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Eric Njuki

Boris B. Bravo-Ureta

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Charles J. Zwick Center for Food and Resource Policy
Department of Agricultural and Resource Economics
College of Agriculture and Natural Resources
1376 Storrs Road, Unit 4021
Storrs, CT 06269-4021
Phone: (860) 486-2836
Fax: (860) 486-1932
ZwickCenter@uconn.edu
www.zwickcenter.uconn.edu

A Bayesian Approach to Analyzing the Economic Costs of Environmental Regulation in U.S. Dairy Farming

Eric Njuki[1] and Boris B. Bravo-Ureta[2]

This paper develops a comprehensive pollution index based on EPA (2009) methodologies, which contrasts with previous studies that rely on partial measures based only on surplus nitrogen stemming from the over-application of fertilizer. Second, it uses a directional output distance function on a Bayesian framework, to generate empirical estimates of the economic impact associated with hypothetical environmental regulations in the dairy sector. Results indicate that on average, values of foregone output following regulatory intervention lead to revenue losses ranging from 1.8% to 13.1% across different regions between 1978 and 2007.

Keywords: environmental regulation, undesirable outputs, directional output distance function, Morishima elasticity of substitution, Bayesian framework, shadow prices, dairy farming.

JEL Codes: D22; Q15; Q52

[1] Postdoctoral Fellow, Department of Agricultural and Resource Economics, University of Connecticut
[2] Professor, Department of Agricultural and Resource Economics, University of Connecticut

Background

In 2009, the Environmental Protection Agency (EPA) announced guidelines to impose strict reporting standards on greenhouse gas emissions (GHG) across all sectors of the U.S. economy. The Agricultural industry in general, and livestock operations in particular were listed among the sectors that would be required to participate in this reporting process. The objective of the guidelines was to improve the effectiveness of the design of programs, voluntary or mandatory, aimed at emission reductions. Any attempt to limit emissions, and hence undesirable outputs, imposes additional constraints on firms by requiring that inputs be diverted away from production and towards abatement. This article examines the potential impact of these guidelines on dairy farming in the U.S. and makes two important contributions to the literature.

According to the U.S. Department of Agriculture (2013a), in 2012 the United States was the single largest producer of fluid milk in the world, with an output of 199 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, of which 97% were family owned. Dairy farming was the top agricultural activity in several states including California, Wisconsin, New York, Pennsylvania, Idaho, Michigan, New Mexico, Vermont, Arizona, Utah, and New Hampshire.

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 this has trended upward for a number of years (EPA 2013a). The Environmental

Protection Agency (EPA), which has been charged with monitoring and regulating GHG emissions in the U.S., launched a Greenhouse Gas Reporting Program (GHGRP) in 2009. This program requires several sectors to report directly their GHG emissions. The goal is to better understand where these emissions are coming from and to improve the design of sound policies and regulations. 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.

Bearing the above in mind, this article sets out to establish how these EPA guidelines could impact dairy farming in the U.S. In doing so, it makes two important contributions to the literature. First, it develops a new comprehensive pollution index for dairy farms that combine 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) have accounted only for surplus nitrogen generated from the over-application of fertilizer. Second, it uses a directional output distance function along with a Bayesian framework, to estimate the likely economic costs associated with hypothetical environmental regulations, and abatement activities in the dairy sector. 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 regulatory intervention in major milk producing areas across the U.S.

Abatement activities and environmental regulations are two approaches aimed at pollution reduction, which are already utilized and that could be implemented on a wider scale. Statutory approaches include the Clean Air Act Amendments (1990), which envisaged a market driven process and, more recently, the American Clean Energy and Security Act of 2009 that was debated but not passed by the U.S. Congress. Anaerobic digester technology, which is a form of a manure management system, is an example of a voluntary abatement approach. Such systems are good for the environment because they help to capture and burn methane that would have otherwise escaped into the atmosphere. Though digester systems have multiple benefits, they have not been widely adopted in the U.S. (Bishop and Shumway 2009) and are more suitable for large operations because of pronounced economies of scale in both their construction and maintenance (Key and Sneeringer 2012).

This article considers the opportunity cost of abatement activities, and the cost of environmental regulation. 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 has usually been sidestepped has been the impact of abatement activities, as well as the cost of 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 firms, one in an unregulated environment (Case 1), and the other under regulation (Case 2).

In Case 1, the unregulated firm maximizes profits by radially expanding its output vector towards the frontier in a manner that expands the production of the desirable output without contracting production of the undesirable output. However, the key assumption is that the representative firm 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 having a regulator impose a cap 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 firm. 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 intensive counties from the U.S. Department of Agriculture (USDA) Census for several years, this article proposes to estimate the impact that abatement activities and environmental regulation would have on dairy production across the U.S. The specific objectives are to:

1. Construct a comprehensive index of an undesirable output using three sources of pollution originating from dairy farming: fuel, fertilizer, and livestock;

2. Establish the value of the foregone desirable output associated with environmental regulation, and abatement activities.

3. Calculate the tradeoff between dairy output and emissions using the output elasticity of substitution.

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. Christainsen and Haveman (1981) consider the likely contribution of environmental regulations to the observed decrease in productivity growth between 1965 and 1979. The authors establish that an estimated 8% to 12% of the economic slowdown experienced in the U.S. during that period could be attributed to environmental regulations. Gollop and Roberts (1983) examine 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 establish that indeed environmental regulations had 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) examine U.S. economic growth in the postwar period going from 1947 to 1973. The authors conduct simulations of the U.S. economy using a general equilibrium model, with and without environmental regulations. They provide evidence that the long-run cost of pollution abatement and emissions control account for at least 2.6% of U.S. GNP during the period under review. Brannlund, Färe and Grosskopf (1995) analyze the impact of environmental regulation on firm profits in the Swedish pulp and paper industry. Using a non-parametric programming approach, the authors measure the short-run profits, with and without regulation, and use these results to determine regulatory costs. They establish that environmental regulations place a burden on the overall industry but the prevailing regulatory system is skewed in favor of smaller firms.

In a different analysis, Hernandez-Sancho, Picazo-Tadeo and Reig-Martinez (2000) use a cross section of Spanish producers of wooden goods to analyze the impact of environmental regulation in the industry. They develop an output-oriented efficiency measure, and their findings indicate that firms involuntarily have to sacrifice production of desirable outputs when they are required to reallocate inputs towards waste reduction. Isik (2004) examines how differences in environmental regulation in the U.S. dairy sector impact the spatial location of dairy operations. Results indicate that stringent environmental regulations lead dairy operations to migrate into areas with more lax regulation. Picazo-Tadeo, Reig-Martinez and Hernandez-Sancho (2005) construct 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 find 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) analyze the value of the foregone desirable output associated with abatement activities, using a model that distinguishes between an environmental production function and a directional environmental distance function. The environmental production function credits producers solely for expanding good output, whereas the directional environmental distance function credits producers for simultaneously raising production of the good output and reducing production of bad outputs. Using data for coal-fired power plants they establish a 17.6% reduction in electricity production associated with abatement activities.

In a study of solid waste generation, Arimura, Hibiki and Katayama (2008) report that voluntary approaches that involve self-reporting are more flexible, effective and less costly than command-and-control regulatory approaches. Sneeringer and Key (2011) observe that environmental regulations in the U.S. livestock industry often vary by operation size, with stricter enforcements for larger operations. They find evidence that some farms avoid oversight by shrinking their operations to within a threshold that is less regulated. More recently, Färe et al. (2012) measure the substitutability of undesirable outputs, specifically SO_2 for NO_x in electric utility plants, 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. This article builds upon these previous studies by using the directional output distance function as a means 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, several 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 assumptions: 1) that in a multi-dimensional production frontier, the decision-making unit wishes to expand the production of the desirable output while contracting the production of the undesirable output; 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 can be decomposed into measures of technical and of environmental efficiency.

