choosing to go through the lengthy organic conversion process which allows them to sell USDA certified organic milk. The response has been swift; total organic milk cows have increased from 38,196 in 2000 to 254,771 in 2011, representing over a five-hundred percent increase in just eleven years (USDA 2013). But what motivates conventional dairies to convert? In this paper, we argue that technological characteristics of production play an important role in the decision of conventional farms to convert to organic practices.

Several studies have examined the factors that induce conventional farms to transition to organic production. Two consider the role of technical efficiency in conversion (Kumbhakar, Tsionas and Sipiläinen 2009; Latruffe and Nauges 2014). Kallas et al. (2010) summarize demographic and farm-level attributes that previous studies have shown to be important, such as education, age, opinions and perceptions of the environment, and social contact. While these factors have been found to be economically and statistically significant, prior literature has neglected examination of several other factors that economic theory and the nature of the organic certification requirements suggest may be important. Another limitation in the existing literature concerns the strong emphasis on European agriculture. The difficulty arises due to differences in organic standards between the U.S. and the European Union (Rosati and Aumaitre 2004), which raises questions about the legitimacy of extrapolating results derived from European data to the U.S. The final significant limitation in the organic conversion literature is a lack of studies specific to the dairy industry, which has a very different set of certification requirements compared to field
crops, again raising the issue of whether non-dairy results can be extended to milk production. In this analysis, we address the limitations of the current literature with the goal of providing a more complete view of technological reasons why some conventional dairies are converting to organic in the U.S. and others are not.

We specifically address the role of technical efficiency, returns to scale, output diversification, and elasticities of substitution between key input combinations as potential drivers of conversion to organic milk production. The focus on technical efficiency and returns to scale is warranted by current trends in the U.S. conventional dairy sector, where research has documented the existence of non-decreasing returns to scale across nearly all firm sizes (Melhim and Shumway 2011) and the significance of returns to scale in driving industry consolidation (Mosheim and Lovell 2009). We hypothesize that less technically efficient firms operating with higher returns to scale have a higher likelihood of converting to organic production in an attempt to remain profitable since they are unable to compete with larger, more efficient farms. We also hypothesize that firms that can easily substitute between key inputs find it easier to satisfy the organic conversion requirements, which increases the probability of organic adoption.

To test these hypotheses, we employ a two-step estimation procedure using data from the 2005 and 2010 U.S. Department of Agriculture’s Agricultural Resource Management Survey (ARMS). This survey collects cost and input usage data from a large, stratified random sample of farms in the U.S. In the first step, we estimate a multi-output input distance function to simultaneously estimate firm-level technical efficiency, returns to scale, and direct elasticities of substitution. In the second step, we estimate a linear random utility model to assess the impact of the estimated technical characteristics on the probability that a conventional farm converts to organic production. We also control for operator characteristics that have previously been identified in the literature associated with organic adoption.
This paper is also the first to employ the new Box-Cox Fourier functional form for a multi-output input distance function. Previous researchers seeking a more robust functional form than the translog for stochastic frontier analysis utilized the Fourier-flexible form of Gallant (1981), which allows for a global approximation to an unknown data generating process. However, due to approximation problems at the tails of the data, authors resorted to data truncation, introducing a source of bias into their results (Berger and Mester 1997). The Box-Cox Fourier functional form retains the robustness of the original Fourier-flexible form without the associated boundary approximation errors (Skolrud 2015).

Empirical results demonstrate the economic and statistical significance of technical efficiency, returns to scale, and several elasticities of substitution in determining organic conversion. The direction of the effects conforms to the initial hypotheses. Specifically, technically inefficient firms with higher returns to scale and higher elasticities of substitution between feed and land, capital and land, feed and labor, and medicine and labor are more likely to convert. Our results suggest that the organic dairy industry may experience continued difficulty in providing enough organic milk to meet rising consumer demand due to the presence of less-efficient firms that have failed to reach the scale necessary to remain competitive in the conventional dairy industry. If agricultural policymakers intend to incentivize adoption, our results imply that the subsidization of close substitutes for inputs restricted by organic regulations and the removal of sources of diseconomies of scale through the relaxation of land and feed requirements may be effective incentives.

2. Firm-level motivation

Consider the case of a conventional dairy employing a vector of inputs $z_i^c$ in the production of milk $y_i^c$ in accordance with the production function $y_i^c = f(z_i^c, \Gamma_i)$, where $\Gamma_i$ is a vector of firm-specific production characteristics (e.g. elasticities of substitution between inputs, returns to scale,
technical efficiency). The subscript \( i \) emphasizes variables that are firm-specific and the superscript \( c \) designates the variable’s association with conventional production. Assuming perfectly competitive input and output markets, profit for a conventional firm is given by \( \pi_i = p^c f(z_i^c, \Gamma_i) - w^c z_i^c \), where \( p^c \) is the price of conventional milk paid to producers and \( w^c \) is a vector of input prices corresponding to inputs \( z_i^c \).

If transitioning to organic production, a conventional producer faces a new set of output and input prices \( p^o \) and \( w^o \) (the \( o \) superscript associates the variable with organic production) in addition to the one-time payment of a fixed transition cost, \( F_i \). Assuming perfectly competitive markets in the organic industry, profit can be represented as \( \pi_i^o = p^o f(z_i^o, \Gamma_i) - w^o z_i^o - F_i \).

Conversion from conventional to organic occurs when

\[
(1) \quad U(\pi_i^o, \beta_i) \geq U(\pi_i^c, \beta_i),
\]

where \( U(\pi_i^j, \beta_i) \) represents the utility to the producer from choosing option \( j = c, o \), and operator-specific factors are contained in vector \( \beta_i \) and include characteristics such as age, education, animal-welfare concerns, attitude towards risk, etc. For a list of operator characteristics previously found to be associated with conversion to organic production, see Table 2 of Kallas et al. (2010).

We model the conversion decision as a function of the difference in utilities to be consistent with the majority of organic adoption literature which suggests that factors beyond pure profit incentives have a strong influence on adoption.

In this study, we are most interested in the role played by \( \Gamma_i \), the vector of production characteristics. In the conversion to organic production practices, input quantity choices will be affected by three issues: (1) higher input prices, (2) input scarcity, and (3) organic regulations restricting input usage. When conversion occurs, \( \Gamma_i \) dictates how production is impacted, which

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1 Boldface type indicates vectors throughout.
directly impacts the potential for organic profitability. These factors are firm-specific, resulting in a heterogeneous mixture of firms that convert and is not simply based on the size of the organic price premium \( p^o - p^c \) and fixed costs \( F_j \). By assessing the direct impact of \( \Gamma_i \) on conversion, controlling for \( \beta_i \), we can better understand the association between variations in conventional production technology and the propensity for organic conversion.

3. Production-specific conversion factors

In this section, we outline specific components of the estimated production characteristics contained in the vector \( \Gamma_i \), only one of which has been considered in previous literature (technical efficiency). The idea of including measures of substitutability between inputs and returns to scale as conversion factors is an innovation of this study, and we highlight the reasoning behind their inclusion below.

3.1 Technical efficiency

Of the two studies that have focused on the role of the production technology, both (Kumbhakar, Tsionas, and Sipiläinen, 2009; Latruffe and Nauges, 2014) have highlighted the impact of technical efficiency as a potential conversion factor. \(^2\) Latruffe and Nauges (2014) find evidence of a positive relationship between conversion and technical efficiency for large firms, but the opposite is true for small firms. Using a sample of Finnish dairy farms, Kumbhakar et al. (2009) find that technically inefficient firms are less likely to adopt organic technology. The authors reason that the subsidy available to converting firms is large enough to attract the most efficient conventional operators. We hypothesize that in the U.S., where the organic subsidy is less than four percent of

\(^2\) While many studies have analyzed the technical efficiency of organic and conventional agriculture (Mayen, Balagtas, and Alexander 2010), only the two cited studies have investigated the role of technical efficiency as a conversion factor.
the total transition cost for the average-sized firm, technically inefficient firms will be more likely to adopt organic practices in an attempt to remain profitable. Viewing conversion as an “exit” from the conventional industry followed by entrance into the organic industry, this is consistent with research empirically linking technical inefficiency with a significantly higher probability of industry exit (Tsionas and Papadogonas 2006).

