12-12-2013

Environmental Efficiency and Regulations, and Productivity Growth in the Face of Climate Change: An Analysis of U.S. Agriculture

Eric Njuki
eric.njuki@uconn.edu

Environmental Efficiency and Regulations, and Productivity Growth in the Face of Climate Change: An Analysis of U.S. Agriculture

Eric Njuki, Ph.D.

University of Connecticut, 2013

Abstract

The objectives of this dissertation are threefold: 1) To measure the environmental efficiency of Northeast U.S. dairy farms in the presence of undesirable outputs; 2) To evaluate the economic costs of environmental regulations and abatement activities on dairy farms using county level data for the major dairy producing areas in the U.S.; and 3) To analyze total factor productivity (TFP) in U.S. agriculture in the face of climate change by utilizing a TFP index that satisfies key properties.

The first essay builds upon recent developments in productivity analysis where the productive unit generates both desirable and undesirable outputs. Using a Northeast U.S. dairy dataset, this study makes two novel contributions to the literature. First, it uses EPA (2009) methodologies to construct a comprehensive index of emissions that incorporates three major sources of pollution that originate from dairy farms: fuel, fertilizer, and livestock. This contrasts with previous studies that rely on partial measures based only on surplus nitrogen stemming from the over-application of fertilizer. Second, using a directional output distance function (DODF) on a Bayesian framework, we establish the shadow value of emissions. Key results indicate that smaller dairy farms face higher shadow values than larger operations. Consequently, the smaller units would face higher costs than their larger counterparts when reducing pollution. These results are

crucial from a public policy perspective because they will assist in crafting an appropriate response to the challenge of pollution reduction while considering the potential impact on smaller operations.

The second essay examines the potential impact of regulatory intervention on dairy farming in the U.S. The pollution index and the econometric methods are the same as in the previous essay. Results indicate that on average, values of foregone output following regulatory intervention vary widely across different regions. Revenue losses range from 1.8% to 13.1% of total revenue across the U.S. between 1978 and 2007.

Climatic factors play an important role in agricultural output but this issue has not been addressed explicitly in the econometric analysis of total factor productivity growth (TFP). The third essay addresses this gap in the literature and makes two important contributions: 1) It utilizes a TFP index, the Färe-Primont-O'Donnell (FPO) index, that satisfies key axiomatic and economic-theoretic approaches; and 2) It uses this index to evaluate TFP change in U.S. agriculture in the face of climatic variability. The TFP index is multiplicatively complete and is decomposed into climatic effect, technological progress, technical efficiency and scale efficiency changes. The climatic effect component, which combines temperature and precipitation, contributed positively to TFP growth in eight southern states, and negatively in the rest of the contiguous states.

Environmental Efficiency and Regulations, and Productivity Growth in the Face of Climate Change: An Analysis of U.S. Agriculture

Eric Njuki

B.A. University of Nairobi, 2001

M.A. University of Kansas, 2004

M.S. University of Connecticut, 2012

A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

at the

University of Connecticut

2013

Approval Page

Doctor of Philosophy Dissertation

Environmental Efficiency and Regulations, and Productivity Growth in the Face of Climate Change: An Analysis of U.S. Agriculture

Presented by

Eric Njuki

Major Advisor ______________________________

Boris E. Bravo-Ureta

Associate Advisor ______________________________

Farhed Shah

Associate Advisor ______________________________

Thomas Morris

The University of Connecticut

2013

Acknowledgments

The process of writing this dissertation has been a journey filled with valuable lessons. I have learned that my success is not mine alone but the culmination of several interactions that I have developed over the years. My heartfelt gratitude is first extended to my God, who has seen me through this journey. I owe a great deal of gratitude to my parents for their constant love and support. I will be eternally grateful to them. In my advisor, Professor Boris Bravo-Ureta, I have been fortunate to find a dedicated mentor and a friend to whom I will forever be indebted. His encouragement, support and guidance assisted me in clarifying my thoughts and ideas into something coherent. He saw potential in what I had to offer and he supported me throughout the process.