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

$$T = \left\{(x, y, b): x \in \Re_+^k, y \in \Re_+^m, b \in \Re_+^i: x\ can\ produce\ (y, b)\right\} \quad (1)$$

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 firm using the input vector, *x*. More formally, $P(x) = \{(y, b): x\ can\ produce\ (y, b)\}$. 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. When firms 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

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

where β is a scaling factor. The firms' objective is to expand production of the good output by βg_y, and contract the undesirable output by the factor βg_b. For purposes of this article, the directional vector, $g = (g_y, -g_b)$, is determined exogenously. 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

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

In words, if a firm uses the same amount of inputs but generates more good output and less bad output, inefficiency does not increase. Conversely, if the firm 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

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

Another property of the DODF is weak disposability in good and bad outputs, i.e.,

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

This means that firms can proportionally reduce all outputs (Kuosmanen 2005) and that abatement requires a reduction in the firm's activity levels.

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:

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

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

As indicated above, one of our objectives is to compare two representative firms under two alternative regulatory scenarios. In the first case, the representative firm is unregulated, and thus maximizes profits by radially expanding production towards the frontier in a manner that expands the quantity of desirable outputs without contracting production of the undesirable output. Though unregulated, the modeling will assume a polluting technology and therefore will incorporate both desirable and undesirable outputs.

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

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

Case 2: Environmental regulation

Case 2 assumes that a policy is in place that seeks to minimize 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). Either way, 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 firm. These costs may be in the form of firms diverting inputs from good production towards abatement activities, or giving up some production of the good in order to generate less undesirable output.

Figure 2 illustrates the DODF facing a representative firm for this second case. The efficient combination of the desirable and the undesirable output is determined by the tangency 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 firm in figure 2 is initially producing inside the output set at point $A = (y_1, b_1)$. The objective for the firm 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, the solution to this problem is given by $\vec{D}o(x, y, b;\ 1, -1) = 0$. The specification for this case differs from the first in the values of the directional vector. Here, we choose the values $g = (1, -1)$ to reflect the firm's desire to expand production of the desirable output while simultaneously contracting production of the undesirable output. These values are chosen for their convenience and the ease of interpretation of results and also because equal weights for goods and bads are considered suitable.

The DODF facing the representative firm is given by

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

In the empirical analysis below, we use a quadratic specification for this model 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).

Empirical specification

Following Kumbhakar and Lovell (2000) we estimate the DODF as a stochastic frontier that takes the following form:

$$\vec{D}o\left(x, y, b;\ g_y, -g_b\right) + \varepsilon = 0 \tag{9}$$

where $\varepsilon = v - u$ represents the statistical and the inefficiency errors, respectively. The distributional assumptions adopted are $v \sim N(0, \sigma^2)$ and $u \sim Ga(\mu_u, \lambda)$ where the latter follows from Greene (1990). The quadratic specification used is given by:

$$\vec{D}o\left(x, y, b;\ g_y, -g_b\right) =$$

$$\alpha_0 + \sum_{n=1}^{7} \alpha_n x_{nit} + \ \phi_1 y_{1it} + \ \psi_1 y_{2it} + \gamma_1 b_{it} + \sum_{n=1}^{7} \sum_{n'=1}^{7} \alpha_{n,n'} x_{nit} x_{n'it} + \frac{1}{2}\phi_2 y_{1it}^2 +$$

$$\frac{1}{2}\psi_2 y_{2it}^2 + \frac{1}{2}\gamma_2 b_{it}^2 + \sum_{n=1}^{7} \delta_n x_{nt} y_{1it} + \sum_{n=1}^{7} \tau_n x_{nit} b_{it} + \kappa y_{1it} b_{it} + \omega y_{2it} b_{it} + \varepsilon_{it} \tag{10}$$

From the translation property, the term $\vec{D}o\left(x, y, b;\ g_y, -g_b\right) - \beta$ can be substituted by $\vec{D}o\left(x, y + \beta g_y, b + \beta g_b; g_y, -g_b\right)$. Taking the scaling factor β to the left hand side, for the k^{th} observation, β^k is added to y^k and subtracted from b^k, hence the revised quadratic form is now

$$-\beta^k = \vec{D}o\left(x^k, y^k + \beta^k, b^k - \beta^k g_b; g_y, -g_b\right) + \varepsilon^k \tag{11}$$

In order for the translation property to hold, and to account for our choice of directional vector, we impose the following parameter restrictions, $\alpha_{n,n'} = \alpha_{n',n}$, $\phi_1 - \gamma_1 = -1$, and $\phi_2 = \gamma_2 = \omega$ (Färe et al. 2005).

The Bayesian framework and endogeneity

As indicated earlier, we use a Bayesian approach in our estimation, which makes it possible to draw exact finite sample inferences concerning the unknown parameters (Rossi, Allenby, and McCulloch 2006). In addition, adopting the Bayesian approach helps to mitigate problems associated with endogeneity, and facilitates the imposition of monotonicity constraints (Fernandez, Koop, and Steel 2002; O'Donnell 2007). Proper priors on the parameters of the frontier models are required to ensure the existence of the posterior density (Fernandez, Osiewalski, and Steel 1997).

In estimating equation 10 one concern is that the variable y_{1it} may be correlated with the error term; therefore, we postulate the existence of an instrumental variable that is independent of the error term. Following Anderson and Hsiao (1982), the lag of y_{1it}, i.e., y_{1it-1}, is selected as the instrument assuming that $cov\ (y_{1it-1}, \varepsilon_{it} = 0)$. The resulting system of equations to be estimated is:

$$b_{it} = X_{it}\alpha_n + y_{1it}\phi_i + y_{2it}\psi_i + \varepsilon_{1it} \qquad (12)$$

$$y_{1it} = y_{1it-1}\,\xi_i + \varepsilon_{2it}$$

where the second equation models the relationship between current and lagged output. Following Rossi, Allenby and McCulloch (2006), we assume a joint distribution for the errors ε_1 and ε_2 such that $\begin{bmatrix}\varepsilon_1\\ \varepsilon_2\end{bmatrix} \sim N(0,\, \Sigma\,)$. Similarly, a joint distribution of

(b_{it}, y_{1it}) gives us the likelihood $P(y_{1it}, b_{it}|\xi, \phi, \Sigma)$. A Bayesian inference is implemented by applying the Gibbs sampler consisting of three sets of conditional posterior distributions as follows (Conley et al. 2008):

$$\phi|\xi, \Sigma, b_t, y_t, y_{t-1} \tag{13}$$

$$\xi|\phi, \Sigma, b_t, y_t, y_{t-1}$$

$$\Sigma|\phi, \xi, \alpha, X_t, y_t, y_{t-1}$$

The full posterior conditional distribution for the parameter space is given as (ϕ, ξ, Σ). We sample from the posterior and present the results based on a Markov Chain using a Gibbs sampler (see Casella and George 1992) of 100,000 draws and a burn-in of the initial 10,000. The estimates of the means, standard deviation and numerical standard errors, reported in table 2, will be discussed below following the presentation of the data.

Data

The dataset utilized for this article is at the county-level and comes from the U.S. Department of Agriculture (USDA) census. The USDA census consists of all farms that generated and sold $1,000 or more of agricultural products during a given census year. It covers just about every facet of U.S. Agriculture and is conducted every 5 years by the National Agricultural Statistics Service (USDA 2013b). Census of agriculture data has been used previously by several authors, among them Isik (2004) and Sneeringer and Key (2011). Isik (2004) relied on data from the 1992 and 1997 census to study the impact of environmental regulation on the spatial structure of the U.S. dairy industry, while Sneeringer and Key (2011) employed data from the 1997, 2002 and 2007 census to examine the impact of regulatory intervention on the size of livestock operations. In this article, we utilize a considerably longer time span, which covers seven census years: 1978, 1982, 1987, 1992, 1997, 2002, and 2007[3]. The dataset includes a total of 132 counties, spread across 26 states, covering all geographic regions of the country for a total of 924 observations. The 'State and County Rankings' volume, published alongside every Agricultural Census Report, was used to select the counties included in this article, which correspond to those with the highest dairy cow inventories.

