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THE ECONOMIC COSTS OF ENVIRONMENTAL REGULATION IN U.S. DAIRY FARMING: A DIRECTIONAL DISTANCE FUNCTION APPROACH

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Analyses of the costs of regulating greenhouse gas emissions from dairy production, which could be used to assess the effectiveness of alternative policy measures, is a missing link in the literature. This article addresses this gap by establishing the economic impact associated with a hypothetical greenhouse gas environmental regulatory regime across major dairy producing counties in the United States. In doing so, the article makes three important contributions to the literature. First, it develops a comprehensive pollution index based on Environmental Protection Agency methodologies, which contrasts with previous studies that rely on partial measures based only on surplus nitrogen stemming from the over-application of fertilizer. Second, the article uses a directional output distance function, an approach that has not been employed previously to evaluate polluting technologies in the U.S. dairy sector. Third, the article incorporates a four-way error approach that accounts for unobserved county heterogeneity, time-invariant persistent technical efficiency, time-varying transient technical efficiency, and a random error. The results indicate that regulating greenhouse gas emissions from dairy farming would induce a 5-percentage point increase in average technical efficiency. In addition, the economic costs of implementing this hypothetical regulatory framework exhibit significant spatial variation across counties in the United States.

Key words: Dairy farming, directional output distance function, environmental regulation, shadow prices, undesirable output.

JEL codes: D22, Q15, Q52.

According to the U.S. Department of Agriculture (2014), in 2013 the United States was the largest producer of fluid milk in the world, with an output of 201 billion pounds and $140 billion in economic activity. In addition, the U.S. dairy industry accounted for about 900,000 jobs that generated $29 billion in household earnings. Furthermore, there were approximately 51,000 dairy farms in operation, 97% of which were family owned. Dairy farming accounted for the largest share of farm sales in several states, including California, Wisconsin, New York, Pennsylvania, Idaho, Michigan, New Mexico, Vermont, Arizona, Utah, and New Hampshire (USDA 2014).

On the downside, the U.S. dairy industry was responsible for generating 137 million metric tons of greenhouse gas (GHG) emissions in 2008 (Thoma et al. 2012) and these discharges have trended upward for a number of years (U.S. Environmental Protection Agency 2013a). The Environmental Protection Agency (EPA), which has been charged with monitoring and regulating GHG emissions in the United States, launched a Greenhouse Gas Reporting

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Program (GHGRP) in 2009. This program requires several sectors to directly report their GHG emissions in order to better understand where these emissions are coming from and to improve the design of sound policies and regulations. The EPA (2009) listed the agricultural industry in general and livestock operations in particular among sectors that would be required to participate in this reporting process. Any attempt to limit emissions, and hence undesirable outputs, imposes additional constraints on decision making units (DMUs) by requiring that inputs be diverted away from production and towards abatement.

Bearing the above in mind, this article aims to establish how these EPA guidelines could impact dairy farming in the United States. In doing so, the paper makes three contributions to the literature. First, it develops a comprehensive pollution index for the dairy sector that combines livestock emissions, constructed using EPA (2009) methodologies, with fuel and fertilizer emissions. By contrast, previous studies (e.g., Reinhard, Lovell, and Thijssen 1999; Fernandez, Koop, and Steel 2002) accounted only for surplus nitrogen generated from the over-application of fertilizer. Second, the article uses a directional output distance function, an approach that has not been used to model polluting technologies in dairy farming. Third, the article incorporates a four-way error approach recently introduced in the literature (Colombi et al. 2014; Filippini and Greene 2014; Kumbhakar, Lien, and Hardaker 2014; Tsionas and Kumbhakar 2014), which accounts for individual DMU-effects, persistent (time-invariant) technical efficiency, transient (time-varying) technical efficiency, and random errors. The results from this model are used to estimate the likely economic costs associated with hypothetical GHG environmental regulations in the U.S. dairy industry. Moreover, Isik (2004) argues that an important missing link in the literature is quantifying the cost of environmental regulations in order to evaluate the effectiveness of alternative policies. This article addresses this gap by establishing the costs of GHG environmental regulatory intervention in major milk-producing areas across the United States.

Some abatement activities are already in place stemming from statutory regimes such as the Clean Air Act Amendments (1990), which envisaged a market-driven process, and the Clean Water Act (1972), under which the EPA regulates discharges from large concentrated animal-feeding operations (i.e., with 700 or more dairy cattle) in order to protect surface water. Other abatement options are voluntary, such as anaerobic digester technologies, which are a form of manure management systems. Such systems are good for the environment because they help to capture and burn methane that would otherwise escape into the atmosphere. Though digester systems have multiple benefits that are more pronounced in larger operations, because of economies of scale in both their construction and maintenance, adoption in the United States has been limited (Bishop and Shumway 2009; Key and Sneeringer 2012).

Over the years, traditional methods of productivity analysis that model polluting technologies have focused on obtaining measures of conventional indexes of productivity change, as well as conventional measures of technical efficiency (Reinhard, Lovell, and Thijssen 1999). In the presence of environmentally detrimental by-products, a key factor that is often ignored is the impact of GHG environmental regulation in the dairy sector. In this article, the modeling will assume a polluting technology and therefore will incorporate both desirable and undesirable outputs. The article compares two representative DMUs, one in an unregulated environment (case 1), and the other under regulation (case 2).

In case 1, the unregulated DMU maximizes production, given inputs, by radially expanding its output vector towards the frontier in a manner that expands the production of the desirable output while holding production of the undesirable output constant. However, the key assumption is that the representative DMU neither diverts inputs, nor allocates any resources towards abatement activities. Case 2 assumes that a policy is in place that seeks to minimize the production of the undesirable output, either by the imposition of a cap by a regulator on the production of the undesirable output, or through a market mechanism that levies a monetary charge on the production of the undesirable output. In either case, the overarching goal would be the reduction of emissions. The movement away from the unregulated point to a different point on the frontier, with less of both outputs, desirable and undesirable, imposes additional costs to the DMU. These costs may be due to the diversion of inputs from good production towards abatement activities, and/or giving up some production of the good output in order to generate less of the undesirable output. Using data for dairy-farming intensive counties from the USDA Census of Agriculture for several years, this article estimates the impact that GHG environmental regulation would have on dairy production across the country.

Environmental Regulation and Polluting Technologies

Along with modeling the joint production of desirable as well as undesirable outputs, researchers have been interested in measuring the impact of environmental regulation on firm output and productivity. The study of the role of environmental regulation and its impact on productivity growth can be traced back to the 1980s, when Christainsen and Haveman (1981) considered the likely contribution of environmental regulations to the observed decrease in productivity growth in the United States between 1965 and 1979. The authors established that an estimated 8–12% of the economic slowdown experienced during that period could be attributed to environmental regulations. Further, Gollop and Roberts (1983) examined the effect of sulfur dioxide (SO_2) emission restrictions on the rate of productivity growth during the 1973 to 1979 business cycle. Using a sample of 56 electric utilities and a translog cost function, they established that environmental regulations did have a significant negative impact on the rate of productivity growth, with an average decline of 0.59% per year over the period analyzed.

Jorgenson and Wilcoxen (1990) examined U.S. economic growth from 1947 to 1973. The authors conducted simulations of the U.S. economy using a general equilibrium model, both with and without environmental regulations, and provided evidence that the long-run cost of pollution abatement and emissions control accounted for at least 2.6% of U.S. GNP during the examined period. Further, Brannlund, Färe, and Grosskopf (1995) analyzed the impact of environmental regulation on firm profits in the Swedish pulp and paper industry. Based on a non-parametric programming approach, the authors measured the short-run profits, both with and without regulation, and used these results to determine regulatory costs. The authors established that the size of the firm matters, and that large firms tend to be worse off than small ones when placed under environmental regulations.