I would also like to thank my associate advisors, Professor Farhed Shah and Professor Thomas Morris for their guidance and positive criticism. My appreciation also goes to Professor Christopher O'Donnell of the University of Queensland, Australia, who was kind enough to share his thoughts, ideas, feedback and comments that enabled me to develop my third essay. My deepest appreciation goes to Christine Hare for her kindness, warmth, tremendous support and affection. I will be eternally grateful to her. I cannot forget the moral support that I have received from my entire family. They were a constant source of encouragement. I extend my appreciation to my fellow graduate students, friends and colleagues for their friendship and support. And special mention goes to Claire Bazzano and Karen Nye for their support while I was a graduate student. To Dr. Deep Mukherjee, I am grateful for the assistance and the positive comments. I do not believe this task would have been possible without the help of the aforementioned.

I dedicate this to my parents, Philip Njuki and Martha Wambeti, who taught me the value of hard work.

"...the difficulty lies, not so much in developing new ideas, as in escaping from old ones."

John Maynard Keynes

Table of Contents

Chapter 1

An Overview of the Challenges and Implications of Climate Change

1.1 Introduction

The United Nations (UN) in its 2013 report on the Millennium Development Goals (MDG) indicates that global emissions of CO_2 have increased by 46% since 1990 and this has resulted in a major decline in the global resource base and threatens the achievement of the MDG goals. This decline in the global resource base has been characterized by a continued loss in forest cover, a reduction in the availability of arable land, and overexploitation of marine fish stocks. This decline in resources directly threatens poverty reduction efforts and the provision of sustainable livelihoods to some of the world's most vulnerable populations. According to the United Nations Population Fund, the current global population stands at 7 billion and is projected to rise to 8.9 billion by 2050. Of immediate concern is how to provide food and sustenance to the world's population. Moreover, the Food and Agricultural Organization reported that, between 2010 and 2012, at least 870 million people around the globe experienced chronic malnutrition (FAO 2012).

Given the numerous challenges brought about by climate change, several countries are beginning to take remedial measures to address the global warming

phenomenon. In the United States, concern about the impact of climate change has led the Environmental Protection Agency (EPA) to take action. In 2009, the EPA imposed strict reporting standards on greenhouse gas (GHG) emissions across all sectors of the economy. The objective of these reporting standards was to improve the understanding of emission rates, and actions that firms can take to reduce such emissions. In addition, the standards were aimed at improving the effectiveness of the design of programs, voluntary or mandatory, aimed at reducing emissions (EPA 2009).

Within U.S. agriculture, particular attention has been focused on livestock farming because this industry was responsible for generating 44 million metric tons of carbon dioxide equivalents (CO_2e) (EPA 2010). This represented 7.5% of total anthropogenic Methane (CH_4) emissions, and 4.7% of nitrogen dioxide (N_2O) emissions. U.S. dairy farms are responsible for generating pollutants such as carbon dioxide emissions, Methane (CH_4), Oxides of Nitrogen (NO_x), Ammonia (NH_3) and acid gases (EPA 2012a). In anticipation of a policy that could be implemented on a wide scale, and with far-reaching implications this dissertation will analyze environmental performance in dairy farms.

Another dimension of this dissertation is to investigate the extent to which climatic variability has impacted U.S. agriculture. Specifically, we evaluate how temperature and rainfall variations affect Total Factor Productivity (TFP) as well as how irrigation and expenditures in research and development ameliorate climatic variability.

1.2 Overview

This dissertation consists of three essays, and builds upon recent developments in productivity analysis where productive units generate both desirable and undesirable outputs. The first and second essays model the polluting technology as a non-separable production process where the desirable and the undesirable outputs are generated jointly. It improves upon previous analyses by constructing a comprehensive measure of environmental emissions for dairy farms that incorporates livestock, fuel and fertilizer emissions using EPA standards. The objectives of this dissertation are threefold: 1) To measure the environmental efficiency for Northeast U.S. dairy farms in the presence of undesirable outputs; 2) To evaluate the economic costs of environmental regulations and abatement activities on dairy farms using county level data for the main dairy producing areas in the U.S.; and 3) To analyze total factor productivity (TFP) in U.S. agriculture in the face of climate change.

There are two broad categories of environmental performance that have been proposed in the literature: 1) those that adjust conventional measures of technical efficiency; and 2) those that adjust conventional measures of productivity change. This dissertation improves upon previous analyses in two salient dimensions: 1) by constructing a comprehensive index of emissions originating from dairy farms that incorporates livestock, fuel and fertilizer emissions using EPA (2009) standards; and 2) by constructing a TFP index that satisfies key axiomatic and economic-theoretic approaches while incorporating explicitly the effects of climatic variability.