This dataset 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 and hence should be included in the production function (e.g. Mukherjee, Bravo-Ureta, and De Vries 2013). Moreover, according to a recent USDA (2013c) 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 temperature in 4 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 all at the county level. The variables include total number of farms, total value of agricultural sales, broken down into crop, and livestock sales. Other variables include market value of plant, machinery and equipment, total pastureland in acres, harvested cropland in acres, and irrigated land. Total farm expenses are broken

[3] The instrumental variable, y_{1it-1}, is drawn from the census years between 1974 and 2002.

down into feed, fuel and energy, fertilizer and chemical, and labor. Finally, the dataset includes a breakdown of 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% feed concentrate for the respective year, which was obtained from 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 (Reinhard, Lovell, and Thijssen 1999; Fernandez, Koop, and Steel 2002). By contrast, we introduce an index of pollution that incorporates three major sources of pollution: 1) fuel; 2) livestock; and 3) fertilizer. Fuel based emission is constructed using 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, carbon dioxide emission equivalents (CO_2e) 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 NASS and then an estimate of the total amount of fertilizer (in tons) used in the county is computed. The direct emission of nitrous oxide (N_2O) derived from the nitrogen applied to the soil via fertilizers is calculated using formulae from Mosier (1994).

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 does not collect information on manure management systems; hence our estimates of (CH_4) emission are constructed using information about the type, and the size of the herd, and the location of the dairy operations. The total volatile solids are a product of the average annual animal population at the facility, 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 volatile solids for each animal type are state specific. These estimates are then 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 facility, the typical mass of the livestock, the state where the facility is located, and an emissions factor. These estimates are then multiplied by 310, the global warming potential of N_2O (EPA 2009). The combination of all three major sources of pollution -- 1) Livestock, 2) Fuel, and 3) Fertilizer -- is the measure of total *emissions* that constitutes the undesirable output in this article.

Table 1 provides descriptive statistics for the variables used in this article. There are two desirable outputs consisting of *milk* and *oprod* (other products), and one undesirable output, *emissions*. In developing the trade-off between the good and the bad output, *oprod* is held constant. The inputs are *cows*, *labor*, and *cstock* or capital stock (in constant 2012 dollars). The *cstock* is constructed using the perpetual inventory method, which is a means of imputing net additions. 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 in order to obtain the variable, *cstock*. Other inputs are *cfeed* and *ofeed* representing commercial feed and forage, respectively. The variable *temp* represents average annual temperatures at the county-level in degrees Celsius.

The shadow price

Before moving on to the results and analysis, we need to make some comments regarding the shadow price of the bad output. We follow Färe et al. (2005) and define it as the value of the good output that must be foregone once all inefficiency has been eliminated and the firm is producing on the frontier of $P(x)$. One might also interpret this as the dollar value of the undesirable output that is generated at the tangency of the price-line and the output frontier. 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:

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

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

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

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

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

$$^{p_y}/_{p_b} = \{\partial\vec{D}o\ (x, y, b;\ g_y, -g_b)/\partial b\}/\{\partial\vec{D}o\ (x, y, b;\ g_y, -g_b)/\partial y\} \tag{17}$$

where p_y is the market price of good y and p_b is the shadow price of the bad output. Since we know all parts of the equation except for p_b, we can solve for this and thus have the needed shadow price.

The Morishima elasticity of output substitution

We now turn to the Morishima elasticity of output substitution (MES). The MES is "..a measure of curvature, or ease of substitution" (Blackorby and Russell 1989, p. 883). 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 quadratic parameterization of the directional distance function, the MES can be expressed as:

$$MES_{by} = y^* \left\{ \left(\frac{\varphi_2}{\gamma_1 + \gamma_2 b + \mu y} \right) - \left(\frac{\varphi_1}{\varphi_1 + \varphi_2 y + \mu y} \right) \right\} \quad (18)$$

In this article, the MES is interpreted as a measure of the ability of the firm to trade reductions in dairy output for reductions in emissions.

The value of the foregone desirable output

In order to compute the total revenue from the good output foregone following an environmental regulatory intervention, we subtract the revenue function for the representative firm under regulation from the revenue function of the unregulated firm. The revenue function for the unregulated firm (case 1) is given by:

$$R_1(y_2'; g) = max_y \left\{ p_y y_2' : \vec{D}o \left(x, y_1 + \beta g_y;\ 1, 0 \right) \geq 0 \right\} \quad (19)$$

whereas that of the regulated firm (case 2) is given as:

$$R_2(y_2; g) = max_y \left\{ p_y y_2 : \vec{D}o \left(x, y_1 + \beta g_y, b_1 - \beta g_b;\ 1, -1 \right) \geq 0 \right\} \quad (20)$$

The difference between the two expressions can be rewritten in a more synthetic form as:

$$V(y_2', y_2, g; p_y) = R_1(y_2'; g) - R_2(y_2; g) \quad (21)$$

Equation 21 yields the value of the foregone desirable output following the hypothetical environmental regulation (Case 2).

Results

Now we turn to the results obtained with the county level data for the seven agricultural census years: 1978, 1982, 1987, 1992, 1997, 2002 and 2007. The 132 counties included in the dataset, spread across 26 states. We group them into 7 geographic regions that share similar agro-climatic and market conditions. The regions are: 1) Northeast, composed of counties in Connecticut, Maine, Massachusetts, New Hampshire, Vermont, and New York; 2) The Mid-Atlantic, comprising counties in Pennsylvania, Maryland, and Virginia; 3) The Midwest, with counties in Illinois, Iowa, Michigan, Minnesota, Ohio, and Wisconsin; 4) The Pacific, consisting of counties in Oregon, and Washington State; 5) Mountain, that includes counties in Colorado, Idaho, New Mexico, and Utah; 6) Southern and Plains, consisting of counties in Florida, Louisiana, Oklahoma, and Texas; and 7) California. Figure 3 below shows the location of the 7 geographic regions across the U.S. Region 0, which is shown in white in figure 3, consists of states that do not have leading dairy counties and thus are not included here.

We report the posterior parameter estimates (i.e. sample mean, standard deviation and numerical standard error[4]) in table 2 based on a Markov chain using a Gibbs sampler of 100,000 draws and a burn-in of the initial 10,000. These estimates are dependent on the conditional posterior distributions depicted in equation 13, and will also be used to derive the shadow value of the undesirable output and the Morishima elasticity of output substitution. Geweke's diagnostics are computed for randomly selected sections of the Markov chain and the resulting Z-scores are presented as diagnostic plots in figure A-1 and A-2. The horizontal dotted lines indicate the 95% confidence interval. A large number of the Z-scores fall within the interval indicating convergence (Geweke 1992).

Average shadow prices are reported for each agricultural census year for the

[4] According to Chibb (1995, p.1315)"..the numerical standard error gives the variation that can be expected in the estimate if the simulation were to be done afresh."

seven different regions in table 3 and figure 4 below. To illustrate the meaning of the shadow prices in this context, let us take the average $42.7 value for the Northeast. This value indicates that $42.7 worth of the desirable output (milk) would have to be foregone in order to reduce emissions by one unit (metric ton) at the margin. On the other hand, the average dairy operation in California would have to give up only $20.9 of the value of the desirable output in order to achieve full efficiency. We interpret these results as follows: Northeast dairy operations face the highest marginal abatement cost whereas California dairy facilities face the lowest. A carbon tax set at the marginal abatement cost level would result in Northeast counties bearing the highest costs relative to other regions.

The MES is a measure of how the good-bad shadow price ratio changes as the desirable-undesirable output ratio changes (Färe et al. 2005). It evaluates the ability of the dairy facility to trade reductions in milk for reductions in emissions. The more negative the MES estimate, the more difficult it is for the dairy facility to substitute away from emissions and towards dairy output. This is because higher elasticity of substitution values reflects fewer substitution possibilities. Table 4 and figure 5 present MES estimates for the seven different regions. California, with an average estimate of -0.634 faces the highest elasticity of substitution rates. Conversely, counties in the Northeast faced the lowest rates at -0.072. The implication of this result is as follows: California dairy operations are producing on a steeper point of the frontier where the ratio of dairy-output to emissions is high. Reducing pollution by one more unit would require giving up more than one unit of the desirable output. We also observe that the elasticity of substitution rates trended upwards for all regions over the years, indicating a reduction in substitution possibilities from 1978 to 2007.