3.2 Returns to scale

The majority of empirical studies examining returns to scale in the conventional dairy industry demonstrate the predominance of non-decreasing returns to scale and its role in increasing average farm size. In their study using ARMS firm-level data, Mosheim and Lovell (2009) show that increasing returns to scale exist over all firm sizes in the survey. Using their preferred specification, the authors estimate an average long-run scale elasticity of 2.06 after accounting for both technical and allocative inefficiency in their parameter estimates. Even for large firms with herd sizes of at least 2,000, the long-run scale elasticity is still 1.25, indicating that average costs can still be diminished by increasing scale. The relationship between marginal and average costs imply that returns to scale decline with size, but for now, it is clear that in the conventional dairy industry, bigger is better.

However, research indicates that the production technology employed by conventional U.S. dairy farms is fundamentally different than that of organic dairies (Mayen, Balagtas, and Alexander 2010). U.S. organic milk certification (USDA National Organic Program (NOP) 2014) requires that animals have access to certified organic pasture for at least 120 days a year, be fed

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3 The National Organic Program only allows for partial recuperation of conversion costs, amounting to less than $1,000 per farm (USDA AMS 2014). For the average conventional dairy in our sample producing approximately 34 thousand cwt per year, and using an estimated $0.84/cwt transition cost (McBride and Greene 2009), this subsidy amounts to just three percent of the total economic cost of transition.
100% organic feed, and be allowed free access to the outdoors for the entire year. Each of these requirements has the potential to substantially reduce economies of scale. For example, organic certification dramatically increases the required land in comparison to conventional dairy operations which is a disincentive to large scale, especially in areas where land prices are high. Further, in an analysis of 2005 ARMS data, McBride and Greene (2009) find that for the largest organic dairies, those with herd sizes of 200 or more, sourcing organic feed was reported as the most significant difficulty of organic farming. This has the potential to act as a major conversion deterrent for larger conventional dairies, which are more likely than smaller dairies to rely on commercial feed rather than pasture for forage (McBride and Greene 2009).

The organic regulations could result in a more traditionally U-shaped average cost curve, where expanding beyond a certain scale begins to increase average costs. If this is in fact the case, smaller conventional dairy farms (i.e., with higher returns to scale) may be incentivized to transition to organic, where the optimal scale may be much smaller. Thus, we hypothesize a positive relationship between the propensity to convert and returns to scale.

3.3 Elasticities of substitution

When faced with NOP restrictions regarding input use, a farm’s inability to substitute non-restricted or relatively lower priced inputs could play a significant role in determining how output and profit will be affected. All else equal, a farm that can more easily substitute away from a restricted input will experience a comparatively smaller impact on total output as a result of the restriction. In the case of the NOP, restrictions limit three important input categories: (1) medical and veterinary services, (2) physical capital, and (3) feed.

The goal of NOP restrictions governing the use of medicine and veterinary services is to
emphasize the role of preventative care. This means that antibiotics and most synthetic drugs are not allowed, and that no drugs can be administered in the absence of illness.\footnote{For complete details on NOP restrictions and a full listing of exceptions, refer to Title 7 of the Code of Federal Regulations (CFR), Part 205.} To accommodate these restrictions, organic farms can employ more labor to monitor herd health and more capital to allow for structural improvements associated with better health outcomes (e.g. clean bedding, more shade structures, barns allowing for more movement and ventilation).

The NOP also requires significant capital improvements, many of which are aimed at improving herd health. For example, organic dairies must provide “year round access for all animals to the outdoors, shade, shelter, exercise areas, fresh air, clean water for drinking, and direct sunlight…” (NOP §205.239, 2006).

While any of these restrictions can be difficult to implement, perhaps none are as difficult as the requirement of using 100% organic feed. With very few exceptions, all feed must come from organic operations that are NOP-certified.

With these specific input requirements in mind, we suspect that a farm’s ability to substitute away from medicine, capital, and commercial feed can mitigate the impact of the restrictions on potential output and thus be associated with the propensity to convert to organic production. Labor and capital can partially substitute for medicinal and veterinary inputs, and land for pasture can substitute for commercial feed (McBride and Greene 2009). Thus, we include all elasticities of substitution between labor, capital, land, and medicine as components of the $\Gamma_i$ vector in the adoption decision model.

3.4 Additional production factors

In addition to the estimated production characteristics discussed above, we include several non-estimated firm characteristics as components of $\Gamma_i$. They include herd size, an indicator variable
for the type of manure distribution system employed (pasture or non-pasture), an indicator variable for the use of artificial insemination (AI), a measure of output diversification (dairy sales divided by total sales), a measure of risk aversion (purchased insurance divided by total value of production), and an indicator variable for the use of pasture for grazing. These variables have either been identified in the literature as determinants of adoption, i.e., herd size, pasture (Mayen, Balagtas, and Alexander 2010), and risk aversion (Kallas, Serra, and Gil 2010), or they are expected to be associated with NOP restrictions. For example, use of AI has been found to be more important for organically managed herds (Reksen, Tverdal, and Ropstad 1999), so we hypothesize that conventional firms already employing AI may be more likely to transition to organic management. Also, we include output diversification as a measure of the ease with which additional land may be converted to organic crop production for use as feed.

4. Methodology

To identify the impact of production characteristics on the organic adoption decision, we proceed in two steps. Using data from a sample of conventional firms in 2005, we estimate an input distance function using stochastic frontier analysis in the first step. This allows us to estimate firm-level production characteristics hypothesized by our theoretical model to have an impact on the adoption decision. In the second step, we use these estimates along with the additional farm and operator characteristics in a random-utility model to assess the importance of these factors in driving organic adoption between 2005 and 2010.

4.1 Input distance function

In previous studies comparing the efficiency of conventional and organic dairies (Mayen, Balagtas, and Alexander 2010; Oude Lansink, Pietola, and Bäckman 2002), technical efficiency estimates
are obtained from estimating stochastic production frontiers, which are only suitable for single-output technologies. However, dairies often produce multiple outputs, suggesting that estimating a stochastic production frontier may be inappropriate. Instead, we estimate an input distance function which allows the specification of multiple outputs. Assuming $M$ outputs and $N$ inputs, the input distance function is specified as

$$d_i = d(z_{i1}, z_{i2}, \ldots, z_{Ni}, y_{i1}, y_{i2}, \ldots, y_{Mi}),$$

where $z_{ni}$ is the $i$th firm’s use of input $n$ and $y_{mi}$ is the $i$th firm’s production of output $m$. Defining $z_i$ and $y_i$ as the respective sets of input and output vectors for firm $i$, the input distance function $d$ is defined as

$$d(z_i, y_i) = \max\{\rho : (z_i, \rho) \in L(y_i)\},$$

where $L(y_i)$ represents the set of input vectors that can produce output vector $y_i$, and $\rho \geq 1$ is a scalar defining the maximal contraction factor of inputs such that the desired output vector $y_i$ can still be produced. The input distance function has several important properties, notably that it is non-decreasing, linearly homogenous and concave in inputs and non-increasing and quasi-concave in outputs (Coelli et al. 2005).

### 4.2 Functional form

To increase the robustness of our first-stage estimation to problems associated with functional form misspecification, we utilize the Box-Cox Fourier (BCF) functional form of Skolrud (2015). In stochastic frontier analysis, the original Fourier-flexible form as proposed by Gallant (1981) has often been used as a more robust alternative to the popular translog functional form (Berger and Mester 1997; Fenn et al. 2008; Berger and DeYoung 1997). However, as noted by Berger and Mester (1997), this form, which we refer to as the translog Fourier flexible form (TLF) due to the
nesting of the translog, has significant approximation problems at the lower and upper tails of the data. Berger and Mester (1997) address this problem by simply removing the smallest 10% and largest 10% of observations from their sample. This approach is infeasible in our study due to the higher percent of smaller conventional firms that convert to organic. In fact, were we to employ this approach, our second-stage sample size would be reduced by over 30%. To circumvent this problem, we employ a version of the BCF functional form which has been shown to ensure the robustness of the Fourier-flexible form with good approximation properties at the boundaries of the data (Skolrud, 2015).