The first essay will estimate and establish how technical efficiency is impacted

when undesirable outputs are incorporated in the model in Northeast United States. This essay will analyze whether environmental efficiency has improved or deteriorated over time for farms differing is size. The second essay measures the economic costs of limiting emissions by establishing the value of the foregone desirable output associated with environmental regulations and abatement. It evaluates polluting technologies under two different environmental regulatory frameworks. In the first case, the firm is not regulated and maximizes revenue by radially expanding production in a manner that expands the desirable output without contracting production of the undesirable output. In the second case, the firm is regulated and must reduce emissions. Quantifying the cost of environmental regulations in order to assess policy effectiveness has been a missing link in the literature, and this essay seeks to address this gap by establishing such costs across major dairy producing areas of the U.S. Posterior parameter estimates are used to estimate shadow prices, Morishima elasticities of substitution and technical efficiency estimates. In this case, county level data from the United States Census of Agriculture is utilized. The third essay measures environmental performance by adjusting conventional measures of productivity change. We employ a TFP index, the Färe-Primont-O'Donnell index, which satisfies several basic axiomatic and economic-theoretic properties.

1.3 Methodology

The theoretical and the empirical framework to be used for modeling the first and second essays is the directional output distance function (DODF). The directional distance function is appropriate for modeling polluting technologies because it assumes a non-separable production process in which the polluting technology jointly generates

desirable as well as undesirable outputs. It allows for the simultaneous expansion of the desirable output and the contraction of the undesirable output. It consists of two parts: 1) an output set, that represents the boundary of the feasible set; and 2) a directional vector, which represents the direction in which the output vector is adjusted. The DODF makes two assumptions: 1) that in a multi-dimensional production frontier, the decision-making unit desires to simultaneously 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 get to the frontier of the output set.

The third essay analyzes the extent to which climatic variability has impacted U.S. agricultural productivity. It utilizes a Cobb-Douglas stochastic production frontier approach. The essay begins by presenting a productivity index, the Färe-Primont-O'Donnell (FPO) Index, that can be decomposed into measures of climatic effects, technological progress, technical efficiency change and scale efficiency change. The FPO Index satisfies the basic economically relevant axioms of monotonicity, linear homogeneity, identity, commensurability, proportionality, and transitivity. Furthermore, it is multiplicatively complete, which means that it can be written in terms of aggregate input, and output quantities (O'Donnell 2012a).

Three separate datasets will be used in the empirical analysis. The first essay utilizes a dataset that is constructed from average dairy farm level information from the Northeast U.S. that corresponds to four farm size groups: small, medium, large and very large. The data was collected and summarized over the years 1980 to 2011 by the Northeast Farm Credit. In total, there are 128 observations and 16 variables. All farms in this dataset received the majority of their income from dairy activities.

The second essay utilizes a dataset that consists of U.S. Department of Agriculture county-level census data across seven years: 1978, 1982, 1987, 1992, 1997, 2002 and 2007. The dataset includes the top 132 dairy counties across all the geographic regions of the country, for a total of 924 observations. Finally, the third essay employs data prepared by the Economic Research Service (ERS) of the U.S. Department of Agriculture comprising indices of farm output and inputs at the state level across the 48 contiguous states. It spans the 45-year period between 1960 and 2004. The dataset is similar to one previously used by Ball et al. (1997, 2004) and O'Donnell (2012b, 2012c) to analyze agricultural productivity in the United States. The variables used are a combination of output data, and input data that includes capital, land, labor, irrigation, R&D expenditures, temperature and precipitation.

1.4 Concluding Remarks

The results from the first essay show that smaller dairy operations in the Northeast U.S. face higher shadow prices and higher marginal costs of abatement. The implication is that smaller farms would face higher costs and more limited opportunities in substituting away from the undesirable output. Larger farms on the other hand face lower Morishima output elasticity of substitution estimates indicating that they face greater substitution opportunities than smaller farms. In sum, it appears that policy actions taken to curb emissions could have adverse effects on smaller dairy operations. This finding compounds the relative competitive disadvantage of smaller farms in light of evidence that supports the presence of economies of size in U.S. dairy production (e.g. Mosheim and Lovell 2009).