In a different analysis, Hernandez-Sancho, Picazo-Tadeo, and Reig-Martinez (2000) used a cross-section of Spanish producers of wooden goods to analyze the impact of environmental regulation in the industry. These authors developed an output-oriented efficiency measure, and their findings indicated that firms involuntarily have to sacrifice production of desirable outputs when they are required to reallocate inputs towards waste reduction. Isik (2004) examined how differences in environmental regulation in the U.S. dairy sector impact the spatial location of dairy operations. Results indicate that stringent environmental regulations led dairy operations to migrate into areas with more lax regulation. Picazo-Tadeo, Reig-Martinez, and Hernandez-Sancho (2005) constructed an index to measure the opportunity costs arising from the environmental regulation for a sample of Spanish ceramic tile producers using a directional technology distance function. These authors found that, in the presence of environmental regulation, desirable output production drops 2.2%. Conversely, under a free disposability of waste assumption, aggregate good output could be increased by 7.0%. Färe, Grosskopf, and Pasurka (2007) analyzed the value of the foregone desirable output associated with abatement activities using data from coal-fired power plants. The model that they use distinguishes between an environmental production function and a directional environmental distance function. Whereas the environmental production function credits coal-fired power plants solely for expanding good output, the directional environmental distance function credits them for simultaneously raising production of the good output while reducing the production of bad outputs. The authors established a 17.6% reduction in electricity production associated with abatement activities.

In a study of solid waste generation, Arimura, Hibiki, and Katayama (2008) reported that voluntary approaches that involve self-reporting are more flexible, effective, and less costly than command-and-control regulatory approaches. Sneeringer and Key (2011) observed that environmental regulations in the U.S. livestock industry often vary by operation size, with stricter enforcements for larger operations. These authors found evidence that some farms avoided oversight by shrinking their operations to within a threshold that is less regulated. More recently, Färe et al. (2012) measured the substitutability of undesirable outputs, specifically SO_2 for NO_x in electric utility plants, by using a directional output distance function. Calculations based on the Morishima elasticity of substitution between the undesirable outputs reveal that, indeed, SO_2 and NO_x are substitutes. Thus, increasing regulation on the emission of SO_2 leads electric utility plants to substitute for the less regulated NO_x. Our work builds upon these previous studies in order to evaluate the potential effects of environmental regulations on U.S. dairy farms.

Methodology

Distance functions (DF), developed by Shephard (1970), are the theoretical basis for several recent studies of multi-output and multi-input technologies. Given a technically feasible set, the output DF measures the largest radial expansion of an output vector, given inputs, while the input DF measures the largest radial contraction of an input vector, given outputs (Färe and Primont 1995). When it comes to modeling polluting technologies, the DF is not appropriate because it radially expands both the desirable and the undesirable outputs towards the frontier. An alternative is the directional distance function (DDF), developed by Chambers, Chung, and Färe (1996) and extended as a technique for modeling polluting technologies by Chung, Färe, and Grosskopf (1997). Since then, other studies have analyzed the joint production of desirable as well as undesirable outputs using the DDF (e.g., Ball et al. 2001; Atkinson and Dorfman 2005; Färe et al. 2005; O'Donnell 2007).

The DDF makes two key assumptions: 1) that in a multi-dimensional production frontier, the DMU wishes to expand the production of the desirable output while contracting the production of the undesirable output, given inputs and the technology; and 2) that there are many projections that the directional vector can take to the frontier of the output set. In this framework, the distance from an observed point to the frontier provides a measure of environmental technical efficiency (Färe et al. 2005).

We begin by defining a technology set as a list of all feasible combinations of inputs and outputs. Let $x \in \Re^k_+$ be a vector of k inputs, and $y \in \Re^m_+$ and $b \in \Re^i_+$ be the vectors of the desirable and the undesirable outputs, respectively. Then, the technology set is defined as

$$(1) \qquad T = \{(x, y, b) : x \in \Re^k_+, y \in \Re^m_+, \\ b \in \Re^i_+ : x \; can \; produce (y, b)\}.$$

We define an output set $P(x)$ to be a multi-dimensional production possibility frontier that represents the combination of goods (y, b) that are generated by the DMU using the input vector x. More formally, $P(x) = \{(y, b) : x \quad can \; produce \quad (y, b)\}$. The output set is assumed to satisfy the standard production axioms (see Färe and Primont 1995). In addition, we assume that outputs are weakly disposable (Shephard 1970), which means that it is costly to discard the bad outputs; that is, when DMUs face environmental regulations, disposing of waste becomes a costly undertaking. Another key property is the null-joint assumption (Shephard and Färe 1974), which indicates that goods and bads must be produced jointly, such that if $b = 0$, then it is not possible to generate any of good y. That is, if $(y, b) \in P(x)$, and $b = 0$, then $y = 0$.

The Directional Output Distance Function

The technology assumed in this article restricts the input directional vector to zero; hence, ours is a directional output distance function or DODF (Färe 2010). We let $g \in \Re^m \times \Re^i$ be an output directional vector. The DODF to be modeled takes the form

$$(2) \qquad \vec{D}o\,(x, y, b; g_y, -g_b) \\ = \max\{\beta: (y + \beta g_y, b - \beta g_b) \in P(x)\}$$

where β is a scaling factor. The DMUs' objective is to expand production of the good output by βg_y, and contract the undesirable output by the factor βg_b. In this article, and consistent with the related literature, the directional vector, $g = (g_y, -g_b)$, is determined exogenously (e.g., Färe et al. 2005 and 2012; Picazo-Tadeo, Reig-Martinez, and Hernandez-Sanchez 2005). The properties of the DODF are inherited from the output set and are summarized here.

First, the DODF is non-negative and concave for all feasible output vectors $(y, b) \in P(x)$. It also exhibits monotonicity denoted as

$$(3) \quad \vec{D}o\,(x, y', b; g_y, -g_b) \geq \vec{D}o\,(x, y, b; g_y, -g_b) \times \forall\,(y', b) \leq (y, b) \in P(x).$$

Equation (3) says that if a DMU uses the same amount of inputs but generates more good output and less bad output, inefficiency does not increase. Conversely, if it raises production of the bad output while holding production of the desirable output constant, then inefficiency does not decrease. Formally, this property can be stated as

$$(4) \quad \vec{D}o\,(x, y, b'; g_y, -g_b) \geq \vec{D}o\,(x, y, b; g_y, -g_b) \times \forall\,(y, b') \leq (y, b) \in P(x).$$

Another property of the DODF is weak disposability in good and bad outputs, that is,

$$(5) \quad \vec{D}o\,(x, \theta y, \theta b; g_y, -g_b) \geq 0 \, for \times (y, b) \in P(x) \forall 0 \leq \theta \leq 1.$$

This means that abatement requires a reduction in the firm's level of production activity (Kuosmanen 2005).

A final important property is translation, which is analogous to the homogeneity property of the Shephard (1970) output distance function. The translation property can be expressed as

$$(6) \quad \vec{D}o\,(x, y + \beta g_y, b - \beta g_b; g_y, -g_b) = \vec{D}o\,(x, y, b; g_y, -g_b) - \beta \,\forall\, \beta \in \Re.$$

This property states that if the vector of the good output is expanded by a factor β, and the bad output is contracted by the same factor, then the value of the resulting distance function will be more efficient by the amount β (Färe et al. 2005).