In table 5 and figure 6, we report the total revenues for dairy operations without regulation, and the percentage of revenues that would have been lost following a hypothetical environmental regulatory framework. We interpret these results as follows: In 1978, the average county in the Mountain region would have incurred approximately $1.042 million in lost revenues whereas the average county in California would have forfeited approximately $6.148 million. These values represent 13.06% and 7.1% of total revenue, respectively. Similarly, in 2007 the highest losses were incurred in the Mid-Atlantic where the average county would have lost approximately $5.998 million. The lowest losses on the other hand where in California, where the average county would have incurred $9.45 million in foregone revenue, representing 5.16% and 1.8% of the corresponding total value of output.

Another dimension stemming from the analysis concerns technical efficiency (TE), which is defined as the ratio of observed to maximum feasible output along the frontier $P(x)$. We report two sets of TE results: 1) the first set consists of TE estimates for the regulated firm; and 2) the second set consists of TE estimates for the unregulated firm. These estimates are reported in tables 6 and 7, and their graphical illustrations in figures 7 and 8. Values less than one are evidence of technical inefficiency. Mid-Atlantic and California dairy operations report higher TE scores when there is no regulation. Other regions report only slight variations in TE scores, with and without regulation. Overall, these TE scores are consistent with findings from traditional stochastic frontier studies conducted on dairy farming in the U.S. (Bravo-Ureta et al. 2007).

Concluding remarks

The primary objective of this article was to evaluate the impact of a hypothetical environmental regulatory framework on the dairy sector in the U.S. Over the last several years, there have been concerted efforts aimed at imposing strict reporting standards on GHG emissions across all the 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 in the dairy sector in order to assess policy effectiveness has been a missing link in the literature (Isik 2004) and this article addresses this gap by establishing such costs across major dairy producing areas of the U.S.

Based on county level data derived from seven USDA agricultural census for 1978, 1982, 1987, 1992, 1997, 2002 and 2007, we estimate and report the value of the foregone desirable output that would have followed an assumed regulatory intervention. We summarize the results of the 132 counties into seven geographic regions that represent similar agro-climatic and market conditions. The results reveal discernible trends across the various geographical areas. We find large variations in the shadow price across regions, with critical policy implications. For example, if the regulatory intervention involved a cap on emissions or a carbon tax, the economic costs would be higher for dairy operations in the Northeast because this region exhibits the highest marginal abatement costs, at $42.7 for the last ton of emission at the margin. On the other hand it would have been relatively inexpensive for dairy operations in California to pollute because they would have had to pay only $20.9 for the last metric ton of emission at the margin.

The results for the Morishima elasticity of substitution (MES) rates, which are interpreted as a measure of the dairy facility's ability to trade reductions in milk output for reductions in emissions, also provide some useful insights into the impact of environmental regulation. We find that California dairy operations face much higher MES rates than other parts of the U.S. There could be several reasons behind this. For one, California is already heavily regulated with specific State and Federal regulatory policy as well as regulatory action at the local level (Sneeringer and Hogle 2008; Sneeringer 2011). This points towards fewer substitution possibilities for dairy operations located there. The policy implications we draw from these are as follows. A command-and-control type of intervention, where the regulator imposes a cap on emissions would have resulted in dairy operations in California facing huge costs in emission reduction.

This article demonstrates that the economic impact from any regulatory intervention aimed at reducing emission of carbon dioxide equivalent (CO_2e) would vary significantly across regions in the U.S. with some regions finding it cheaper to pollute than to abate. 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. Thus, these results should provide a basis for policy-makers to design sound policy and regulatory decisions.

Therefore policy-makers ought to consider the cost-effectiveness of such policies before implementing them. Imposing a command-and-control approach is both inflexible and costly, and will only exacerbate losses to some regions in the country. On the other hand, a cap-and-trade regime would also result in unequal benefits. And levying taxes above their Pigovian levels only results in excessive abatement (Hart 2008). Conversely, promoting renewable energy and supporting voluntary mechanisms that encourage the widespread adoption of anaerobic digesters could be viable options. Policy intervention should be directed towards assistance programs such as direct subsidies, loan guarantees, tax exemptions, and accelerated depreciation. Other mechanisms include a carbon-offset system that compensates dairy operations for CO_2e reductions.

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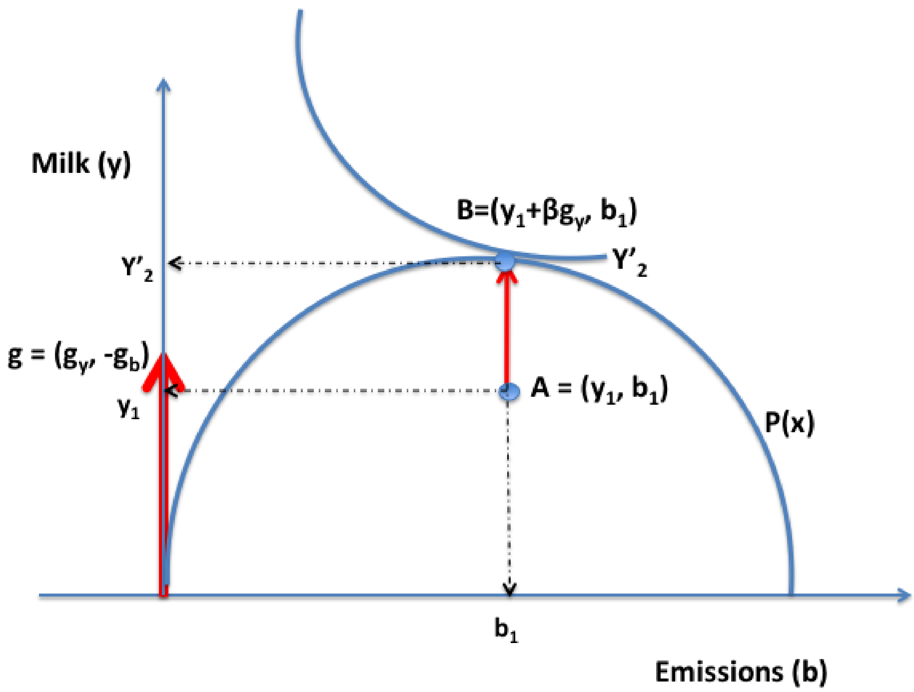


Figure 1: The directional output distance function for Case 1: No regulation

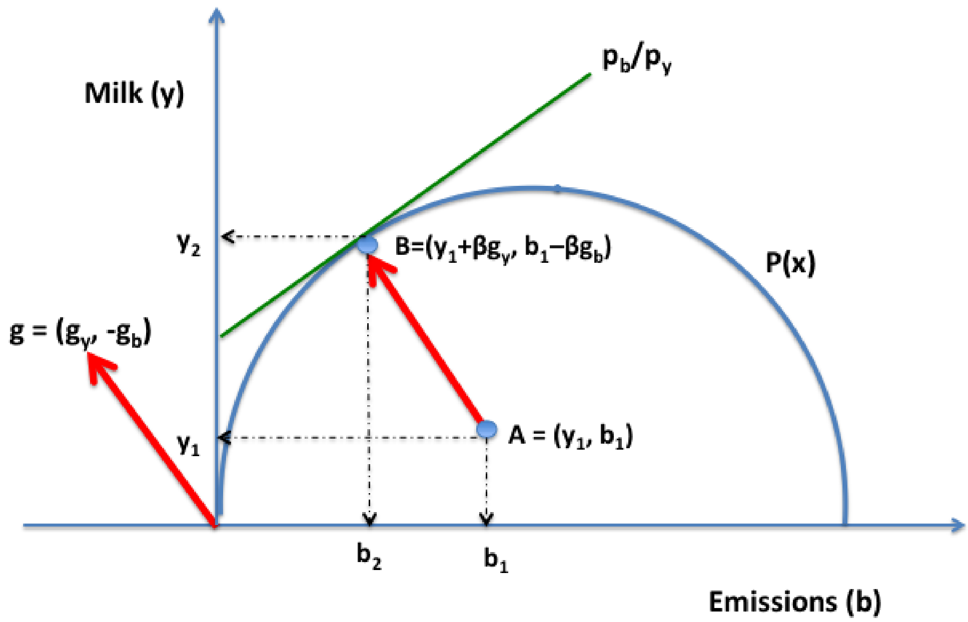


Figure 2: The directional output distance function for Case 2: Environmental regulation