The BCF functional form is composed of a truncated Fourier-series appended to a second-order expansion in Box-Cox polynomials:

\[
\ln d_i = a_0 + b'x_i^{(4)} + \frac{1}{2} x_i^{(2)} C x_i^{(2)} + \sum_{\alpha=1}^{4}(u_{0\alpha} + [u_{\alpha} \cos(k_\alpha' x_i) + v_\alpha \sin(k_\alpha' x_i)])
\]

where \(x_i\) is a vector of explanatory variables \(x_i \equiv [z_i, y_i]\) for firm \(i\), scaled to fit in an interval of 0 to \(2\pi\), \(\theta \equiv \{a_0, b', C, (u_{0\alpha}, u_{\alpha}, v_{\alpha})_{\alpha=1}^{4}\}\) is the set of parameters to be estimated (with dimensionality depending on the order of approximation), \(k_\alpha\) is an integer-valued set of vectors that determines the order of approximation, and \(x_i^{(4)}\), is a Box-Cox transformation, defined as \(x_i^{(4)} = (x_i^\lambda - 1)/\lambda\).\(^6\)

Note that as \(\lambda \rightarrow 0\), \(x_i^{(2)}\) becomes \(\ln(x_i)\) and the function in equation (4) becomes the original Fourier-flexible form of Gallant (1981). Employing the rule suggested by Eastwood and Gallant (1991), which sets the number of parameters equal to the sample size raised to the two-thirds power, we estimate a second-order Fourier series approximation, implying that \(A = 15\). The \(k_\alpha\) vectors associated with this level of approximation are shown in Appendix A.1, along with more details relevant to the appropriate construction of multi-indices. For the sake of brevity, we refer

\(^6\) Scaling data to an interval \([0, 2\pi]\) is a requirement for orthogonality to be satisfied in the truncated Fourier series.
to (4) as $\ln d_i = BCF(\mathbf{x}_i, \theta, \lambda)$.

Linear homogeneity in inputs requires that $d_i(\omega_i \mathbf{z}_i, \mathbf{y}_i) = \omega_i d_i(\mathbf{z}_i, \mathbf{y}_i)$, for any $\omega_i > 0$. Arbitrarily choosing the $N$th input $z_{Ni}$, such that $\omega_i = 1/z_{Ni}$, allows us to write $d_i(z_i / z_{Ni}, \mathbf{y}_i) = d_i(\mathbf{z}_i, \mathbf{y}_i) / z_{Ni}$, as suggested in Coelli and Perelman (1999). Applying this restriction to our functional form gives $\ln(d_i / z_{Ni}) = BCF(\mathbf{x}_i, \theta, \lambda)$, where $\mathbf{x}_i$ is the set of normalized inputs and outputs, $\mathbf{x}_i = [z_i / z_{Ni}, \mathbf{y}_i]$. Rearranging this expression and adding a stochastic term to account for statistical variation, provides an estimable form of the input distance function,

$$(5) \quad -\ln(z_{Ni}) = BCF(\mathbf{x}_i, \theta, \lambda) + v_i - u_i,$$

where $u_i \equiv \ln d_i \geq 0$ is a term associated with the unobservable input distance, from which we can obtain estimates of firm-level technical efficiency. Equation (5) is expressed in a form suitable for estimation via stochastic frontier analysis. The inclusion of two error terms prevents unbiased estimation by ordinary least squares (OLS). Multiple estimation methods have been suggested; corrected OLS (COLS), maximum likelihood, and method of moments. In general, maximum likelihood is preferred to COLS for its desirable asymptotic properties (Coelli et al. 2005). Results from a Monte Carlo experiment by (Olson, Schmidt, and Waldman, 1980) suggest that maximum likelihood is preferred to method of moments in terms of mean-squared error for sample sizes greater than 400. As our sample of conventional dairy farms greatly exceeds that threshold, we choose maximum likelihood estimation.

We impose standard assumptions (Mayen, Balagtas, and Alexander, 2010) on the stochastic components of (5), namely that $E(v_i) = 0$, $E(v_jv_i) = 0$ for all $i$ and $j$, where $i \neq j$, $E(v^2_i) = \sigma_v^2$, $E(u_i) > 0$, $E(u_iu_j) = 0$ for all $i \neq j$, and $E(u^2_i) = \sigma_u^2$. Due to our maximum likelihood approach we also have to make distributional assumptions on the error terms. Again, we follow standard
practice and assume that the two-sided statistical noise term follows the normal distribution, \( v_i \sim N(0, \sigma_v^2) \), and that the stochastic component associated with technical efficiency follows the half-normal distribution, \( u_i \sim N^+(0, \sigma_u^2) \). Re-parameterizing the model with \( \sigma^2 = \sigma_v^2 + \sigma_u^2 \) and \( \gamma^2 = \sigma_u^2 / \sigma_v^2 \) yields the following log-likelihood function:

\[
\text{ln } L(\theta, \lambda, \sigma^2, \gamma \mid \bar{x}) = -\frac{I}{2} \ln \left( \frac{\pi \sigma^2}{2} \right) + \sum_{i=1}^{I} \ln \Phi \left( -\frac{\varepsilon_i \gamma}{\sigma} \right) - \frac{1}{2\sigma^2} \sum_{i=1}^{I} \varepsilon_i^2,
\]

where \( \Phi \) is the cumulative distribution function for a standard normal random variable, \( I \) is the sample size, and \( \varepsilon_i = v_i + u_i - \ln(z_{Ni}) - BCF(\bar{x}_i, \theta, \lambda) \). Parameter estimates are obtained through a three-step estimation process which we now describe.

### 4.3 Estimation

To obtain the maximum likelihood estimates of the parameters in (6), \( \lambda, \sigma^2, \gamma, \) and \( \theta \), we adapt the three-step process of stochastic frontier estimation introduced by Coelli (1995). In the first step, we obtain parameter starting values by estimating equation (5) under the assumption of complete technical efficiency, \( u_i = 0 \) for all \( i \), which result from the maximization of the following log-likelihood function:

\[
\text{ln } L'(\theta, \lambda, \sigma^2 \mid \bar{x}) = -\frac{I}{2} \ln \left( \frac{\pi \sigma^2}{2} \right) - \frac{1}{2\sigma^2} \sum_{i=1}^{I} (-\ln(z_{Ni}) - BCF(\bar{x}_i, \theta, \lambda))^2 - \sum_{i=1}^{I} \ln(z_{Ni}).
\]

The particular form of \( \text{ln } L'(\theta, \lambda, \sigma^2 \mid \bar{x}) \) is derived from the normality assumption of the statistical noise component \( v_i \), adjusted by the absolute value of the Jacobian of the nonlinear transformation of the dependent variable. We can analytically solve for their optimal estimators of \( \theta \) and \( \sigma^2 \) (which assume their typical OLS form) as functions of unknown \( \lambda : \theta(\lambda) \) and \( \hat{\sigma}^2(\lambda) \). Substituting these estimators into (7) yields the concentrated log-likelihood function \( \text{ln } L'(\lambda \mid \bar{x}_i) \) which is only

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a function of one unknown parameter, $\lambda$:

$$
\ln L'(\lambda \mid \bar{x}) = -\frac{I}{2} \ln(2\pi) - \ln(I) + 1 - \sum_{i=1}^{I} \ln(z_{Ni})
$$

$$
-\frac{I}{2} \ln \sum_{i=1}^{I} (-\ln(z_{Ni}) - BCF(\bar{x}, \theta(\lambda), \hat{\lambda}))^2.
$$

We use the interior-point algorithm in MATLAB R2011a to solve for the value of $\hat{\lambda}$ that minimizes (8). The optimal value, which we denote by $\hat{\lambda}$, determines the functional form of the input distance function and remains unchanged throughout the remainder of the estimation.