Case 1: No Regulation

One of this paper's objectives is to compare two representative DMUs under two alternative regulatory scenarios. In the first case, the representative DMU is unregulated, and thus maximizes output, given the technology and inputs, by radially expanding production towards the frontier in a manner that expands the quantity of the desirable output without contracting the undesirable output.

Figure 1 is an illustration of the representative DMU for case 1. Initial production is at a point inside the output set, labeled $A = (y_1\, b_1)$, that is clearly inefficient. The DMU's objective is to maximize the production of the good output, given inputs. By expanding the desirable output while holding the undesirable output fixed, production moves to the point labeled $C = (y_1 + \beta g_y\, b_1)$. The DMU is producing on the boundary of the output set and therefore it is technically efficient. The values of the directional vector are $g = (1, 0)$. These values are chosen for their simplicity and for ease of interpreting the results, and they reflect the DMU's sole objective of maximizing production of the desirable output, given inputs and the technology. The shadow price of the undesirable output at point $\mathcal{C}$ is effectively zero. The DODF facing this representative DMU is given as:

$$(7) \quad \vec{D}o\,(x, y, b; 1, 0) = \max\{\beta : (y + \beta g_y, b) \in P(x)\}.$$

Case 2: Environmental Regulation

Case 2 assumes that a policy is in place that seeks to reduce the production of the undesirable output, either by having a regulator enact a cap on the production of undesirable outputs (e.g., EPA (2008) limitations on concentrated animal feeding operations), or through a market mechanism that levies a monetary cost on the production of undesirable outputs as envisaged by the Clean Air Act Amendments (1990). Under both of these options, the overarching goal is the contraction of emissions. The movement away from the unregulated point to a different point on the frontier, with less of both the desirable and the undesirable outputs, imposes additional costs to the DMU. These costs may be due to the diversion of inputs from good production towards abatement activities, or giving up some production of the good output in order to generate less undesirable output.

Figure 1 illustrates the DODF facing a representative DMU for case 2. The efficient combination of the desirable and the undesirable output is determined by the tangency

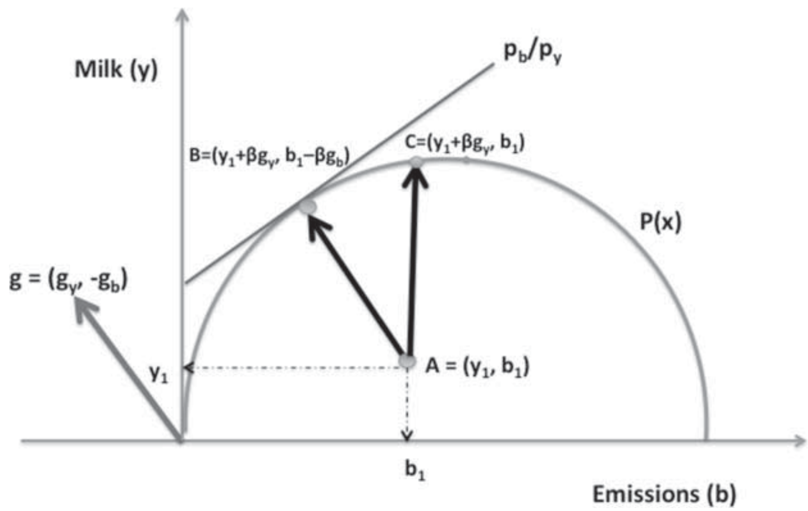

Figure 1. The directional output distance function

of the price ratio (p_b/p_y) and the frontier of the output set, $P(x)$. The vector $g=(g_y-g_b)$ represents the directional vector. By the translation property, the scaling of the vector, from point A to point B, parallel to the directional vector and towards the output set, represents a solution to $\vec{D}o\,(x,y,b;g_y,-g_b)=\max\{\beta:(y+\beta g_y,b-\beta g_b)\in P(x)\}$. The representative DMU in figure 1 is initially producing inside the output set at point $A=(y_1 b_1)$. The objective of the DMU is to raise its efficiency by scaling the vector to point $B=(y_1+\beta g_y,b_1-\beta g_b)$. At the point of tangency of the price ratio (p_b/p_y) and the frontier of the output set, the solution to this problem is given by $\vec{D}o\,(x,y,b;1,-1)=0$. The specification for this case differs from case 1 in the values of the directional vector. Here, we choose the values $g=(1,-1)$ as the directional vectors. These values are chosen for the following reasons: 1) because we assign equal weights to both desirable and undesirable outputs; 2) for their convenience and ease of interpreting the results; and 3) to reflect the DMU's desire to expand production of the desirable output while simultaneously contracting an equal proportion of the undesirable output. The choice of these values for the directional vector is consistent with other studies that consider polluting technologies (e.g., Chung, Färe, and Grosskopf 1997; Färe et al. 2005 and 2012; Picazo-Tadeo, Reig-Martinez, and Hernandez-Sancho 2005).

The DODF facing the representative DMU is given by

$$\text{(8)}\qquad \vec{D}o\,(x,y,b;1,-1) = \max\{\beta\colon (y+\beta g_y, b-\beta g_b)\in P(x)\}.$$

In the empirical analysis below, we use a quadratic specification for the DODF because we are interested in estimating shadow prices for the undesirable output, and the second-order approximations will serve to estimate this unknown function (Färe et al. 2005). We estimate the DODF as a stochastic frontier that takes the form of $\vec{D}o\,(x,y,b;g_y,-g_b)+(\omega+\varepsilon)=0$. The error component $(\omega+\varepsilon)$ captures random noise, individual DMU-effects, and persistent and transient technical inefficiency. More details on this error structure are provided below.

We closely follow Färe et al. (2005) in applying the translation property so that for the i^{th} observation the scaling factor β^i is added to y^i and subtracted from b^i such that

$$\text{(9)}\qquad \vec{D}o\,(x^i,y^i+\beta^i g_y,b^i-\beta^i g_b;g_y,-g_b)+\beta^i = \vec{D}o\,(x^i,y^i,b^i;g_y,-g_b).$$

Thereafter, the left-hand term in equation (9), $\vec{D}o\,(x^i,y^i+\beta^i g_y,b^i-\beta^i g_b;g_y,-g_b)+\beta^i$ is substituted for $\vec{D}o\,(x^i,y^i,b^i;g_y,-g_b)$. In this article, we set $\beta^i = b^i$, and thus we are able to obtain variation on the left-hand side by choosing a β^i that is specific to each observation. Consequently, the stochastic frontier to be estimated can be written as

$$(10)\quad -\beta^i = \vec{D}o\,(x^i, y^i + \beta^i g_y, b^i - \beta^i g_b; g_y, -g_b) + (\omega^i + \varepsilon^i).$$

Persistent and Transient Technical Efficiency, and DMU Heterogeneity

Early stochastic production frontier (SPF) studies modeled efficiency as consisting of two components: a statistical error and a technical inefficiency part (e.g., Aigner, Lovell, and Schmidt 1977; Meeusen and van den Broeck 1977). Subsequent SPF studies modeled technical efficiency as either persistent (time-invariant) efficiency (e.g., Schmidt and Sickles 1984), or time-varying (e.g., Kumbhakar 1991; Battese and Coelli 1992).

Succeeding stochastic production frontier models went a step further and developed methods that could decompose overall technical efficiency into persistent (time-invariant) technical efficiency and transient (time-varying) technical efficiency (e.g., Kumbhakar and Hjarmarsson 1995; Kumbhakar and Heshmati 1995). A major shortcoming of these models was their failure to disentangle time-invariant firm effects from persistent and transient inefficiency. In a slightly different approach, Ahn, Good, and Sickles (2000) analyzed long-term technical inefficiency levels in the U.S. airline industry using an autoregressive approach that allowed technical efficiency levels to be serially correlated over time. Greene (2005a, 2005b) proposed the "true fixed" and the "true random" effects models in an attempt to disentangle firm heterogeneity from time-varying inefficiency. However, these models did not identify persistent time-invariant inefficiency, thus confounding persistent inefficiency with firm effects.