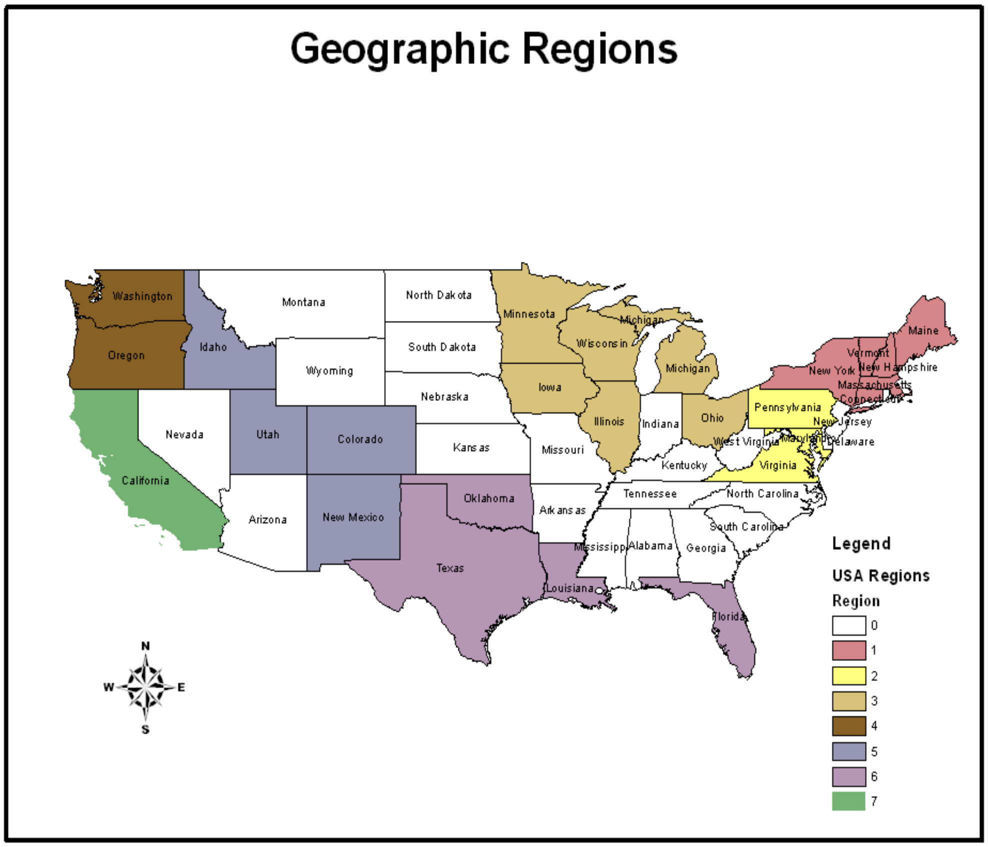


Figure 3: The geographic location of dairy counties

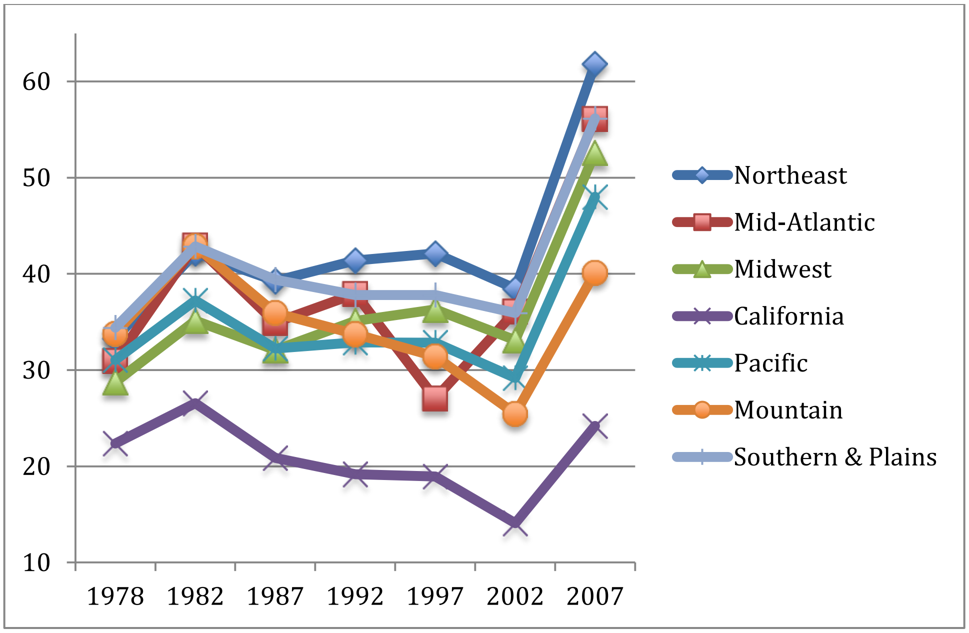


Figure 4: Average shadow prices ($)