In the second stage, parameter estimates $\theta(\hat{\lambda})$ and $\hat{\lambda}$ are substituted into the log-likelihood function in (6) and we perform a grid-search for $\gamma$ over its parameter space $[0,1]$. Note that from our definition of $\gamma$, a value of $\gamma = 0$ indicates that no technical efficiency effects are present and that all deviations are due to statistical variation (Coelli et al. 2005).

In the third and final stage, $\theta(\hat{\lambda})$ and the value of $\gamma$ selected from the grid-search are used as starting values in the nonlinear optimization of (6). This produces the final maximum-likelihood parameter estimates.

### 4.4 Production characteristics

For our model of organic adoption, we require firm-level estimates of technical efficiency, returns to scale, and elasticities of substitution. Each estimated production characteristic is a function of input and output data and the maximum likelihood parameter estimates obtained from the previous section. An input-oriented measure of technical efficiency is defined by Coelli et al. (2005) as $TE_i = \exp(-u_i)$. To obtain estimates $TE_i$, we require estimates of $u_i$, which are obtained through its half-normal probability density function conditional on data and maximum-likelihood parameter estimates.

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Footnote: During the grid search for $\gamma$, the intercept and $\sigma^2$ are updated in accordance with the corrected ordinary least squares formulas in Coelli (1995).
parameter estimates, \( p(u_i \mid \bar{x}_i, \theta, \hat{\sigma}^2, \hat{\lambda}) \). Battese and Coelli (1988), demonstrate that a mean-square error minimizing predictor of firm-level technical efficiency derived from \( p(u_i \mid \bar{x}_i, \theta, \hat{\sigma}^2, \hat{\lambda}) \) is given by:

\[
TE_i = E\{\exp(-u_i) \mid X_i, \theta, \hat{\sigma}^2, \hat{\lambda}\} = \left[ \Phi\left( \frac{u_i^*}{\sigma_*} \right) / \Phi\left( \frac{\mu_i^*}{\sigma_*} \right) \right] \exp\left( \frac{\sigma_*^2}{2} - u_i^* \right),
\]

where \( u_i^* = -\varepsilon_i \sigma^2_u / \sigma^2, \sigma_* = \sigma^2_u \sigma^2 / \sigma^2, \) and \( 0 \leq TE_i \leq 1 \), with \( TE_i = 1 \) indicating no technical inefficiency, and \( TE_i = 0 \) indicating that the firm is completely inefficient.

To estimate returns to scale, we employ the commonly used elasticity of scale measure, which is the summation of output elasticities across all \( N \) inputs:

\[
RTS_i = \sum_{j=1}^{N} \frac{\partial y_{ij}}{\partial z_{ij}} \frac{z_{ij}}{y_{ij}},
\]

where \( y_{ij} \) represents the fluid milk output of farm \( i \). Note that this measure is product specific, meaning that all other outputs \( y_{-1,i} \) are held constant. This formulation (or the equivalent dual version) is commonly used in the technical efficiency literature (Coelli and Perelman 1999; Coelli et al. 2005; Fenn et al. 2008). Returns to scale are decreasing, constant, or increasing for \( RTS_i \) values less than, equal to, or greater than one, respectively.

Of the numerous elasticities of substitution available to applied researchers (see Stern (2011) for a summary), we choose a measure best suited to use in a multi-output input distance function, the symmetric elasticity of complementarity proposed by Stern (2010). Defining \( D_k \) as the first-partial derivative with respect to input \( k, k = 1, \ldots, N \), we define the elasticity of substitution for firm \( i \) of good \( k \) for good \( l \) as:

\[
EOS_{kl,i} = \left. \frac{\partial \ln(D_k(\bar{x}_i) / D_l(\bar{x}_i))}{\partial \ln(z_{il} / z_{kl})} \right|_D \text{ for all } k, l = 1, \ldots, N.
\]
Positive values of $\text{EOS}_{kl,i}$ indicate that goods $k$ and $l$ are substitutes in production for firm $i$, and negative values indicate that the goods are complements in production for the firm. This measure is preferable to alternatives as it holds the values of other inputs, outputs, and input distance constant, leading to a direct measure of the curvature of the typical production isoquant (Stern, 2010).

4.5 Organic adoption model

With the firm-level production characteristics estimated, we can proceed to the estimation of the adoption model. Recall that conversion occurs if $U(\pi^o_i, \beta_i) \geq U(\pi^c_i, \beta_i)$. This decision rule is well-suited to estimation within the framework of a random-utility model.

To estimate the random-utility model, we define the expected utility of a technology decision for firm $i$, $EU^j_i$, for $j = c, o$:

$$EU^j_i = U(\pi^j_i, \beta_i) + \epsilon^j_i,$$

(12)

where $\epsilon^j_i$ represents the unobservable component of the expected utility function. We assume that utility is linear in profit and operator characteristics, $U(\pi^j_i, \beta_i) = \pi^j_i + \phi^j \beta_i$. Because we only observe the discrete technology choice and not the level of utility, we define an observable variable $Y_i$ which takes a value of one if $EU^c_i \geq EU^o_i$ and zero otherwise. We can express the probability that $Y$ takes a value of one in the following way:

$$\text{Pr}(Y_i = 1) = \text{Pr}(EU^o_i \geq EU^c_i )$$

$$= \text{Pr}(\pi^o_i + \phi^o \beta_i + \epsilon^o_i \geq \pi^c_i + \phi^c \beta_i + \epsilon^c_i)$$

(13)

$$= \text{Pr}((\pi^o_i - \pi^c_i) + (\phi^o - \phi^c) \beta_i + \epsilon^o_i - \epsilon^c_i \geq 0).$$

We also require a parametric assumption governing the relationship between production characteristics $\Gamma_i$ and the difference in profit, $\Delta \pi_i \equiv \pi^o_i - \pi^c_i$. Specifically, we assume that the
difference in profit can be linearly decomposed into three components: 
\[ \Delta \pi_i = \eta \Gamma_i + \omega g(p^o - p^c, w^c - w^o) - \kappa F_i. \]
This construction separates the difference in profit into: 
(1) a linear function of production characteristics, (2) a function of the organic output and input price premia, and (3) a linear function of the fixed transition cost. The assumption of a linear relationship between \( \Delta \pi_i \) and \( \Gamma_i \) may be slightly restrictive, but it permits the functional form of the profit function to remain unspecified which provides a higher degree of generality. Importantly, \( \Gamma_i \) contains the elasticities of substitution between inputs, the critical piece of information describing the changes in input combinations resulting from exogenous changes in organic input prices and organic input regulations, which have a direct impact on the level of output and the associated profit corresponding to the technology choice.

Substituting this linear decomposition of \( \Delta \pi_i \) into equation (13), we have:

\[ \Pr(Y_i = 1) = \Pr(\eta \Gamma_i + \omega g(p^o - p^c, w^c - w^o) - \kappa F_i + \phi \beta_i + \epsilon_i \geq 0), \]

where \( \phi = \phi^o - \phi^c \) and \( \epsilon_i = \epsilon_i^o - \epsilon_i^c \). Due to the perfectly competitive nature of the input and output markets for the organic and conventional dairy industry, differences in prices are not identifiable as they are not expected to vary across firms. Therefore, the \( \omega \) parameter is not identified in the empirical model. Assuming a logistic distribution for the error term, we employ a logit model to estimate the probability of conversion.\(^8\)

The presence of the technical efficiency term on the right-hand side of the empirical adoption model has been recognized as potentially endogenous (Mayen, Balagtas, and Alexander 2010; Kumbhakar, Tsionas, and Sipiläinen 2009; Latruffe and Nauges 2014). The concern revolves around the issue of simultaneity bias – is organic a less-efficient technology or is it that less efficient firms are simply more attracted to organic technology? When technical efficiency and

\(^8\) Assuming a normal distribution for the error term and using a Probit model specification does not have a significant impact on results.
adoption are estimated contemporaneously, this is an issue that must be dealt with. Mayen, Balagtas and Alexander (2010) address the issue through the use of propensity score matching, and Kumbhakar, Tsionas and Sipiläinen (2009) construct a single-step maximum likelihood estimation procedure that simultaneously estimates technical efficiency and the propensity to adopt. We deal with the issue in a manner similar to Latruffe and Nauges (2014), by using estimates of technical efficiency lagged five years which are much less likely to be endogenous in the adoption prediction model.