Recent studies have developed four-way error structure procedures to disentangle unobserved heterogeneity across DMUs, time-invariant persistent technical efficiency, time-varying transient technical efficiency, and standard random errors (e.g., Colombi et al. 2014; Filippini and Greene 2014; Kumbhakar, Lien, and Hardaker 2014; Tsionas and Kumbhakar 2014). Within the dairy industry, persistent inefficiency levels may vary across DMUs for various reasons that include prior institutional and statutory regimes (e.g., federal marketing orders, minimum pricing laws that effectively set price floors on fluid milk products, food and safety regulations, and various environmental regulations at the state and county levels). Transient inefficiency levels may vary because of shocks associated with new production technologies (Kumbhakar, Tsionas, and Sipilainen 2009), human capital (Kumbhakar, Ghosh, and McGuckin 1991), and learning by doing. Moreover, as the discussion of the data below will demonstrate, dairy production in the United States is conducted in geographically diverse regions that face distinct environmental conditions. Following Filippini and Greene (2014), we implement the generalized true random effects (GTRE) model that nests a pooled frontier model and the true random effects model. The functional form to be estimated is

$$(11)\quad -b_{it} = \omega_0 + \sum_{n=1}^{5} \alpha_n x_{nit} + \delta_1 z_{it} + \pi_1 t + \pi_2 t^2 + \phi_1 y_{1it} + \psi_1 y_{2it} + \tfrac{1}{2}\phi_2 y_{1it}^2 + \tfrac{1}{2}\gamma_2 b_{it}^2 + \omega_i + \varepsilon_{it}$$

where the variable x_{nit} represents the conventional inputs of *cows, machinery, labor, concentrate feed*, and *forage*; z_{it} is an environmental variable that denotes *temperature*; t and t^2 are a quadratic *time trend* that capture technical change; y_{1it} and b_{it} represent *milk* output and *emissions*, respectively; and y_{2it} measures *other outputs*. In order for the translation property to hold, and to account for our choice of directional vector, as a parametric restriction we impose $\phi_1 - \gamma_1 = -1$ (Färe et al. 2005).

The error structure for the GTRE model consists of a two-part disturbance. The first part is a time-varying component, $\varepsilon_{it} = v_{it} - u_{it}$, where v_{it} and u_{it} represent statistical errors and a transient inefficiency term, respectively. This time-varying component follows a skew normal distribution with parameters $\lambda = \sigma_u/\sigma_v$ and $\rho = (\sigma_v^2 + \sigma_u^2)^{1/2}$. The second part is a time-invariant component, $\omega_i = \xi_i - \eta_i$, where ξ_i and η_i capture DMU heterogeneity and persistent inefficiency, respectively. This component also follows a skew normal distribution with parameters $\kappa = \sigma_\eta/\sigma_\xi$ and $\theta = (\sigma_\eta^2 + \sigma_\xi^2)^{1/2}$ (see Filippini and Greene 2014). The benefit of this formulation is that we can now disentangle persistent technical efficiency from transient technical efficiency while accounting for DMU-specific heterogeneity. Following Filippini and Greene (2014), the maximum simulated log likelihood function for the GTRE model is

$$(12)\quad \log L(\omega,\alpha,\lambda,\sigma,\kappa,\rho,\theta) = \sum_{i=1}^{N} log\frac{1}{R}\sum\nolimits_{r=1}^{R}$$
$$\times\left\{\prod\nolimits_{t=1}^{T}\left[\frac{2}{\sigma}\phi\left(\frac{y_{it}-\omega-\alpha' x_i-(\sigma_\xi\xi_{ir}-\sigma_\eta|\eta_{ir}|)}{\sigma}\right)\Phi\left(\frac{-(y_{it}-\omega-\alpha' x_i-(\sigma_\xi\xi_{ir}-\sigma_\eta|\eta_{ir}|)\lambda}{\sigma}\right)\right]\right\}.$$

The estimation of technical efficiency uses a moment-generating function for the multivariate closed skew normal distribution as follows (see Colombi et al. 2014):

$$(13)\quad \mathrm{E}[\exp(t' u_i)|e_i] = \frac{\bar{\Phi}_{T+1}(Re_i + \Lambda t, \Lambda)}{\bar{\Phi}_{T+1}(Re_i, \Lambda)} \times \exp\left[t' Re_i + \tfrac{1}{2}t'\Lambda t\right]$$

where $e_i = y_i - X_i\alpha - 1_T\omega$. Equation (13) gives the conditional expected value of the ith element of the inefficiency vector, $\exp\{-u_i\}$. A discussion of the coefficient estimates and various statistical tests is provided following the presentation of the data.

Data

County-level data obtained from the USDA census is utilized in this article. The USDA census consists of all farms that generated and sold $1,000 or more of agricultural products during a given census year. The census covers just about every facet of U.S. agriculture and is conducted every 5 years by the National Agricultural Statistics Service (USDA NASS 2013). Using aggregate data to analyze farm production economics is not ideal but is often necessary given the absence of farm-level panel data. Moreover, a long list of visible studies have relied on aggregate data to analyze various economic aspects related to farm economics, including Ball et al. (1997; 1999; Ball, Hallahan, and Nehring 2004) and O'Donnell (2012), who used state-level data to analyze productivity in U.S agriculture. Other examples include Binswanger (1974a, 1974b), who used county-level data to measure technical change biases and factor demand elasticities. More recently, Isik (2004) used county-level data from the 1992 and 1997 censuses to study the impact of environmental regulation on the spatial structure of the U.S. dairy industry. Sneeringer and Key (2011) employed data from the 1997, 2002, and 2007 censuses to examine the impact of regulatory intervention on the size of livestock operations.

In this article, we utilize a considerably longer time span compared to the papers cited above. In particular, we use the following years: 1978, 1982, 1987, 1992, 1997, 2002, and 2007. The dataset includes a total of 132 counties spread across 26 states, covering most geographic regions of the country for a total of 924 observations (see figure 2). The "State and County Rankings" volume, published alongside every USDA Agricultural Census Report, was used to select the counties, which correspond to those with the highest dairy cow inventories.

The dataset derived from the census is then augmented with annual average temperatures at the county level obtained from the National Oceanic and Atmospheric Administration (NOAA). Available evidence indicates that temperature variability can have significant effects on dairy production (e.g., Mukherjee, Bravo-Ureta, and De Vries 2013; Key and Sneeringer 2014). Moreover, according to a recent USDA Agriculture Research Service (2013) report, temperature increases ranging from $1.0\,C^0$ to $3.0\,C^0$ are likely to cause declines in yields of major U.S. agricultural commodities. Furthermore, the report indicates that livestock productivity is affected by

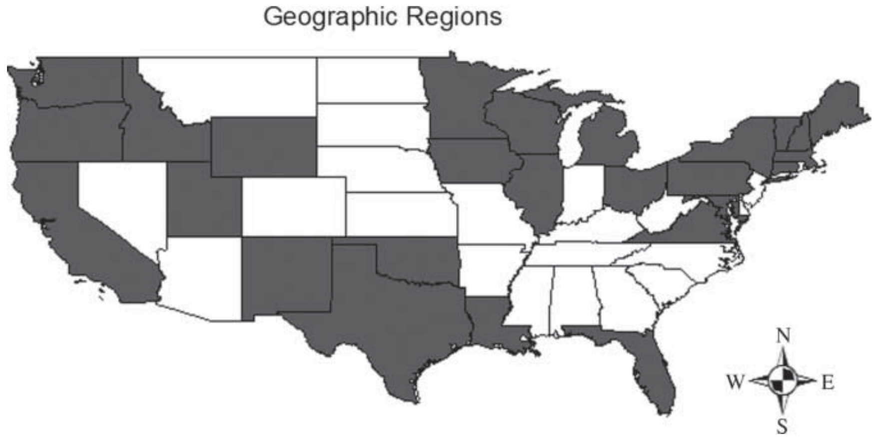

Figure 2. Geographical location of counties in the dataset

temperature in four ways: 1) feed grain production; 2) pasture and forage crop production; 3) animal health growth and reproduction; and 4) disease and pest distributions.