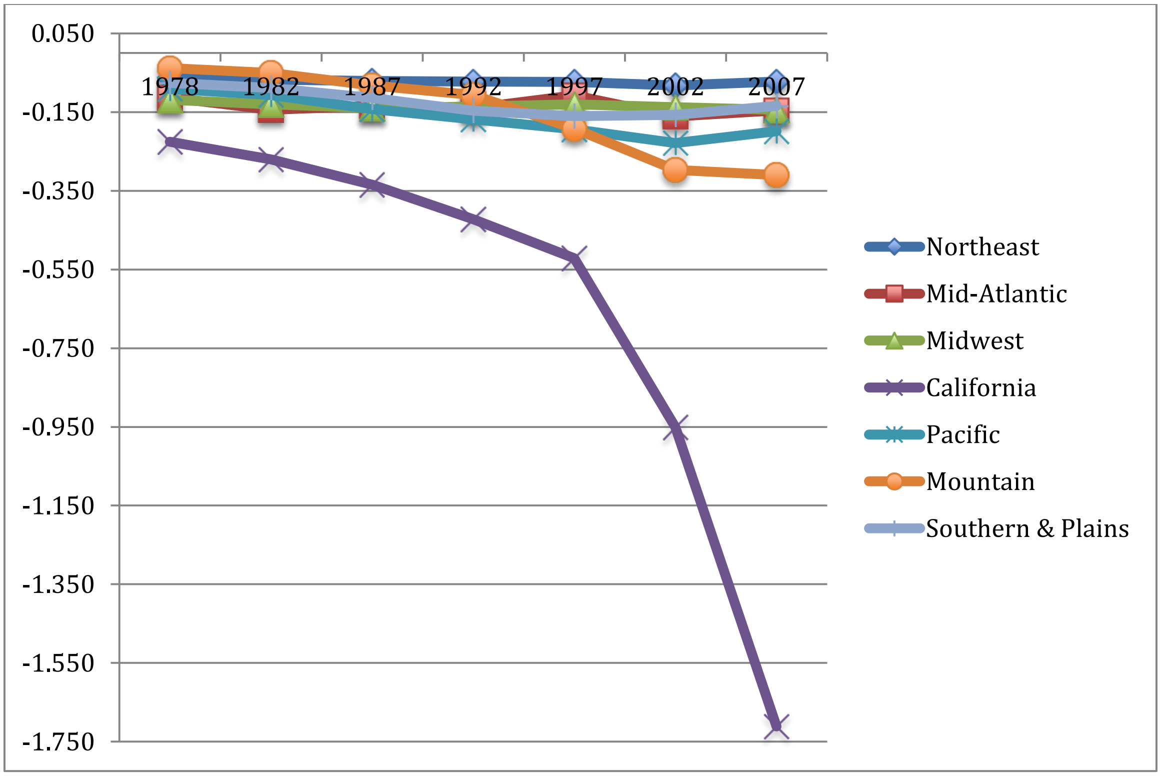


Figure 5: Morishima elasticity of substitution estimates

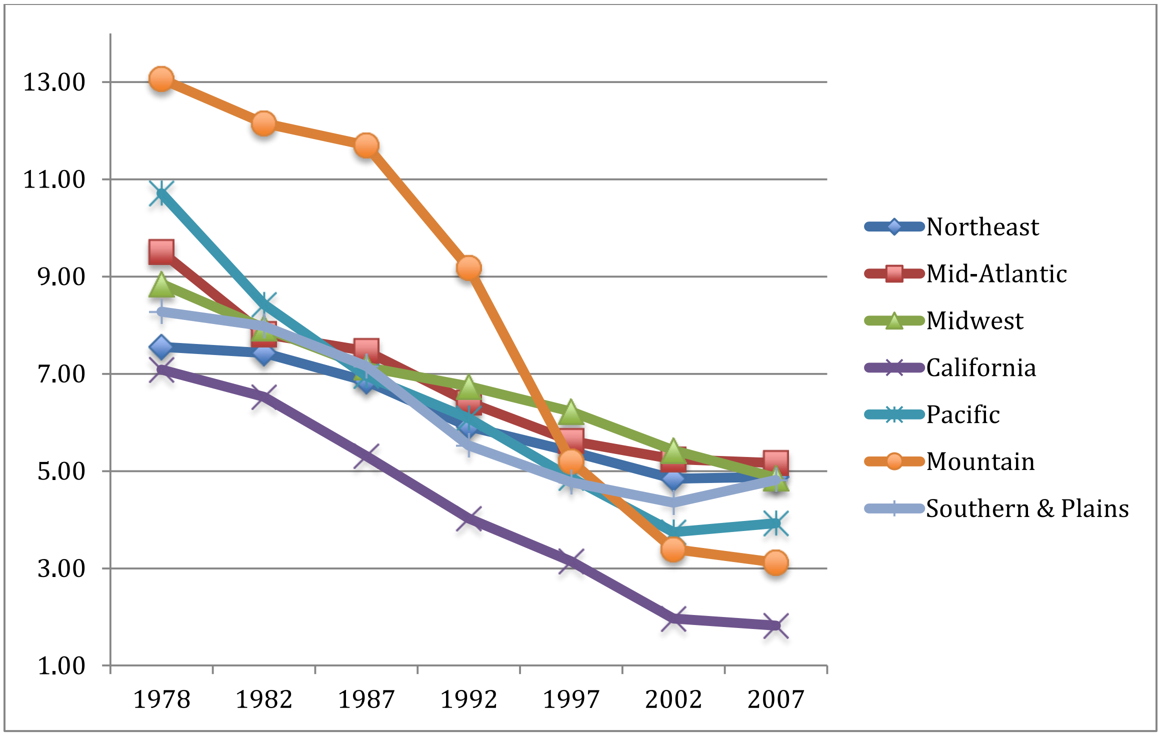


Figure 6: Percentage share of total output foregone

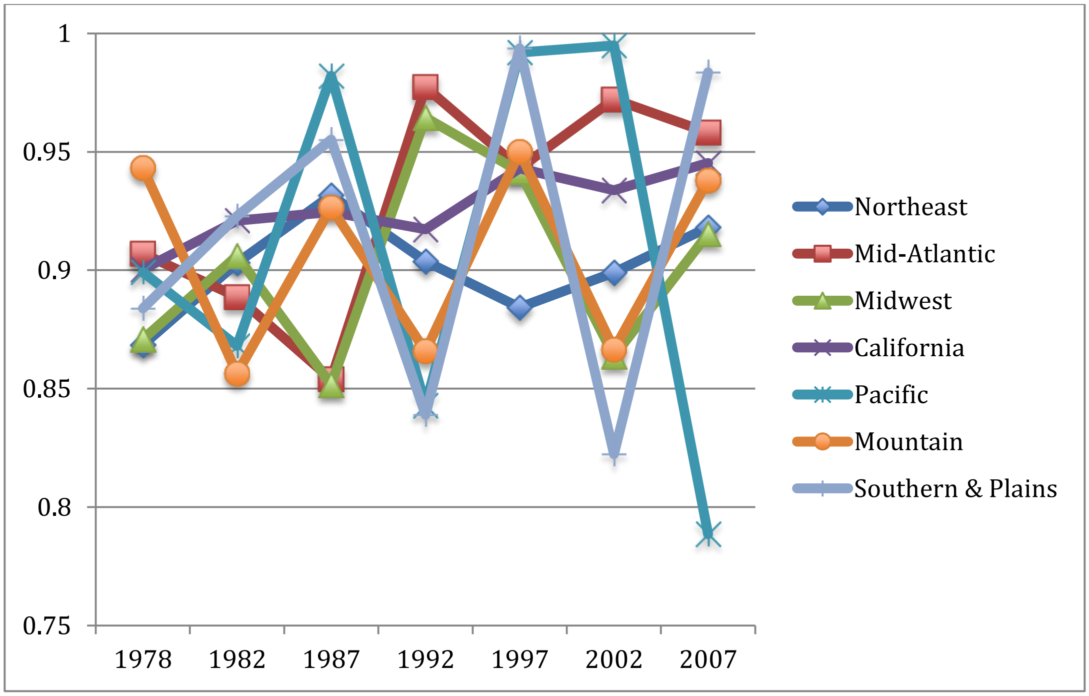


Figure 7: Average technical efficiency estimates for Case 1 (Unregulated) g = (1, 0)

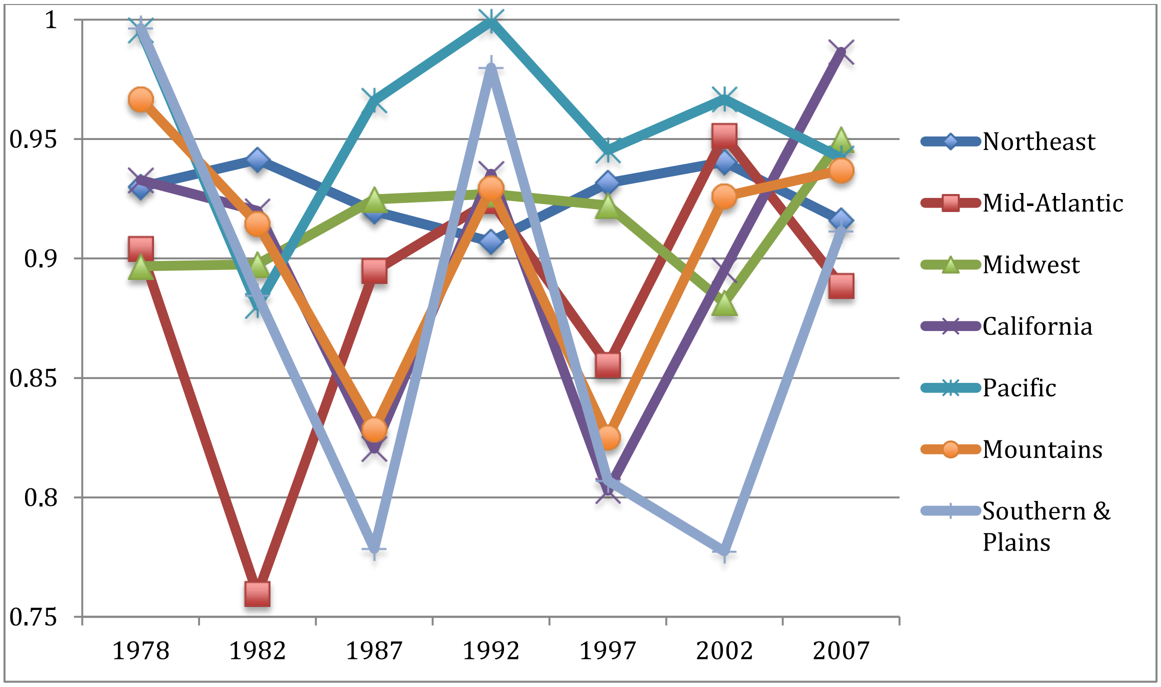
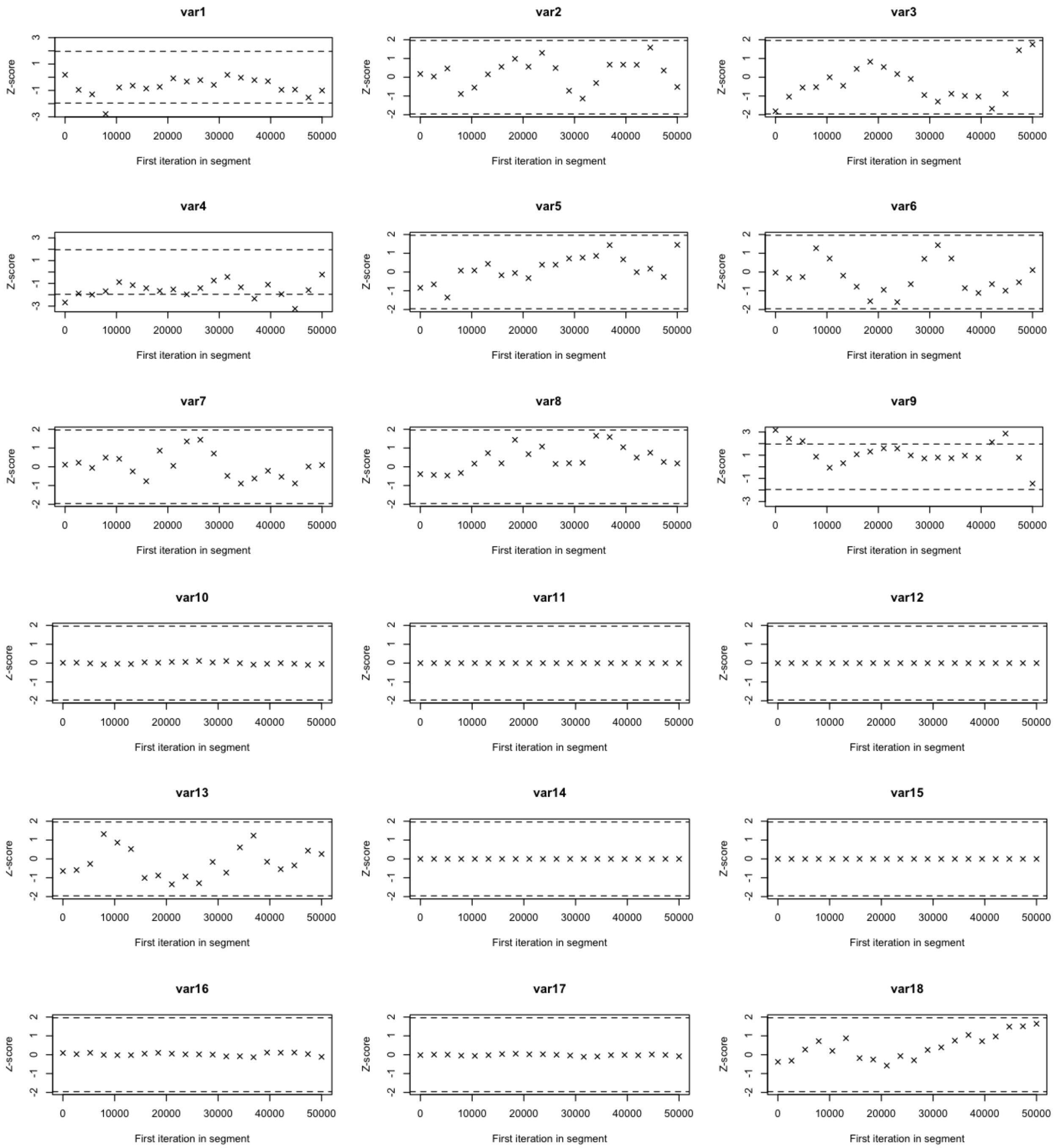