5. Data

We use the Phase III Cost and Returns Report of the ARMS data for 2005 and 2010. This report contains firm-level data on input cost, input quantities, output revenues, and several other variables detailing operator and farm characteristics. The survey is a nationally representative stratified random sample containing data on dairies in the top 24 dairy producing states. Each farm in the survey represents itself and a number of similar farms equal to an expansion factor calculated by the National Agricultural Statistics Service (NASS). When the expansion factors are applied as frequency weights in estimation, as recommended by Dubman (2000) for population-representative empirical estimates, they represent a random sample of dairy farms in the 24 surveyed states (McBride and Greene 2009). In 2005 and 2010, the USDA also targeted a sample of organic dairies, so there are several questions specifically relating to organic production practices. To ensure that the number of organic dairies was representative of the population, they were oversampled in the surveying process. Thus, even though organic operations account for 18

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10 A subset of 14 states from the original group of 24 included data from organic dairies: Iowa, Ohio, Michigan, Minnesota, Wisconsin, Maine, New York, Pennsylvania, Vermont, Washington, Oregon, and Idaho.
percent of the sample in 2005, they only constituted 2 percent of the total number of dairy farms (McBride and Greene 2009).

While the survey does not constitute a true panel, a portion of firms that participated in the 2005 survey also participated in the 2010 survey. Of the 1,814 observations in the 2005 data, 138 observations can be matched to the 2010 survey. Of the 138 matched observations, 104 firms were conventional in both years, 26 firms transitioned from conventional in 2005 to organic in 2010, and 8 firms transitioned from organic back to conventional in 2010. In the estimation of the input distance function, the full sample of conventional firms from the 2005 data is utilized, of which there are 1,236. The second estimation step, the discrete choice model of organic adoption, uses only the subset of firms that match across samples that either started out as conventional and remained conventional (104), or started out as conventional and switched to organic (26), totaling 130 observations.

In the estimation of the distance function, we employ seven inputs and two outputs. The inputs consist of milk cows (average herd size), land (acres operated), labor (total hours worked), feed (tons/year), capital (recovery cost), medicine (expenditure), and other inputs (expenditure). Because not all feed types are used on each farm, we employ a weighted arithmetic mean index to aggregate multiple feed types into our feed variable. Feed types include commercial feed mixes, supplements, corn, barley, sorghum, wheat, oats, alfalfa, soybeans, hay, and multiple types of silage. For a full list, refer to Appendix A.2. Units are converted to tons/year and weighted by their expenditure share. The capital variable is a USDA-calculated estimate of capital recovery costs—defined as the cost of replacing capital investment in machinery and equipment plus the interest that leftover capital could have earned in an alternative investment (Key and Sneeringer 2014). The medicine input includes expenditures on artificial insemination, branding, hormone injections, antibiotics, and other medical and veterinary services. The remaining inputs aggregated into the
‘other’ variable include expenditures on marketing, repairs, chemicals, and energy.

We aggregate outputs into two categories, dairy and non-dairy. The dairy output is simply fluid milk; we do not disaggregate this output into separate milk products or co-products. The non-dairy output is an index of all other farm outputs, constructed using an arithmetic mean with revenue shares as weights. Most dairies in our sample produce milk as the primary output; on average, 86% percent of a farm’s total revenue is derived from milk sales. However, to capture the remaining non-dairy output and intermediate outputs, we construct an arithmetic mean index which includes quantities of non-dairy livestock and several field crops including corn, sorghum, barley, wheat, and oats weighted by their revenue shares. A full list of livestock and crops comprising the non-dairy output is reported in Appendix A.2. After removing observations with missing variables, we are left with 1,090 usable observations of conventional dairies. Summary statistics are provided in Table 1.

The variables included in the estimation of the discrete choice model consist of all the estimated firm-level production characteristics (technical efficiency, returns to scale, elasticities of substitution), non-estimated firm characteristics, state-level organic price premium, and a set of operator characteristics. Differences in the non-estimated firm and operator characteristic variables are reported in Table 2. They include the number of milk cows, an indicator of the type of manure distribution system employed (1 if pasture-based, 0 otherwise), an indicator for the use of artificial insemination, a measure of output diversification (dairy sales divided by total sales), a measure of risk aversion (purchased insurance divided by total value of production), and an indicator for the use of pasture for grazing. Operator characteristics include an indicator for the completion of high school (or above), an indicator for participation in a Johne’s disease program which we use as a

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11 To ensure field crops are not double-counted in the non-dairy output variable, we subtract the amount used on the operation from the total value, e.g., if 100 bushels of corn are produced but 80 bushels are used as feed, only 20 bushels are included in the non-dairy output index.
proxy for attentiveness to animal welfare, an indicator for business-related internet usage, and operator age.12

Because we don’t have time-varying, firm-level data for the organic milk price premium, we use state-level averages of the difference between the price paid to organic producers (per hundredweight) and to conventional producers. Organic milk prices are partially governed by the same Federal milk marketing orders that determine conventional milk prices, with the exception of a processor-specific premium for the value added from organic production (McBride and Greene 2009). By using state-level differences, we account for part of the variation in the organic premium.

Referring to Table 2, farms that converted to organic were much smaller on average (85 average herd size vs. 193). More converting farms used pasture for grazing and used a pasture-based manure distribution system, differences which are statistically significant at the one-percent level. They were also more risk averse and faced a modestly higher price premium for organic milk. In terms of operator characteristics, farmers who converted were younger (significant at ten percent), less-educated (significant at one percent), and more likely to participate in a Johne’s disease program (significant at five percent).

6. Results

We first consider results relating to selection of functional form for the multi-output input distance function. The first step of our econometric estimation identifies a Box-Cox parameter estimate of \( \hat{\lambda} = 0.27 \). To assess the fit of this new functional form in comparison to the most popular alternatives, we perform likelihood ratio tests to test the suitability of the BCF with \( \hat{\lambda} = 0.27 \) versus

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12 Johne’s disease is associated with a significant reduction in milk production. Dairy farmers can volunteer to enroll in Johne’s disease programs, which provide education on disease prevention and management techniques. Programs also test herds for Johne’s disease (USDA 2010).
the translog Fourier (TLF), translog (TL), and Cobb-Douglas specifications, the results of which are summarized in Table 3. Tests indicate a strong preference for the BCF with rejections of each alternative valid at the 1% level of statistical significance. Rejection of these alternatives suggest that functions of their estimates will be subject to a degree of bias from functional form misspecification. To illustrate the extent of this potential bias, we highlight differences in estimated production characteristics between the BCF and the most popular alternative, the TL. Additionally, we run two models of organic adoption, one with BCF estimates and one with TL estimates to illustrate how functional form misspecification can alter adoption probabilities.

6.1 *Input distance function results*

Estimates of technical efficiency, returns to scale, and elasticities of substitution are presented in Table 4. Results are separated into two parts: the four left columns of the table show results from the BCF functional form, and the four right-most columns summarize results from the TL functional form. We highlight not only the difference in means between the estimates, but the difference in several sample moments that govern the shape of the distributions of estimates.