The output information derived from the census data is a combination of crop and livestock variables at the county level. The variables include total number of farms and total value of agricultural sales, which are broken down into crop and livestock sales. Other variables include the market value of plant, machinery, and equipment, total pastureland in acres, harvested cropland in acres, and irrigated land. Total farm expenses are broken down into feed, fuel and energy, fertilizer and chemical inputs, and labor. Finally, the dataset includes a breakdown of the livestock inventory and an inventory of selected crops.

The quantity of concentrate feed was constructed by dividing the nominal figures for total feed expenses per cow by the nominal state-level price for 16% concentrate feed for the respective year, which was obtained from the USDA National Agriculture Statistics Service (NASS). The labor input is in worker equivalent hours, and is constructed by dividing total labor expenses by the hourly wage rate of the state where the respective counties are located. All monetary figures are converted into constant 2012 dollars using the producer price index formulae provided by the U.S. Department of Labor (2013).

Construction of the Undesirable Output

The few farm-level analyses available for dairy consider emissions as emanating solely from nitrogen surplus (e.g., Reinhard, Lovell, and Thijssen 1999; Fernandez, Koop, and Steel 2002). By contrast, we introduce an index that incorporates three major sources of GHG pollution: livestock, fuel, and fertilizer. According to the Gerber et al. (2013), feed production and processing are responsible for at least 45% of GHGs from livestock operations. Digestion by cows accounts for another 39% of GHG emissions, whereas manure decomposition accounts for 10%, and the remainder of GHG emissions are attributable to the processing and transportation of animal products. The fertilizer and fuel components of the pollution index in this article capture GHG emissions from the feed production and processing stage, whereas the livestock component of the pollution index is meant to capture GHG emissions emanating from the digestive process and manure decomposition in dairy operations. In this article, GHGs from the processing and transportation part of the fluid milk supply chain are considered off-farm emissions, and hence constitute emissions from different sectors of the economy.

The livestock component of this index of pollution is developed using methodologies enumerated in EPA (2009). The fuel portion of this index is constructed using information on fuel expenditures by dairy operations. Finally, the fertilizer component is constructed using information on fertilizer expenditures incurred by the dairy operations.

Regarding the EPA (2009) methodologies, they came about when the EPA was authorized by the U.S. Congress, under the Consolidated Appropriations Act (2008),

"… to develop and publish a draft rule no later than 9 months and a final rule not later than 18 months after the date of enactment of the act, to require mandatory reporting of greenhouse gas emissions above appropriate thresholds in all sectors of the economy of the United States." The objectives of the proposed reporting rules were to improve the collection of accurate and timely information on GHG emissions, to enable a better understanding of where emissions were coming from, and to improve the design of sound policies and regulations. In the course of developing the final rule, these methodologies were challenged and received wide attention from academics and other interest groups. The EPA held two public hearings, met with over 4,000 persons and 135 groups, and received approximately 16,800 written public comments (EPA 2009).

Specific concerns were expressed about the EPA's decision to include livestock facilities, because some deemed that manure management systems in such facilities were not a major source of GHG emissions in the United States. In addition, some argued that the environmental benefits of subjecting livestock facilities to regulation would be minimal compared to the effort required to report emissions (EPA 2009). The EPA disagreed with this assessment and contended that manure management systems had been determined to be a major source of emissions based on the "key source category" methodology that was developed by the Intergovernmental Panel on Climate Change (IPCC 2000). Furthermore, the EPA observed that "…while livestock manure GHG emissions represent a relatively small fraction of total U.S. GHG emissions, these emissions are large in absolute terms," (EPA 2009).

Another concern was that the monitoring and reporting requirements would be burdensome and difficult to comply with. Consequently, in order to mitigate these concerns, the EPA, in the revised version that followed the draft rule, reverted back to default values for reporting Nitrogen (N) and volatile solids (VS) using Intergovernmental Panel on Climate Change (IPCC) Tier II methodologies for beef and dairy cows. Furthermore, the EPA "… reviewed many protocols and approaches prior to selecting the proposed methodology," (EPA 2009). The selected methodology was based on the EPA's inventory of U.S. GHG emissions and sinks and the IPCC guidelines for national GHG inventories.

The EPA's procedures differ markedly from other methodologies that have been used to evaluate GHG emissions in the U.S. dairy sector. Most prominent is the Life Cycle Assessment (LCA) that has been used to evaluate the extent of GHG emissions in the fluid milk supply chain in the United States (e.g., Thoma et al. 2012, 2013; Ulrich et al. 2013; Nutter et al. 2013). The fluid milk supply chain includes production, processing, transportation, and retail. Our pollution index and EPA methodologies categorize off-farm emissions from fluid milk processing, transportation, and retail as coming from other sectors of the economy. Our approach considers only production; consequently, the other links in the value chain are considered beyond the scope of this article. However, we augment the EPA methodologies with information on emissions that come from fuel as well as fertilizer, in much the same way as the LCA approach does.

The LCA approach utilizes the American Society of Agricultural Engineers manual (ASAE 2005) to predict the quantity of manure generated, and peer-reviewed surveys to predict enteric methane emissions. On the other hand, the EPA uses the IPCC Tier II methodology to calculate default values for volatile solids (VS) and Nitrogen (N) excretion for beef and dairy cows, heifers, and steers (EPA 2009).

Livestock-based emissions are constructed using methodologies delineated in the EPA (2009) guidelines. These emissions, which are measured in metric tons of carbon dioxide equivalents (CO_2e), are a combination of methane (CH_4) and nitrous oxide (N_2O). Methane (CH_4) is a product of total volatile solids excreted per animal type, the fraction of volatile solids per animal type that is managed at the dairy facility, and a methane conversion factor. The USDA Agricultural Census, which is conducted at the county-level, does not collect information on manure management systems; hence, our estimates of CH_4 emissions are constructed using information about the type and size of the herd and the state where the county is located. The total volatile solids are the product of the average annual animal population of the county, the typical animal mass for each animal type (for dairy cows, the default value is given as 604 kg), and the volatile solids excretion rate for each animal type. The

Table 1. Descriptive Statistics

Variable	Observation	Mean	Std. Dev.	Min.	Max.
Emissions (Tons)	924	125,079.4	135,640.3	1,870.9	1,352,795.0
Milk (Tons)	924	698,408.8	14,100,000.0	3,794.8	430,000,000.0
Other Output ($)	924	128,000,000.0	298,000,000.0	224,000,000.0	3,290,000,000.0
Cows (Number)	924	33,555.5	36,165.5	124.0	474,497.0
Machinery ($)	924	158,000,000.0	136,000,000.0	6,166,626.0	1,160,000,000.0
Labor (Hours)	924	3,888,116.0	9,226,716.0	6,451.6	71,400,000.0
Concentrate Feed (Tons)	924	195,827.6	325,340.8	3,879.1	3,293,370.0
Forage Feed (Tons)	924	413,392.7	394,807.1	3,887.0	4,124,080.0
Temperature (Celsius)	924	8.6	4.0	2.5	23.4

volatile solids for each animal type are state specific and these estimates are multiplied by 21, the global warming potential of CH_4 (EPA 2009).