In the second essay, results indicate that, on average, regulatory intervention leads to revenue losses ranging from 1.8% to 13.1%. We also find that Northeast U.S. dairy operations face the highest shadow prices, whereas California dairy operations face the lowest. The implication is that Northeast dairy operations face the highest marginal costs of abatement relative to their California counterparts. Conversely, California dairy counties face the highest Morishima elasticity of substitution compared to the rest of the country. The consequence is that these dairy operations have exhausted opportunities for substitution. A command-and-control type of intervention would have resulted in California facing huge costs in emission reduction.

The results from the third essay reveal a strong positive relationship between output and temperature, and a negative relationship between output and precipitation. In addition, the findings indicate that investments in research and development resulted in substantial increases in output. The estimated coefficients are then used to construct the Färe-Primont-O'Donnell (FPO) Index. This TFP index is then decomposed into measures of climatic effects, technological progress, technical efficiency change, and scale efficiency change. TFP growth is estimated to have increased by 63.2% in the U.S. between 1960-2004. The main driver behind this sustained growth in TFP was technological progress. We also find revealing that southern states experienced rapid technological change, which can be attributed to technological catch-up as they would gain the most from diffusion of technical knowledge. The findings also suggest that the climatic effect component was responsible for a 13.0% decline in TFP in the U.S. Only eight states reported positive climatic effects, and they are all located in the southern portion of the U.S. The rest of the 40 contiguous states reported negative climatic effects.

Finally, future research should consider the use of micro-level data (e.g. farm or county level) in order to capture salient characteristics within each individual state including analysis for different crops and livestock systems. Such an approach would be enhanced by the expansion of satellite and remote-sensing capabilities to provide localized climatic information necessary for accurate estimation of micro effects. This combined information would significantly enhance the analysis of the interaction between productivity growth, environmental sustainability, and climatic variability.

References

Ball, V. E., J. Bureau, R. Nehring, and A. Somwaru. 1997. Agricultural Productivity Revisited. *American Journal of Agricultural Economics* 79(4): 1045-1063.

Ball, V. E., C. Hallahan, and R. Nehring. 2004. Convergence of Productivity: An analysis of the catch-up hypothesis within a panel of states. *American Journal of Agricultural Economics* 86(5): 1315-1321.

Mosheim, R. and C. A. K. Lovell. 2009. Scale Economies and Inefficiency of U.S. Dairy Farms. *American Journal of Agricultural Economics* 91(3): 777-794.

O'Donnell, C. J. 2012a. An Aggregate Quantity Framework for Measuring and Decomposing Productivity Change. *Journal of Productivity Analysis* 38(3): 255-272.

O'Donnell, C. J. 2012b. Econometric Estimation of Distance Functions and Associated Measures of Productivity and Efficiency Change. *Journal of Productivity Analysis* DOI: 10.1007/s11123-012-0311-1.

O'Donnell, C. J. 2012c. Nonparametric Estimates of the Components of Productivity and Profitability Change in U.S. Agriculture. *American Journal of Agricultural Economics* 94(4): 873-890.

United Nations Population Fund. 2011. *State of World Population 2011: People and Possibilities in a World of 7 Billion*. U.N., New York.

United Nations Food and Agricultural Organization, World Food Program, and

International Fund for Agricultural Development. 2012. *The State of Food Insecurity in the World: Economic Growth is Necessary But Not Sufficient to Accelerate Reduction of Hunger and Malnutrition.* F.A.O., Rome.

United Nations. 2013. *Millennium Development Goals Report*. U.N., New York.

U.S. Environmental Protection Agency. 2009. *Mandatory Reporting of Greenhouse Gases; Final Rule*. Federal Register 74(209): 56337-56489.

U.S. Environmental Protection Agency. 2013. *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2011*. EPA Report 430-R-13-001, EPA Washington, D.C.