Figure 8: Average technical efficiency estimates for Case 2 (Regulated) g = (1, 1)


var1
var2
var3
var4
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var6
var7
var8
var9
var10
var11
var12
var13
var14
var15
var16
var17
var18
Z-score
First iteration in segment
0
10000
20000
30000
40000
50000

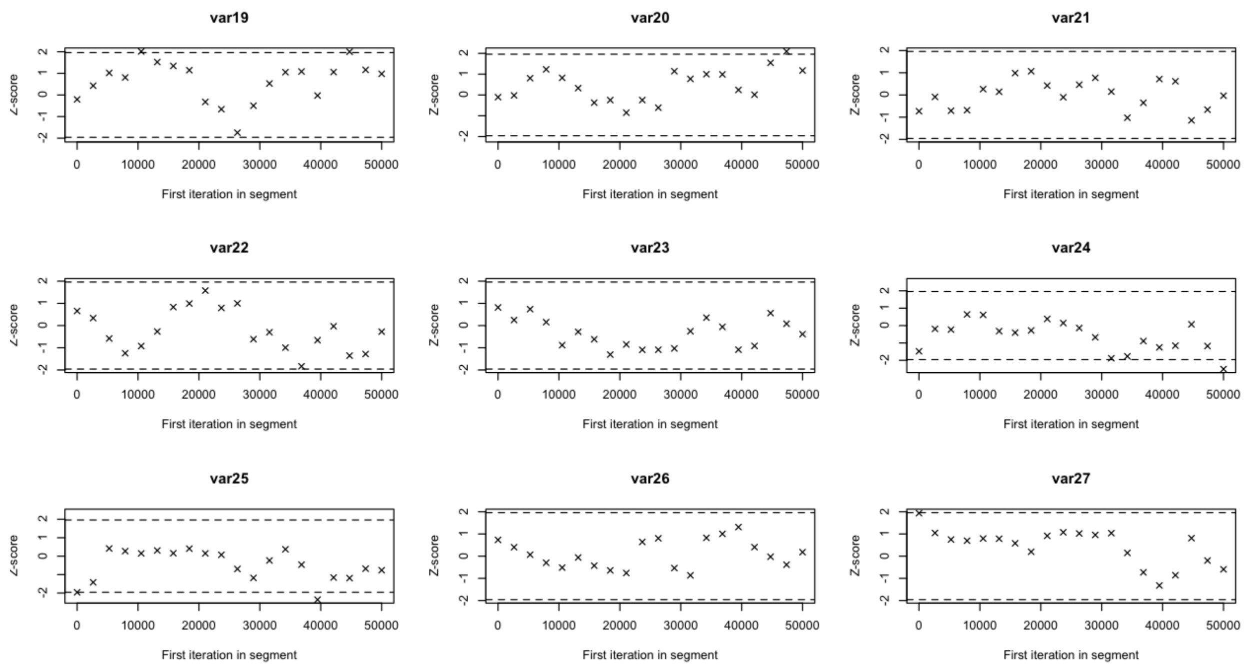

Figure A-1: Geweke's diagnostic plot

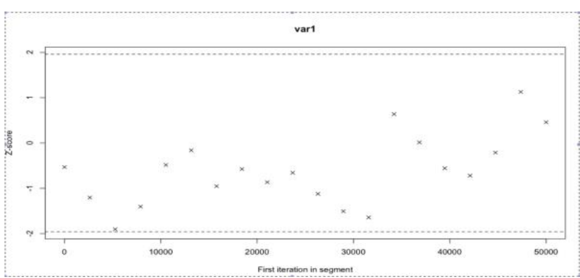

Figure A-2: Geweke's diagnostic plot for $milk_{(t-1)}$

Table 1: Descriptive statistics

Variable (Units)	Mean	Std. Dev.	Min	Max
MILK (tons)	697,003	14,100,000	3795	430,000,000
EMISSIONS (tons)	125,079	135,640	1,871	1,352,795
OPROD($'000)	3,294,060	297,939	2,052	394,060
COWS	33,556	36,165	124	474,497
LABOR (hours)	3,888,116	9,226,716	6,452	71,400,000
CSTOCK ($'000)	158,000	136,000	6,167	1,160,000
CFEED (tons)	195,828	325,340	3,879	3,293,370
OFEED (tons)	413,393	394,807	3887	4,124,080
TEMP (Celsius)	8.6	4.0	2.5	23.4