Livestock-based N_2O is a product of the daily total nitrogen excreted per animal type. This in turn is a function of the average annual animal population in the county, the typical mass of the livestock, the state where the county is located, and an emissions factor. These estimates are then multiplied by 310, the global warming potential of N_2O (EPA 2009).

Fuel-based emission is constructed by utilizing data on gas, fuel, and oil expenditures. Then, using historical conventional gasoline prices from the Energy Information Administration (EIA) of the U.S. Department of Energy, the total amount of fuel consumed (in gallons) is calculated. Finally, CO_2e from fuel are estimated using the EPA greenhouse gas equivalencies calculator (EPA 2013b).

The fertilizer-based emission is constructed using information on fertilizer expenditures incurred by the dairy operations at the county level. Historical fertilizer prices are obtained from the NASS. These prices are then used to estimate the total amount of fertilizer (in tons) used in the county. The direct emission of N_2O derived from the nitrogen applied to the soil via fertilizers is calculated using formulae from Mosier (1994). The measure of emissions that constitutes the undesirable output in this article is the total CO_2e from all three major sources of pollution: livestock, fuel, and fertilizer.

Table 1 provides descriptive statistics for all variables incorporated in our model. There are two desirable outputs—*milk* and *other outputs*—and one undesirable output—*emissions*. In developing the trade-off between the desirable and the undesirable output, *other outputs*, which represents all other agricultural output generated, is a minor contributor to farm revenues in the counties included in the data set, and therefore is held constant.[1] The inputs are the number of *cows*, hours of *labor*, and value of *machinery* (in constant 2012 dollars). The input *machinery* is constructed using the perpetual inventory method, which is a means of imputing net additions to capital stock. Using 1978 as the base year, any changes in plant, machinery, and equipment values in subsequent years are considered to reflect net investment in capital, which are added to the base value. Other inputs are quantity of *concentrate feed* and *forage*. Finally, *temperature* represents the average annual temperatures at the county-level in degrees Celsius.

The Shadow Price

Before moving on to the results and analysis, we present some comments regarding the shadow price of emissions. The shadow price is the dollar value of the undesirable output that is generated at the tangency of the price-line (p_b/p_y) and the output frontier $P(x)$. We interpret this as the marginal abatement cost because it reveals the extent of the DMUs' liability to society as a result of generating an

[1] The selected counties specialize in milk production, which is evidenced by the high share of total farm revenue coming from milk. Consequently, other output is held constant in the analysis given its consistent low weight throughout time.

additional unit of emission at the margin. We use the duality between the revenue function and the DODF to derive relative shadow prices. Following Chambers, Chung, and Färe (1998), we set up the revenue function as follows:

$$(14)\quad R(p_y, p_b; \beta) = max_{y,b}\left\{p_y.y - p_b.b : \vec{D}o\,(x, y, b; g_y, -g_b) \geq 0\right\}.$$

The first-order conditions associated with revenue maximization are given by

$$(15)\quad (p_y.g_y - p_b g_b)\nabla_y \times \vec{D}o\,(x, y, b; g_y, -g_b) = -p_y$$

and

$$(16)\quad (p_y.g_y - p_b g_b)\nabla_b \times \vec{D}o\,(x, y, b; g_y, -g_b) = p_b.$$

The ratio from the above expressions gives the relative shadow price as

$$(17)\quad p_y/p_b = \left\{\nabla_y \vec{D}o(x\,y\,b; g_y - g_b)\right\}/\left\{\nabla_b \vec{D}o(x\,y\,b; g_y - g_b)\right\}$$

where p_y is the market price of good y, and p_b is the shadow price of the undesirable output. Since we know all parts of equation (17) except for p_b, we can solve for the latter and thus recover the needed shadow price.

The Morishima Elasticity of Output Substitution

The shadow price provides information about the slope of the output set $P(x)$ at the point of tangency with the price line (p_b/p_y). In comparison, the Morishima elasticity of output substitution (MES) provides information about the curvature of $P(x)$. The MES is defined as "... a measure of curvature, or ease of substitution," (Blackorby and Russell 1989). In a different analysis, Färe et al. (2005) define the MES as a measure of changes in the desirable-undesirable price ratio relative to changes in the desirable-undesirable output quantities, that is, $MES_{by} = \{\partial ln(p_b/p_y)/\partial ln(y/b)\}$. Based on the directional output distance function, the MES can be specified as follows:

$$(18)\quad MES_{by} = y\left[\frac{\partial^2 \vec{D}o\,(x, y, b; 1, -1)\,/\partial b^2}{\partial \vec{D}o\,(x, y, b; 1, -1)\,/\partial b} - \frac{\partial^2 \vec{D}o\,(x, y, b; 1, -1)\,/\partial y^2}{\partial \vec{D}o\,(x, y, b; 1, -1)\,/\partial y}\right].$$

The MES measures the ability of the DMU to trade reductions in milk output for reductions in emissions.

Results and Analysis

As indicated earlier, this article considers two cases: case 1, which is without regulation, and case 2, which is with regulation. We run separate GTRE regressions where the model in case 1 incorporates a directional vector $g = (1, 0)$, while the model in case 2 utilizes a directional vector $g = (1, -1)$. Parameter estimates for both models are presented in table 2 below. The estimated parameters from case 2, with regulation, are subsequently used to measure the shadow prices of emissions and the Morishima output elasticities of substitution to evaluate the impact of a hypothetical GHG environmental regulation.

A Hausman specification test is used to compare the two models. Under the null hypothesis of no systematic difference between the model under regulation and the model without regulation, the Hausman specification test with a chi-squared distribution returns a statistic $H = 1,594.8$ and a P-value $= 0.000$. Consequently, the null hypothesis that there is no systematic difference between the model with regulation and without regulation is rejected. Results of the distributional parameters $\lambda, \rho, \sigma_\eta$ and σ_ξ are also provided in table 2. The ratio σ_u of σ_v and is given by λ, and it denotes the relative importance of the transient inefficiency term u_{it} with respect to the two-sided statistical error term v_{it}. For the case with regulation, $\lambda = 0.2873$; consequently, we conclude that the statistical error dominates the one-sided transient inefficiency component in the determination of the time-varying component, ε_{it}. On the other hand, the variance of the persistent inefficiency term, σ_η, dominates the variance of the DMU heterogeneity term, σ_ξ; hence,

Table 2. Estimated Random Coefficients Frontier Model

Parameter	With Regulation		Without Regulation	
	Coef.	Std. Err.	Coef.	Std. Err.
α_1	0.2439[a]	0.0183	0.0236	0.0159
α_2	0.2333[a]	0.0104	0.1964[a]	0.0075
α_3	0.0428[a]	0.0041	0.0204[a]	0.0030
α_4	−0.0010	0.0056	−0.0061	0.0038
α_5	0.0450[a]	0.0040	0.0375[a]	0.0029
δ_1	0.1101[a]	0.0122	0.0841[a]	0.0098
π_1	0.2488[a]	0.0413	0.1611[a]	0.0279
π_2	−0.1432[a]	0.0178	−0.1133[a]	0.0123
ψ	−0.0067[c]	0.0035	−0.0063[b]	0.0025
ϕ_1	0.2412[a]	0.0160	0.5862[a]	0.0197
ϕ_2	−0.0284[a]	0.0005	−0.0431[a]	0.0004
γ_2	0.0859[a]	0.0015	0.0857[a]	0.0012
ω_0	−0.0373	0.0562	−0.0079	0.0715
λ	0.2873	0.4396	0.2090	0.8462
ρ	0.1349[a]	0.0109	0.1039[a]	0.0118
σ_η	0.0296	0.0539	0.0977[c]	0.0541
σ_ξ	0.0001	0.0044	0.0024	0.0033
Log simulated likelihood	609.8		797.4	

Note: Superscript a, b, and c denote 1%, 5%, and 10% levels of significance, respectively.

we conclude that the persistent inefficiency term largely determines the composition of the time-invariant component, ω_i.