Chapter 2

The Good and the Bad: Environmental Efficiency in Dairy Farming[1]

2.1 Abstract

This study builds upon recent developments in productivity analysis where the productive unit generates both desirable and undesirable outputs. Using a Northeast U.S. dairy dataset, this study makes two novel contributions to the literature. First, it uses EPA (2009) methodologies to construct a comprehensive index of emissions that incorporates three major sources of pollution that originate from dairy farms: fuel, fertilizer, and livestock. The few related studies available have focused only on nitrogen surplus from application of excess fertilizer and manure. Second, we establish the shadow value of the emissions, as well as the cost of minimizing its production. Key results indicate that in the Northeast U.S., smaller dairy farms face higher shadow values than larger dairy farms. Consequently, smaller dairy operations would face higher costs than their larger counterparts when reducing pollution. These results are crucial from a public policy perspective because they will assist in crafting an appropriate response to the challenge of pollution reduction while considering the potential impact on smaller operations.

Keywords: environmental efficiency, undesirable output, directional distance function, shadow prices, Bayesian framework, dairy farming. JEL Codes: D22; Q15; Q52

[1] The work in this chapter was partially funded by Grant # 2010-85211-20470, Agricultural Food Research Initiative of the National Institute of Food and Agriculture USDA.

2.2 Introduction

Dairy farming remains the largest agricultural sector in the Northeast United States (Winsten et al. 2010). It contributes to the local economy through the direct generation of producer income, and by purchasing inputs and services from local providers as well as generating employment. According to the National Agricultural Statistics Service (NASS), in 2012, dairy operations in the Northeast U.S. generated 16.9 billion pounds of milk, in addition to 3.6 billion dollars in household income (USDA 2013). Moreover, as the Northeast U.S. becomes increasingly urbanized, the importance of dairy farms in helping to preserve rural landscapes and open-spaces has been brought to the forefront (Johnston 2002). These ecosystem services are responsible for helping to maintain heritage values, rural vitality and ambience in the region (Batie 2003). Nonetheless, dairy farming in the Northeast faces serious challenges. Economies of scale and rapidly changing technology are driving farms to consolidate into larger operations at the expense of smaller family-operated farms. The national trend is now for larger, and fewer dairy farms (MacDonald, McBride, and O'Donoghue 2007). According to the NASS, the total number of dairy operations has decreased by 83% since 1960 (USDA 2010).

Another concern has to do with environmental sustainability because dairy farms are responsible for generating pollutants such as carbon dioxide (CO_2) emissions, methane (CH_4), oxides of nitrogen (NO_x), Ammonia (NH_3), and acid gases (EPA 2012a). These Greenhouse Gas (GHG) emissions originating from dairy operations in the U.S. have been on an upward trend (EPA 2013). Dairy operations accounted for 26% and 12% of the total methane and GHG generated, respectively, by the U.S. agricultural

sector from 1990 to 2009 (EPA 2011). Figure 1 illustrates the trend in methane (CH_4) emissions emanating from U.S. dairy farms.

The environmental impact of GHGs is difficult to quantify. First, these gases belong to a class of pollutants referred to as uniformly mixed assimilative pollutants because they are not sensitive to the source of pollution, and when their emission rates exceed the absorptive capacity of the environment, they accumulate over time (Tietenberg 2006; Tietenberg and Lewis 2009). Secondly, undesirable outputs are not priced in markets making it difficult to derive a monetary measure of the environmental impact. Environmental problems created by pollution have raised concerns about the environmental sustainability of dairy farming (Thoma et al. 2013).

2.3 Towards a new form of environmental regulation

In 2003, the United States Environmental Protection Agency (EPA) made two crucial determinations that set in motion a series of events that have led to a more progressive view of the role of markets in tackling global warming. First, the EPA reasoned that it lacked the authority under the Clean Air Act to regulate CO_2 and other GHG for climate change purposes. Second, even if the agency had such authority, it would decline to set GHG emissions standards because of the associated scientific uncertainty. Following these decisions, the State of Massachusetts and 11 other state and local governments argued, through the court systems, that the EPA had abdicated their responsibility to regulate CO_2 and GHG emissions under the Clean Air Act (Supreme Court of the United States 2007). By a 5-4 ruling in 2007, the Supreme Court of the United States ($SCOTUS$), in the Commonwealth of Massachusetts et al. vs. the EPA et al., determined

that CO_2 and other heat trapping gases that cause global warming are pollutants under the definition of the Clean Air Act. The $SCOTUS$ also determined that the federal government has the authority to regulate CO_2 and other heat trapping gases.