Table 2: Summary of Posterior Parameter Estimates

Variables	Parameters	Mean	Std. Dev	Num. se
$Milk_{(t-1)}$	ξ	0.200	0.0025	0.0008
Milk (var1)	ϕ_1	0.230	0.0011	0.0000
Emissions	$\gamma_1 = \phi_1 - 1$	-0.760		
Intercept (var2)	α_0	0.950000	10.0000	0.03200
Cows (var3)	α_1	2.400000	0.0920	0.00031
Cstock (var4)	α_2	0.000500	0.000048	0.00000
Labor (var5)	α_3	0.001100	0.00043	0.00000
Cfeed (var6)	α_4	-0.029000	0.0095	0.00003
Ofeed (var7)	α_5	0.018000	0.0070	0.00002
Temp (var8)	α_6	1.700000	10.0000	0.03200
Trend (var9)	α_7	-4.200000	9.9000	0.03400
Oprod (var10)	ψ_1	0.000081	0.0000098	0.00000
0.5*$dairy^2$ (var11)	ϕ_2	0.00000013	0.0000	0.00000
0.5*$cows^2$ (var12)	α_{11}	-0.000027	0.000002	0.00000
0.5*$temp^2$ (var13)	α_{66}	7.500000	9.9000	0.03500
0.5*$trend^2$ (var14)	α_{77}	25.000000	8.4000	0.02800
Temp*dairy (var15)	δ_6	0.012000	0.0022	0.00001
Trend*dairy (var16)	δ_7	-0.019000	0.00092	0.00000
Cows*temp (var17)	α_{16}	-0.120000	0.0290	0.00010
Cows*trend (var18)	α_{17}	0.200000	0.0110	0.00004
Cstock*temp (var19)	α_{26}	-0.000030	0.0000093	0.00000
Cstock*trend (var20)	α_{27}	0.000017	0.0000038	0.00000
Labor*temp (var21)	α_{36}	-0.000190	0.000053	0.00000
Labor*trend (var22)	α_{37}	0.000180	0.000021	0.00000
Commfeed*temp (var23)	α_{46}	-0.000630	0.0016	0.00001
Commfeed*trend (var24)	α_{47}	0.000500	0.00049	0.00000
Otherfeed*temp (var25)	α_{56}	-0.000550	0.00086	0.00000
Otherfeed*trend (var26)	α_{57}	0.001500	0.00036	0.00000
Temp*trend (var27)	α_{67}	-8.600000	9.2000	0.03200

Table 3: Average Shadow Prices ($/Ton)

Region	1978	1982	1987	1992	1997	2002	2007	Average
Northeast	33.26	42.20	39.27	41.40	42.14	38.46	61.80	**42.70**
Mid-Atlantic	30.97	42.98	34.94	37.92	27.06	36.09	56.14	**38.01**
Midwest	28.76	35.14	32.07	35.10	36.29	33.10	52.60	**36.15**
California	22.38	26.54	20.88	19.18	18.96	14.10	24.21	**20.90**
Pacific	31.06	37.22	32.26	32.90	32.84	29.19	48.00	**34.78**
Mountain	33.79	42.90	35.94	33.75	31.42	25.48	40.14	**34.77**
Southern & Plains	34.40	42.87	39.40	37.80	37.81	35.94	56.15	**40.62**
Average	**30.66**	**38.55**	**33.54**	**34.01**	**32.36**	**30.34**	**48.43**	

Table 4: Morishima Elasticity of Substitution Estimates

Region	**1978**	**1982**	**1987**	**1992**	**1997**	**2002**	**2007**	**Average**
Northeast	-0.063	-0.068	-0.071	-0.073	-0.074	-0.083	-0.073	**-0.072**
Mid-Atlantic	-0.113	-0.144	-0.135	-0.140	-0.108	-0.161	-0.146	**-0.135**
Midwest	-0.119	-0.131	-0.140	-0.136	-0.131	-0.137	-0.144	**-0.134**
California	-0.226	-0.270	-0.335	-0.422	-0.522	-0.951	-1.711	**-0.634**
Pacific	-0.091	-0.107	-0.143	-0.169	-0.194	-0.229	-0.199	**-0.161**
Mountain	-0.039	-0.050	-0.082	-0.107	-0.192	-0.297	-0.310	**-0.154**
Southern & Plains	-0.076	-0.089	-0.114	-0.146	-0.161	-0.157	-0.134	**-0.125**
Average	**-0.104**	**-0.123**	**-0.146**	**-0.170**	**-0.197**	**-0.288**	**-0.388**	

Table 5: Average Value of Output (‘000) and Share of Total Output (%) Foregone

Region		1978	1982	1987	1992	1997	2002	2007	Average
Northeast	Value without regulation	22,008	30,672	29,987	32,383	33,080	34,147	47,799	32,868
	Value of foregone output	1,662	2,277	2,054	1,915	1,787	1,653	2,332	1,954
	% Value of lost output	7.55	7.43	6.85	5.91	5.40	4.84	4.88	6.12
Mid-Atlantic	Value without regulation	37,618	69,545	61,450	69,133	53,167	79,795	108,467	68,454
	Value foregone output	3,576	5,437	4,589	4,436	2,985	4,184	5,598	4,401
	% Value of lost output	9.51	7.82	7.47	6.42	5.62	5.24	5.16	6.75
Midwest	Value without regulation	41,646	58,810	58,011	60,777	58,859	56,911	95,786	61,543
	Value foregone output	3,685	4,669	4,142	4,098	3,663	3,088	4,656	4,000
	% Value of lost output	8.85	7.94	7.14	6.74	6.22	5.43	4.86	6.74
California	Value without regulation	86,775	139,307	153,497	200,178	267,445	317,530	519,221	240,565
	Value foregone output	6,148	9,093	8,147	8,058	8,410	6,242	9,450	7,935
	% Value of lost output	7.09	6.53	5.31	4.03	3.14	1.97	1.82	4.27
Pacific	Value without regulation	25,500	47,674	59,968	76,421	91,420	100,970	138,658	77,230
	Value foregone output	2,730	4,019	4,172	4,652	4,443	3,782	5,449	4,178
	% Value of lost output	10.71	8.43	6.96	6.09	4.86	3.75	3.93	6.39
Mountain	Value without regulation	7,979	20,515	27,094	44,621	85,920	130,086	217,384	76,228
	Value foregone output	1,042	2,493	3,169	4,096	4,469	4,412	6,777	3,780
	% Value of lost output	13.06	12.15	11.70	9.18	5.20	3.39	3.12	8.26
Southern & Plains	Value without regulation	29,111	43,837	55,044	71,306	79,516	72,352	91,788	63,279
	Value foregone output	2,409	3,499	3,939	3,942	3,792	3,145	4,418	3,592
	% Value of lost output	8.28	7.98	7.16	5.53	4.77	4.35	4.81	6.13
Average	% Value of lost output	9.29	8.33	7.51	6.27	5.03	4.14	4.08	

Table 6: Average Technical Efficiency Estimates for Case 1 (Unregulated) g = (1, 0)

Regions	1978	1982	1987	1992	1997	2002	2007	**Average**
North East	0.87	0.9	0.93	0.9	0.89	0.9	0.92	**0.90**
Mid-Atlantic	0.91	0.89	0.85	0.98	0.94	0.97	0.96	**0.93**
Midwest	0.87	0.91	0.85	0.96	0.94	0.86	0.92	**0.90**
California	0.90	0.92	0.93	0.92	0.94	0.93	0.95	**0.93**
Pacific	0.89	0.87	0.98	0.84	0.99	0.99	0.79	**0.91**
Mountain	0.94	0.86	0.93	0.87	0.95	0.87	0.94	**0.91**
Southern & Plains	0.88	0.92	0.96	0.84	0.99	0.82	0.98	**0.91**
Average	**0.89**	**0.90**	**0.92**	**0.90**	**0.95**	**0.91**	**0.92**	

Table 7: Average Technical Efficiency Estimates for Case 2 (Regulated) g = (1, 1)

Regions	1978	1982	1987	1992	1997	2002	2007	**Average**
North East	0.93	0.94	0.92	0.91	0.93	0.94	0.92	**0.93**
Mid-Atlantic	0.90	0.76	0.89	0.92	0.86	0.95	0.89	**0.88**
Midwest	0.89	0.9	0.92	0.93	0.92	0.89	0.95	**0.91**
California	0.93	0.92	0.82	0.94	0.8	0.89	0.99	**0.90**
Pacific	0.99	0.89	0.97	0.99	0.94	0.97	0.94	**0.96**
Mountain	0.97	0.91	0.83	0.93	0.83	0.93	0.94	**0.91**
Southern & Plains	0.99	0.88	0.78	0.98	0.81	0.78	0.91	**0.88**
Average	**0.94**	**0.89**	**0.88**	**0.94**	**0.87**	**0.91**	**0.93**	