Estimates for transient technical efficiency (TTE) and persistent technical efficiency (PTE) are presented in table 3 below. For case 1, the mean TTE and PTE scores are 92.4% and 92.9%, respectively, whereas for case 2, the mean TTE and PTE scores are 97.2% and 97.7%, respectively. The kernel densities for persistent and transient technical efficiency are plotted in figure 3. Overall, these TE scores are higher than findings from traditional stochastic production frontier studies conducted on U.S. dairy farming (e.g., Bravo-Ureta et al. 2007) and other parts of the world (e.g., Moreira and Bravo-Ureta 2009).

The TTE and PTE findings reveal that a GHG environmental regulatory framework would lead, on average, to a 5-percentage point increase in both transient and persistent technical efficiency. Empirical evidence from past studies concerning regulation and technical efficiency is mixed. Some studies suggest that technical efficiency improves following stringent environmental regulation (e.g., van der Vlit, Withagen, and Folmer 2007). Other studies have found technical efficiency falling in response to environmental regulation (e.g., Chintrakarn 2008). An explanation for how and why technical efficiency would increase following stringent environmental regulation comes from Porter and van der Linde (1995), who argue that environmental regulation encourages efficiency by stimulating innovations and cost savings that are more than sufficient to offset the cost of compliance.

The calculated shadow prices for emissions reveal that only six values of 924 are outside the $\Re_+$ support, which suggests that these few negative estimates lie on the negatively sloped portion of $P(x)$. According to Färe et al. (2005), negative shadow prices in a stochastic production frontier model could be an indication of a violation of the monotonicity property. The average shadow price of emissions for the rest of the DMUs (i.e., the 918 non-negative values) is $485.40/ton. We report counties with the highest and the lowest shadow price estimates in table 4 below.[2]

To illustrate the meaning of the shadow price in this context, we take the $936.20/ton value for Addison County (VT) in 2007 shown in table 4. This shadow price indicates

[2] A complete list of estimates of shadow prices for all counties across all the census years is available on the OUP website as part of the supplementary appendix.

Table 3. Technical Efficiency Estimates (by percentage)

		Case 1: Without Regulations		
TE	Mean	Std. Dev.	Max.	Min.
TTE	92.4	0.125	99.7	97.8
PTE	92.9	0.105	99.8	77.2
		Case 2: With Regulations		
TE	Mean	Std. Dev.	Max.	Min.
TTE	97.2	0.003	99.2	93.8
PTE	97.7	0.002	99.2	95.7

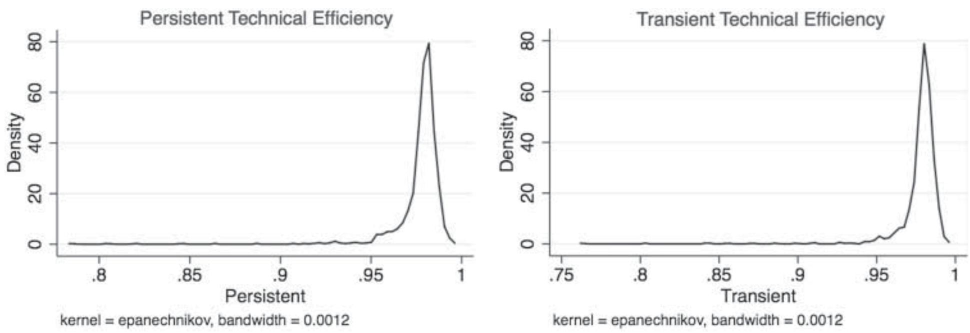

Figure 3. Kernel density for persistent and transient technical efficiency

Table 4. Counties with the Highest and Lowest Shadow Prices

County	Year	Shadow Price ($/ton)	Milk Price ($/ton)	Milk (tons)	Emissions (tons)	Shadow Price/ Milk Price (P_b/P_y)
Highest						
Addison, VT	2007	936.21	454.15	277,094.29	87,165.39	2.06
Brown, WI	2007	913.33	425.49	395,628.91	110,398.28	2.15
Okechobee, FL	2007	929.47	482.81	214,861.94	80,751.23	1.93
Lebanon, PA	2007	906.28	460.77	197,464.60	70,386.53	1.97
Manitowoc, WI	2007	905.42	425.49	449,672.20	128,897.04	2.13
Calumet, WI	2007	905.31	425.49	275,694.85	79,051.07	2.13
Franklin, VT	2007	901.99	454.15	285,256.76	99,197.25	1.99
Dona Ana, NM	2007	899.03	414.47	462,673.87	124,888.45	2.17
Orleans, VT	2007	899.03	454.15	154,093.70	54,034.02	1.98
Cayuga, NY	2007	896.66	434.31	322,897.90	101,147.52	2.06
Lowest						
Kern, CA	1978	43.74	224.87	127,028.10	300,961.54	0.19
Curry, NM	1992	64.23	268.97	33,119.68	74,481.38	0.24
Yakima, WA	1982	82.53	293.22	98,995.68	211,918.47	0.28
Yakima, WA	1978	85.40	233.69	85,408.02	166,332.44	0.37
Twin Falls, ID	1978	96.89	219.36	46,913.76	84,048.76	0.44
Kern, CA	1992	99.59	255.96	242,080.02	459,299.25	0.39
Weld, CO	1978	102.28	246.92	119,614.74	220,790.31	0.41
Fresno, CA	1982	116.33	291.23	317,981.64	596,489.83	0.40
Roosevelt, NM	1978	121.92	253.53	28,422.49	48,819.53	0.48
Fresno, CA	1987	130.32	251.99	440,163.18	727,483.58	0.52

Table 5. Morishima Elasticity of Output Substitution Estimates

County	Year	MES	Milk (tons)	Emissions (tons)	Milk Price ($/ton)	Shadow Price ($/ton)
Highest						
Essex, VT	1992	−7.60	16,220.86	1,870.98	304.24	792.56
Essex, VT	1997	−6.75	16,440.34	2,106.50	315.26	808.43
Grand Isle, VT	1992	−6.34	22,364.08	3,034.01	304.24	773.23
Grand Isle, VT	1997	−5.71	23,104.66	3,430.05	315.26	788.85
Eddy, NM	1987	−4.51	165,332.63	30,007.41	279.99	673.68
Tillamook, OR	2002	−3.39	287,534.02	65,499.20	275.58	627.71
San Bernadino, CA	2002	−2.80	1,554,014.09	408,526.67	241.19	527.44
Dona Ana, NM	2007	−2.70	462,673.87	124,888.45	414.47	899.03
Brown, WI	2007	−2.58	395,628.91	110,398.28	425.49	913.33
San Bernadino, CA	2007	−2.57	1,016,831.83	284,535.99	397.50	852.49
Lowest						
Gooding, ID	1978	−0.01	47,460.81	47,150.26	219.36	223.47
Twin Falls, ID	1992	−0.03	123,297.75	119,726.27	264.56	275.62
Clayton, IA	1982	−0.03	143,098.08	138,720.43	291.01	303.67
Clayton, IA	1978	−0.03	120,794.79	116,971.97	222.67	232.60
Fresno, CA	2002	−0.04	867,219.69	835,371.00	241.19	253.24
Fillmore, MN	1982	−0.04	122,365.10	117,836.83	286.16	300.52
Comanche, TX	1978	−0.04	49,934.26	47,881.18	255.74	269.64
Curry, NM	1987	−0.05	69,763.94	66,338.90	279.99	297.58
Rock, WI	1982	−0.06	132,258.89	125,193.04	291.45	311.12
Chester, PA	2007	−0.07	147,619.36	137,999.61	460.77	497.64

that an increase in milk output at the margin generates $936.20/ton worth of emissions. In contrast, the lowest shadow price was obtained in Kern County (CA) in 1978 at $43.70. These results have the following implications: dairy operations in Addison, VT would have faced the highest marginal abatement costs, whereas dairy facilities in Kern, CA would have met the lowest marginal abatement costs following an environmental regulatory intervention. Consequently, a regulatory intervention set at the marginal abatement cost would have resulted in Addison County, VT bearing the highest cost relative to other counties.