For conventional dairies in 2005, we estimate an average technical efficiency (TE) of 0.81 from the BCF and 0.85 from the TL, which is similar to the results of Mayen, Balagtas, and Alexander (2010) who report a TE estimate of 0.836 for conventional farms. TE is positively associated with size since larger farms are much more technically efficient than smaller farms. In Figure 1, we examine histograms of TE estimates for both BCF (left panel) and TL (right panel) estimates. BCF estimates demonstrate a much higher concentration of efficient firms compared to the TL estimates, which have a higher concentration of firms centered around the mean and lower concentrations at the tails. TE estimates from the BCF are less left-skewed than corresponding TL estimates, and have less kurtosis.
Estimates of returns to scale demonstrate the presence of non-decreasing returns to scale for the majority of the sample of conventional firms, which is generally consistent with the literature (Mosheim and Lovell 2009). We estimate an average returns to scale of 1.05 from the BCF and 1.10 from the TL. The BCF estimate is not significantly different from one, suggesting that constant returns to scale cannot be rejected at the data means. This result varies slightly from Mosheim and Knox Lovell (2009), who find evidence of increasing returns over all farm sizes using data from 2000. We suspect that this contrary finding may be the result of using the BCF functional form, which provides a more accurate estimation of the larger firms which are at the tails of the distribution. Figure 2 presents histograms and fitted normal distributions for returns to scale estimates estimated from the BCF (left panel) and TL (right panel). Both distributions are more similar in shape to a normal distribution compared to the TE distributions in Figure 1, with the BCF estimates much more right-skewed (skewness of 0.89) than their TL-estimated counterparts (skewness of 0.15). The distribution of BCF estimates also have thicker tails, with a kurtosis of 3.89 compared to 2.95 for the TL estimates.

Estimates of the elasticities of substitution between capital, land, labor, and medicine are shown in the last rows of Table 4. With one exception (capital/medicine), both BCF and TL estimates identify similar pairs of inputs as substitutes or complements at the data means. Medicine and labor are the strongest substitutes, followed by feed and land. Feed and labor have the most complementary relationship between the input combinations, which holds for both the BCF and TL. Seven of the ten distributions of BCF elasticity of substitution estimates have thicker tails than do the TL estimates, and eight of the ten distributions are less right-skewed.

Table 5 separates estimates of production characteristics by functional form for farms that remained conventional and those that transitioned to organic for the 130 farms that we were able to match between the 2005 and 2010 surveys. Importantly, these estimates are all derived from
when these farms were *conventional*—the ‘Conventional to Organic’ column is for farms that will make the transition to organic in time for the 2010 survey. Using the BCF estimates, results indicate that firms that remained conventional were more efficient (significant at the five percent level), had lower returns to scale (significant at the ten percent level), and had input pairs with smaller elasticities of substitution (more complementary) than firms that converted by 2010. When evaluating the means, the TL estimates demonstrate consistent differences between conventional and converted firms, but fewer of the differences are statistically significant.

6.2 *Organic adoption results*

Parameter estimates from our discrete-choice model of organic adoption suggest that estimated production characteristics are highly associated with the decision to convert from conventional to organic technology. As evidenced in Table 6, BCF estimates of technical efficiency, returns to scale and several elasticities of substitution are statistically significant predictors of organic adoption. Table 6 is also separated into two columns, those utilizing BCF estimates (left) and those utilizing TL estimates (right). Parameter estimates can be interpreted as semi-elasticities, implying that a marginal change in the regressor is associated with a percentage change in the relative probability of organic adoption equal to the parameter estimate.

Focusing on the BCF results, we find that technical efficiency is negatively associated with adoption, a relationship which is statistically significant at the five-percent level. A one-unit increase in TE results in a 20% decrease in the relative probability of conversion. This result is counter to the findings of Kumbhakar, Tsionas, and Sipiläinen (2009) who estimate the impact of TE using organic farming data from Finland. These authors suggest that more efficient farms are attracted to organic due to the large conversion subsidy. The lack of a corresponding U.S. subsidy may be one of the contributing factors behind the negative relationship that we find between TE
Returns to scale is positively associated with adoption and is significant at the five-percent level. For the mean firm with returns to scale of 1.05, an increase in returns to scale to 1.15 corresponds to a 19% increase in the odds of organic adoption. This finding is consistent with our theoretical prediction and the negative relationship between TE and adoption.

An increase in substitutability between capital and land, feed and land, feed and labor, and medicine and labor are all statistically significant positive drivers of conversion. Substitutability between feed and land is the most significant (one-percent level) followed by feed and labor, and capital and land (five-percent level), with substitutability between medicine and labor significant at the ten-percent level. At the mean level of substitution between feed and land for conventional firms, a one-percent increase in substitution results in a two-percent increase in the odds of conversion.

Several non-estimated production and operator characteristics are also significantly associated with organic adoption, including milk cows (negative and significant at the ten-percent level), the use of a pasture-based manure distribution system and artificial insemination (both strongly positive and significant at the five percent level), and participation in the Johne’s disease program (strongly positive and significant at the one percent level). We find that smaller herd sizes are associated with adoption, similar to results found in previous organic dairy conversion studies (Kallas, Serra, and Gil, 2010; Kumbhakar, Tsionas, and Sipiläinen, 2009; Latruffe and Nauges, 2014; Mayen, Balagtas, and Alexander, 2010). All other variables are statistically insignificant determinants of organic adoption.

Importantly, results from the adoption model when TL estimates are used provide substantially different results. Only five variables are statistically significant predictors of adoption compared to ten BCF parameters. The significant parameters have the same signs as the BCF parameters but
some of the magnitudes differ greatly. They highlight the importance of model selection and the role of functional form misspecification bias, reminding us that the popularity of the TL specification in distance function estimation is no guarantee of accuracy.

7. **Discussion and conclusions**

Using a nationally-representative sample of U.S. dairies, we examine the role of production characteristics in the decision to convert from conventional to organic dairy technology. Previous studies focus primarily on the role of operator characteristics on the propensity to convert, neglecting important features of the existing production technology. While some aspects of production including technical efficiency, firm size, and the use of advanced technology have been considered as conversion determinants, other important production features have been overlooked.

Due to the nature of the requirements specified by the National Organic Program, we hypothesize that returns to scale and the ability to easily substitute between key input combinations will be important drivers of organic adoption for conventional dairies. Ours is the first study to use U.S. firm-level data to examine the impacts of these characteristics measured before the start of the conversion process on organic technology adoption. We find that for conventional firms, higher returns to scale and easier substitutability between capital and land, feed and land, feed and labor, and medicine and labor inputs are all statistically significant drivers of organic adoption. Because of the prevalence of non-decreasing returns to scale in this industry, firms with higher returns to scale are further away from achieving the scale benefits that are such significant drivers of growth and productivity in the conventional dairy industry. Failure to achieve scale benefits as a conventional dairy increases the likelihood of exit from the industry. We suspect it also incentivizes organic adoption as these firms search for alternative uses of the physical and human capital. Additionally, the significant restrictions placed on capital, medicine, and feed as a result
of the National Organic Program requirements drive the association between a firm’s ability to substitute away from these inputs and their propensity for adoption. For example, we find a statistically and economically significant increase in the odds of adoption when a firm’s substitutability between medicine and labor increases. This result is intuitive: firms that can more easily substitute between medicinal/veterinary inputs and labor are less likely to be as adversely impacted by restrictions limiting the usage of medicinal/veterinary inputs.

Our identification of a new set of production characteristics as significant determinants of organic adoption has important implications for U.S. policies aimed at increasing organic dairy production, as well as the future of the organic dairy industry. With no changes to policies or restrictions governing organic dairies, we conclude that conventional firms with comparatively lower technical efficiency and higher returns to scale will be drawn to organic production in an attempt to remain profitable. However, an organic industry comprised solely of these types of firms may be unable to produce milk at the same quantity or scale as the conventional industry, which implies that organic milk prices will continue to be higher than conventional milk prices by an amount that exceeds the additional costs of organic production. Additionally, the exit of inefficient firms will necessarily increase consolidation in the conventional industry.