Following the 2007 ruling, and under a new administration, in April 2009 the EPA declared that $GHGs$ pose a threat to public health and welfare, and would regulate them under the Clean Air Act Amendment (1990). This Amendment seeks to control three major threats to the environment: acid rain; urban pollution; and toxic air emissions. Specifically, the Act seeks to control these environmental threats by utilizing economic incentives through a market driven process that includes performance based standards, and emission banking and trading. In a 2009 report, titled "*Mandatory Reporting of Greenhouse Gases; Final Rule,*" the EPA provides a set of guidelines that seek to impose strict reporting standards on GHG emissions in several sectors of the U.S. economy, including the livestock sector.

A sharp increase in CO_2 and GHG levels in the atmosphere has coincided with a general change in the earth's ecosystem that is characterized by an increase in global average temperatures, rising sea levels, flooding, drought, and more frequent and intense storms. Scientists believe that there exists a causal relationship between these events (IPCC Fourth Assessment Report 2007; National Research Council 2010). Issues surrounding climate change impacts and mitigation have received considerable public attention over the years (e.g. Adams 1989; Mendelsohn, Nordhaus, and Shaw 1994), which in turn have led to rising interest from academic researchers and policy makers.

This article builds upon recent developments in productivity analysis where the

productive unit generates both desirable and undesirable outputs (Färe et al. 1989; Chung, Färe, and Grosskopf 1997; Reinhard, Lovell, and Thijssen 1999; Fernandez, Koop, and Steel 2002; Atkinson and Dorfman 2005; Färe et al 2005; O'Donnell 2007). In this study, we try to answer the following research questions: (1) Is it possible to construct an undesirable output for dairy farms that is comprehensive and consistent with new EPA standards? (2) What is the cost to society of the undesirable output generated by dairy farms differing in size? (3) Has environmental efficiency improved or deteriorated overtime?

In anticipation of a policy that could be implemented on a wide scale, and one that could have far-reaching implications, this analysis seeks to measure the impact that an undesirable output has on the environmental efficiency of dairy farm operations varying in size in the Northeast U.S. This article is structured as follows. First it examines environmental efficiency and various ways of modeling polluting technologies. Then it explains the theory behind the directional output distance function ($DODF$) and demonstrates how this model can be used to evaluate environmental performance. Finally, it describes the data and explains the methodology used to construct the undesirable output, and then presents the results and concluding remarks.

2.4 Environmental efficiency and polluting technologies: An overview of the key literature

Over the years, productivity analysis has concentrated mainly on two major components, technical efficiency and technological change (Nishimizu and Page 1982; Chambers, Chung, and Färe 1996, 1998). However, an important component usually ignored in productivity analysis is environmental efficiency, which is a critical issue when economic

agents generate pollutants. Environmental efficiency seeks to establish the trade-off between the production of pollution and of the desirable output (Fernandez, Koop, and Steel 2002). This dimension is growing in importance in economic analysis (e.g. Chung, Färe, and Grosskopf 1997; Färe et al 1989, 1996, 2005; Atkinson and Dorfman 2005; O'Donnell 2007; Cuesta, Lovell, and Zofio 2009) but work related to dairy farming is limited and notable exceptions are Reinhard, Lovell, and Thijssen (1999), and Fernandez, Koop, and Steel (2002, 2005).

One of the earliest attempts at modeling environmental efficiency was by Pittman (1983), who derived a multilateral productivity index of measures of desirable as well as undesirable outputs. The undesirable outputs were valued based on a shadow price estimate. A weakness in this approach is that the undesirable output estimates are not at the plant level, hence constraining the shadow price to be constant over all observations. Färe et al. (1989), in a non-parametric approach, apply a hyperbolic efficiency measure, which requires data on quantities of undesirable outputs. The hyperbolic efficiency approach can generate a wide variety of performance measures, which can still be biased if the estimates of the undesirable output are not at the plant level. In a different study, Färe et al. (1993) model an undesirable output using a non-parametric approach within an output distance function framework. In addition, they generate shadow prices for the undesirable output. In a later analysis, Färe, Grosskopf and Tyteca (1996) develop an environmental performance indicator that is based on the decomposition of overall productivity into separate pollution and input-output efficiency indexes.