The last column in table 4 considers the price ratio for emissions (p_b) and milk (p_y), which gives the slope of the output frontier $P(x)$ at the point of tangency with the price line (p_b/p_y). It is apparent that the 10 counties with the highest shadow prices generated considerably lower levels of emissions relative to milk output. In contrast, the 10 counties with the lowest shadow prices generated particularly high levels of emissions relative to milk. It is noteworthy to point out that the 10 lowest shadow price estimates were obtained in counties in the Pacific and Mountain regions of the United States. On the other hand, eight of the 10 highest shadow price estimates were obtained in the Northeast and the Great Lakes regions.

Finally, the Morishima elasticity of output substitution (MES) evaluates the ability of the DMU to trade reductions in milk output for reductions in emissions. High MES values (in absolute terms) indicate that changes in the milk-emission output (y/b) ratio resulted in greater changes in the shadow-milk price (p_b/p_y) ratio, thus revealing that there were fewer substitution possibilities, and therefore making it more costly for such DMUs to substitute away from emissions and towards milk output. Table 5 presents MES estimates for the 10 highest and the 10 lowest counties.[3] The highest (in absolute values) estimated MES is for Essex, VT at −7.60 in 1992. Conversely, the lowest (least negative) MES estimated was in Gooding, ID at −0.01 in 1978. The implication of this result is that dairy operations in Essex, VT were operating on a point on the frontier where changes

[3] A complete list of estimates of the Morishima elasticity of output substitution across all the census years is available on the OUP website as part of the supplementary appendix.

in the (p_b/p_y) ratio relative to changes in the milk-emission output (y/b) ratio were high. Consequently, reductions in emissions by one metric ton would have required giving up production of milk output by more than one metric ton. The significance of this result is that, under a hypothetical regulatory intervention, the counties with low MES would have found it relatively inexpensive to reduce emissions. Conversely, lowering emissions would have been relatively costlier for counties with high MES values.

Conclusions

The primary objective of this article is to evaluate the impact of a hypothetical GHG environmental regulatory framework in the dairy sector in the United States. Over the last several years, concerted efforts have aimed at imposing strict reporting standards on GHG emissions across all sectors of the U.S. economy (U.S. Congress 1990; Supreme Court of the United States 2007; EPA 2009). Quantifying the cost of environmental regulations designed to curtail GHG emissions in the dairy sector has been a missing link in the literature (Isik 2004). This article addresses this gap by establishing such costs across major dairy producing counties of the United States. This article adopts EPA (2009) methodologies to develop an emissions measure that combines livestock, fuel, and fertilizer sources of pollution in dairy farming. Thereafter, it utilizes a directional output distance function while incorporating a four-way error approach that accounts for county heterogeneity, transient technical efficiency that is time varying, and persistent technical efficiency that is time-invariant, as well as random errors.

Based on county-level data derived from the USDA Census of Agriculture for the years 1978, 1982, 1987, 1992, 1997, 2002, and 2007, we estimate and report shadow prices, persistent and transient technical efficiency estimates, and Morishima elasticities of output substitution, and present the results for selected counties. The findings reveal marked spatial variations across diverse counties, and these have important policy implications. For example, if a regulatory intervention were imposed at the marginal abatement cost level, the economic costs would have been highest for dairy operations in counties that faced the highest shadow prices, which tend to be located in the Midwest and the Northeast United States.

The results for the Morishima output elasticities of substitution, which are interpreted as a measure of the ability to trade reductions in dairy output for reductions in emissions, also demonstrate that counties would have faced significant disparities in their ability to reduce emissions following a regulatory intervention. That is, counties that faced high MES rates would have found it more costly to substitute away from emissions and towards milk output.

In the United States, average herd size has increased significantly over the years (USDA 2014). Furthermore, "… the correlation between milk produced per cow and the number of milk cows per operation across dairy farms is strong and positive, indicating a potential role for scale economies in determining productivity," (Mosheim and Lovell 2009). Moreover, counties in the Midwest and the East generated 94% of the country's additional milk in 2013 relative to 2012 as a result of productivity increases. Nevertheless, most large dairy operations continue to be concentrated in western states, with the Pacific and the Mountain regions accounting for 19 out of the 20 largest dairy counties in the country (USDA 2014).

In sum, the empirical evidence from our analysis, particularly regarding shadow prices, which we interpret as marginal abatement costs, highlights the challenges faced by counties in the Midwest and the East relative to the Pacific, Mountain, and Southwest regions. McDonald, McBride, and O'Donoghue (2007) argue that the evolution of federal and state regulations, and the rising costs of complying with them, is likely to be offset by cost advantages coming from economies of scale as average herd sizes continue to increase across the country. Moreover, abatement technologies such as bio-digesters are themselves characterized by significant scale economies (Leuer, Hyde, and Richard 2008; Bishop and Shumway 2009). Hence, as dairy operations expand, those who adopt new abatement technology are likely to be less affected by regulation. All these factors combined suggest that structural change will continue to be a driving force in the dairy industry.

These results have critical implications from a policy perspective. Even in the face of GHG environmental regulations, the survival of the dairy sector is crucial given its contribution to household earnings, local economies, and to the preservation of open space and agricultural landscapes. Stringent enforcement of environmental standards without bearing in mind the likely economic repercussions could lead to dairy operations moving to areas where enforcement might be relatively lax (Isik 2004). Alternatively, some operations may be forced to downsize in order to avoid regulation (Sneeringer and Key 2011), thus negating the benefits of economies of scale. Therefore, it is important to consider the cost-effectiveness of regulatory policies prior to implementing them.

The ability to quantify the economic impact of a regulatory intervention is important from a policy perspective because it provides a clear picture of how different regions would be impacted by environmental regulations. Some regulatory approaches (e.g., command-and-control) could be inflexible and costly (Kahn 1998) with wide regional disparities, and this may lead to even greater abatement costs than necessary. By contrast, policy intervention directed towards assistance programs that compensate dairy DMUs for voluntary emission reductions, and that encourage the widespread adoption of anaerobic digesters, would be more flexible. Previous studies (e.g., Bishop and Shumway 2009) have found that digester systems have multiple benefits beyond emission reductions, which include electricity generation and reduced odors. The promotion of renewable energy and voluntary mechanisms that encourage self-reporting are more flexible and less costly than command-and-control approaches (Arimura, Hibiki, and Katayama 2008). The results and analysis presented in this article provide a basis for policy-makers to evaluate alternative regulatory policies.

Supplementary Material

Supplementary material is available at http://oxfordjournals.org/our_journals/ajae/online.

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