Based on our results, we conclude that policies designed to eliminate sources of scale and allow for greater substitutability away from restricted inputs may provide a strong incentive for further organic adoption. For example, diseconomies of scale in the organic may be alleviated by allowing the use of a small percentage of non-organic feed, which may provide incentive for low returns to scale firms (those with higher feed requirements) to adopt. Further, by analyzing the most important elasticities of substitution relating to conversion, policymakers could determine inputs that might be subsidized or given a tax credit to offset the burden of specific organic input regulations. For example, a labor tax credit for organic farmers would help decrease the burden of
medicinal restrictions and predictably lead to higher rates of adoption.

Finally, we stress the importance of functional form misspecification bias from our results. We demonstrate through likelihood ratio testing that, despite its dominance, the translog functional form has important limitations for input distance function estimation relevant to technology adoption. By comparing adoption results using estimates from the translog with the more accurate Box-Cox Fourier model, we show that misspecification bias can have a non-trivial impact. With its ability to provide a global approximation to an unknown function and accurately estimate the boundaries of the data, the Box-Cox Fourier functional form should be considered a viable, robust alternative to the translog and other functional forms for stochastic frontier analysis.
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### Table 1—Summary Statistics for Conventional Dairies, 2005

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Milk (100 lbs.)</td>
<td>34,267</td>
<td>636,487</td>
</tr>
<tr>
<td>Non-dairy output*</td>
<td>8,594</td>
<td>119,427</td>
</tr>
<tr>
<td>Milk cows (head)</td>
<td>178</td>
<td>3,140</td>
</tr>
<tr>
<td>Land (acres)</td>
<td>339</td>
<td>6,310</td>
</tr>
<tr>
<td>Labor (total hours)</td>
<td>10,134</td>
<td>530,490</td>
</tr>
<tr>
<td>Feed*</td>
<td>243,865</td>
<td>9,335,065</td>
</tr>
<tr>
<td>Capital (recovery cost)</td>
<td>92,116</td>
<td>1,724,555</td>
</tr>
<tr>
<td>Medicine (expenditure)</td>
<td>27,736</td>
<td>559,835</td>
</tr>
<tr>
<td>Other (expenditure)</td>
<td>63,811</td>
<td>1,129,865</td>
</tr>
</tbody>
</table>

Observations 1,090

*Index (weighted arithmetic mean)

Source: 2005 USDA ERS ARMS. More information on the ARMS data can be found at:
Table 2—Summary Statistics, Conventional vs. Organic Converting, Matched Firms

<table>
<thead>
<tr>
<th>Variable</th>
<th>Remained conventional</th>
<th>Conventional to organic</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>S.D.</td>
</tr>
<tr>
<td>Milk cows (head)</td>
<td>192.82</td>
<td>932.38</td>
</tr>
<tr>
<td>Manure distribution system (1 if pasture-based)</td>
<td>0.07***</td>
<td>0.25</td>
</tr>
<tr>
<td>Artificial insemination (1 if used)</td>
<td>0.79</td>
<td>0.41</td>
</tr>
<tr>
<td>Output diversification (non-dairy sales/total sales)</td>
<td>0.14</td>
<td>0.15</td>
</tr>
<tr>
<td>Risk aversion (insurance/total value)</td>
<td>51.27</td>
<td>52.09</td>
</tr>
<tr>
<td>Pasture (1 if pasture used for grazing)</td>
<td>0.57***</td>
<td>0.50</td>
</tr>
<tr>
<td>Price premiumc</td>
<td>7.75</td>
<td>1.61</td>
</tr>
<tr>
<td>High school (1 if high school or more)</td>
<td>0.87***</td>
<td>0.34</td>
</tr>
<tr>
<td>Johne’s disease program (1 if participated)</td>
<td>0.23**</td>
<td>0.42</td>
</tr>
<tr>
<td>Internet (1 if used for business)</td>
<td>0.75</td>
<td>0.19</td>
</tr>
<tr>
<td>Age</td>
<td>53.00*</td>
<td>11.18</td>
</tr>
</tbody>
</table>

Observations: 104 (26)

*Estimates and data (ARMS) using only firms that we could match between the 2005 and 2010 data.

*Matched firms that were conventional in 2005 and 2010.

*Matched firms that were conventional in 2005 and organic in 2010.

*State-level average difference between organic and conventional fluid milk prices (per hundredweight)

*10%, **5%, and ***1% significance difference between mean of dairies that remained conventional vs. those that converted.
### Table 3—Functional Form Hypotheses

<table>
<thead>
<tr>
<th>Functional form</th>
<th>Parametric restrictionsa</th>
<th>Test statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Translog-Fourier</td>
<td>$H_o : \lambda \to 0.$</td>
<td>156.91***</td>
</tr>
<tr>
<td>Translog</td>
<td>$H_o : \lambda \to 0,$</td>
<td>223.43***</td>
</tr>
<tr>
<td></td>
<td>and $u_\alpha = 0, v_\alpha = 0$, for $\alpha = 1, \ldots, A.$</td>
<td></td>
</tr>
<tr>
<td>Cobb-Douglas</td>
<td>$H_o : \lambda \to 0,$</td>
<td>260.98***</td>
</tr>
<tr>
<td></td>
<td>$u_\alpha = 0, v_\alpha = 0$, for $\alpha = 1, \ldots, A,$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>and $C = 0.$</td>
<td></td>
</tr>
</tbody>
</table>

***1% significance

*aParametric restrictions imposed on the BCF in (4).*
<table>
<thead>
<tr>
<th>Estimated production characteristics</th>
<th>Box-Cox Fourier</th>
<th>Translog</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>S.D.</td>
</tr>
<tr>
<td>Technical efficiency</td>
<td>0.81</td>
<td>0.11</td>
</tr>
<tr>
<td>Returns to scale</td>
<td>1.05</td>
<td>0.09</td>
</tr>
<tr>
<td>Elasticities of substitution</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capital, land</td>
<td>0.25</td>
<td>0.98</td>
</tr>
<tr>
<td>Capital, labor</td>
<td>0.41</td>
<td>2.54</td>
</tr>
<tr>
<td>Capital, feed</td>
<td>-0.03</td>
<td>1.89</td>
</tr>
<tr>
<td>Capital, medicine</td>
<td>0.30</td>
<td>2.97</td>
</tr>
<tr>
<td>Land, labor</td>
<td>0.09</td>
<td>1.65</td>
</tr>
<tr>
<td>Land, feed</td>
<td>1.58</td>
<td>3.84</td>
</tr>
<tr>
<td>Land, medicine</td>
<td>-0.28</td>
<td>1.93</td>
</tr>
<tr>
<td>Labor, feed</td>
<td>-1.87</td>
<td>0.16</td>
</tr>
<tr>
<td>Labor, medicine</td>
<td>1.89</td>
<td>1.02</td>
</tr>
<tr>
<td>Feed, medicine</td>
<td>1.35</td>
<td>0.98</td>
</tr>
</tbody>
</table>

Observations 1,090

Note: Comparison of the first four sample moments of estimated production characteristics between Box-Cox Fourier and translog input distance function estimates using the sample of conventional dairies from 2005.
### Table 5—Production Characteristics, Conventional vs. Organic Converting

<table>
<thead>
<tr>
<th>Estimated production characteristics</th>
<th>Box-Cox Fourier</th>
<th>Translog</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Remained conventional&lt;sup&gt;a&lt;/sup&gt;</td>
<td>Conventional to organic&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>S.E.&lt;sup&gt;c&lt;/sup&gt;</td>
</tr>
<tr>
<td>Technical efficiency</td>
<td>0.84**</td>
<td>0.05</td>
</tr>
<tr>
<td>Returns to scale</td>
<td>0.94*</td>
<td>0.09</td>
</tr>
<tr>
<td>Elasticities of substitution</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capital, land</td>
<td>-0.27*</td>
<td>0.25</td>
</tr>
<tr>
<td>Capital, labor</td>
<td>-0.49</td>
<td>0.54</td>
</tr>
<tr>
<td>Capital, feed</td>
<td>0.07</td>
<td>0.05</td>
</tr>
<tr>
<td>Capital, medicine</td>
<td>-0.4*</td>
<td>0.12</td>
</tr>
<tr>
<td>Land, labor</td>
<td>-0.18</td>
<td>0.05</td>
</tr>
<tr>
<td>Land, feed</td>
<td>-2.75***</td>
<td>0.95</td>
</tr>
<tr>
<td>Land, medicine</td>
<td>-0.13</td>
<td>0.04</td>
</tr>
<tr>
<td>Labor, feed</td>
<td>-1.16*</td>
<td>1.55</td>
</tr>
<tr>
<td>Labor, medicine</td>
<td>-1.65*</td>
<td>1.49</td>
</tr>
<tr>
<td>Feed, medicine</td>
<td>0.89**</td>
<td>0.05</td>
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</tbody>
</table>

Observations: 104 (26) 104 (26)

<sup>a</sup>Estimates and data (ARMS) using only firms that we could match between the 2005 and 2010 data.

<sup>b</sup>Matched firms that were conventional in 2005 and organic in 2010.

<sup>c</sup>Bootstrap estimate of the standard error.

*10%, **5%, and ***1% significance difference between mean of dairies that remained conventional vs. those that converted.
<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Based on Box-Cox Fourier Estimates</th>
<th>Based on Translog Estimates</th>
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<tbody>
<tr>
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<td>Estimate^a  SE</td>
<td>Estimate^a  SE</td>
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<tr>
<td>Technical efficiency</td>
<td>-0.204**  0.091</td>
<td>-0.083*  0.045</td>
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<td>Returns to scale</td>
<td>1.921**  0.880</td>
<td>-0.281  0.213</td>
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<td>Capital, land</td>
<td>3.721**  1.512</td>
<td>0.913**  0.445</td>
</tr>
<tr>
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<td>0.011  0.014</td>
<td>0.808  12.616</td>
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<td>Capital, feed</td>
<td>-0.109  0.191</td>
<td>0.370  0.378</td>
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<tr>
<td>Capital, medicine</td>
<td>-0.032  0.039</td>
<td>-0.986  2.358</td>
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<tr>
<td>Land, labor</td>
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<td>Labor, feed</td>
<td>0.028**  0.013</td>
<td>0.431**  0.187</td>
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<tr>
<td>Labor, medicine</td>
<td>2.611*  1.501</td>
<td>0.245*  0.137</td>
</tr>
<tr>
<td>Feed, medicine</td>
<td>0.115**  0.054</td>
<td>0.113*  0.064</td>
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<td>Milk cows</td>
<td>-0.004*  0.003</td>
<td>-0.035  0.039</td>
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<tr>
<td>Manure distribution system</td>
<td>5.291**  2.391</td>
<td>2.094  1.560</td>
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<tr>
<td>Artificial insemination</td>
<td>4.138**  2.033</td>
<td>1.945  2.063</td>
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<td>Output diversification</td>
<td>-0.623  0.520</td>
<td>-0.147  0.219</td>
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<tr>
<td>Risk aversion</td>
<td>0.014  0.006</td>
<td>-0.333  0.922</td>
</tr>
<tr>
<td>Pasture</td>
<td>0.221  1.614</td>
<td>1.267  1.015</td>
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<tr>
<td>Price premium</td>
<td>-0.679  0.885</td>
<td>-0.234  0.216</td>
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<tr>
<td>High school</td>
<td>1.503  1.904</td>
<td>1.640*  0.871</td>
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<tr>
<td>Johne’s disease program</td>
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<td>2.709*  1.398</td>
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<td>Internet</td>
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<tr>
<td>Age</td>
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<td>-0.545  1.514</td>
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<tr>
<td>Intercept</td>
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<td>Observations</td>
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<tr>
<td>Pseudo R^2</td>
<td>0.63</td>
<td>0.46</td>
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</table>

*10%, **5%, and ***1% significance

^Expressed as marginal changes in the log odds of conversion
Figures

**Figure 1. Distribution of Technical Efficiency Estimates by Functional Form**

Note: The red line is a beta distribution that has been fitted to the histogram of technical efficiency estimates.
FIGURE 2. DISTRIBUTION OF RETURNS TO SCALE ESTIMATES BY FUNCTIONAL FORM

Note: The blue line is a normal distribution that has been fitted to the histogram of returns to scale estimates.
Appendix

A.1 Multi-indices

In a Fourier series approximation, multi-indices dictate which combination of independent variables exist inside the orthogonal expansion. For simplicity, consider a second-order Fourier series expansion with three independent variables, \( x = [x_1, x_2, x_3] \):

\[
\sum_{\alpha=1}^{A} (u_{\alpha} \cos(k'_{\alpha} x) + v_{\alpha} \sin(k'_{\alpha} x)).
\]

(A1)

In this case, one of the admissible \( k_{\alpha} \) vectors, for example \( k_1 \), will equal \([0,1,-1]\). Thus, the Fourier series expansion can be represented as:

\[
u_i \cos(x_2 - x_3) + v_i \sin(x_2 - x_3) + \sum_{\alpha=2}^{A} (u_{\alpha} \cos(k'_{\alpha} x) + v_{\alpha} \sin(k'_{\alpha} x)).
\]

(A2)

Listed below is a summary of the rules governing the set of admissible multi-indices for a given order of approximation, \( K \), which are described in detail by Gallant (1981). In the following, let \( k_{\alpha i} \) be the \( i \)th element of the \( k_{\alpha} \) vector, and let \( x \) be a set of \( m \) vectors.

1. For conformability, the length of every \( k_{\alpha} \) vector must be \( m \).
2. For a \( K \)th order approximation, \( K \geq \sum_{i=1}^{m} k_{\alpha i} \).
3. \( k_{\alpha} \neq 0 \) \( \forall \alpha = 1, \ldots, A \).
4. No \( k_{\alpha} \) vector may contain a common integer divisor, e.g. \([0,0,3,6]\) is invalid.
5. The first non-zero element of each \( k_{\alpha} \) vector must be nonnegative.

In addition to the proper selection of \( k_{\alpha} \), the total number of parameters in the truncated Fourier series, \( 2A \), has to be selected. Eastwood and Gallant (1991) demonstrate that parameter estimates will be asymptotically normal if the total number of parameters in the model is as close to the sample size raised to the two-thirds power as possible. With the number of parameters in the
second-order expansion preceding the truncated Fourier series fixed at \((N+M)(N+M+1)/2 = 45\), that leaves \(I^{2/3} - 45 = 61\) free parameters available. Following the five rules listed above, a second-order Fourier series expansion in \(N+M-1=8\) variables yields 23 \(k_\alpha\) vectors, so \(2A = 46\). If we were to use a third-order expansion, we would need 66 \(k_\alpha\) vectors, implying \(2A = 132\), which exceeds the requirement for asymptotic normality. Thus, a second-order approximation is most appropriate, and we proceed with 23 \(k_\alpha\) vectors and \(A = 23\). The specific \(k_\alpha\) vectors are listed below:

\[
\begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & -1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & -1 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & -1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 & -1 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 \\
0 & 0 & 1 & -1 & 0 & 0 & -1 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & -1 & 0 \\
0 & 0 & -1 & 0 & -1 & 0 & 0 & -1 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & -1 \\
1 & 2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

A.2 Extended data description

List of feed types included in the aggregate feed input variable:

- Complete commercial feed and complete custom feed mixes
- High moisture corn
- Barley
- Wheat
- Other non-protein by-product
- Protein supplements
- Alfalfa hay
– Milk, milk replacer or calf starter
– Liquid whey

List of non-dairy livestock and field crops included in the non-dairy output variable:

– Corn
– Potatoes
– Sorghum
– Soybeans
– Barley
– Oats
– Wheat
– Alfalfa
– Canola
– Hogs and pigs
– Broilers