Reinhard, Lovell and Thijssen (1999) estimate environmental efficiency for a panel of Dutch dairy farms using a stochastic translog production frontier approach. They

define environmental efficiency as “the ratio of minimum feasible to observed use of an environmentally detrimental input, conditional on observed levels of the desirable output and the conventional inputs” (p. 48). These authors measure the environmental effect based on the nitrogen surplus from fertilizer applications and model it as a conventional input, which is a departure from previous studies (e.g. Ball et al. 1994). A major problem with the Reinhard, Lovell and Thijssen (1999) approach is that the environmental effect is treated as an input and this may result in endogeneity as the variable may be correlated with the error term, leading to biased and inconsistent parameter estimates. In a different analysis, O’Donnell (2007) advocates factoring out the environmental effect by defining a separate (undesirable) output in order to mitigate the endogeneity problem.

Fernandez, Koop and Steel (2002) define environmental efficiency as the amount of pollution that can be reduced by adopting the best-practice technology without sacrificing good outputs. They estimate separate frontiers for the desirable, and the undesirable outputs with a Bayesian framework. Zaim (2004) develops a pollution intensity index, which is defined as pollution emission per unit of desirable output, modeled as the ratio of the quantity indexes of the desirable as well as the undesirable outputs. Färe et al. (2005) use a quadratic directional distance function to model the environmental technical efficiency for a sample of electric utility plants that produce electricity, and a polluting byproduct.

Atkinson and Dorfman (2005) estimate a polluting technology using an input distance function on a Bayesian framework where the bad or undesirable output (i.e. pollution) is treated as an exogenous technology shifter. Cuesta, Lovell and Zofio (2009) use a hyperbolic distance function approach along with a parametric stochastic

framework to measure proportional expansions of the desirable output when the undesirable output is contracted in a multiplicative manner. To model the undesirable output, our study utilizes the $DODF$ developed by Chambers, Chung and Färe (1996), and Chung, Färe and Grosskopf (1997).

The life cycle assessment (LCA) methodology is another approach that places emphasis on compiling an inventory of inputs and outputs used by productive units, and then evaluating the environmental impact linked to the input and output processes. The LCA methodology has been applied in dairy farming (Basset-Mens, Ledgard, and Boyes 2009; Thomassen et al. 2009) and beef production (Subak 1999). Iribarren et al. (2011) combine the LCA with Data Envelopment Analysis (DEA) to examine eco-efficiency for a sample of dairy farms. Eco-efficiency is defined as reductions in resource consumption levels that result in improved environmental performance (Schmidheiny 1992).

The EPA (2009) methodology used in this paper to construct the undesirable output closely corresponds to the LCA approach in its incorporation of the input-output processes of production units. In addition, the LCA approach and our approach are consistent, to the extent that we use the market value of the desirable output to establish the shadow price of the undesirable output, and from there its projected environmental impact. Notwithstanding, the LCA approach does not purport to estimate a production frontier.

The studies mentioned above rely on various modeling strategies. Reinhard, Lovell and Thijssen (1999), Fernandez, Koop and Steel (2002), O'Donnell (2007) and Cuesta (2009) apply parametric econometric techniques. In contrast, Pittman (1983), Färe et al (1989, 1993), Färe, Grosskopf and Tyteca (1996) and Zaim (2004) adopt non-

parametric approaches. It is important to note that from the various studies reviewed above only two (Reinhard, Lovell, and Thijssen 1999; Fernandez, Koop, and Steel 2002) have focused on dairy farming. The work reported in this article differs from Reinhard, Lovell and Thijssen (1999) and Fernandez, Koop and Steel (2002) in the construction and the modeling of the environmental effect. In addition to including nitrogen emissions from the application of fertilizer, we incorporate Methane (CH_4), and Nitrous Oxide (NO_x) from livestock emissions, and carbon dioxide (CO_2) from fuel emissions. Nevertheless, this analysis closely follows Färe et al. (2005), and O'Donnell (2007) in the use of a quadratic DDF in measuring environmental performance. In addition, as the review above demonstrates, there is no generally accepted definition for environmental efficiency. Hence, for purposes of this article, we define environmental efficiency as the minimum level of the undesirable output, given each level of the desirable output along the production frontier. This definition is consistent with the $DODF$ approach.

2.5 Data

The dataset used in this analysis comes from annual publications generated by the Northeast Farm Credit (NFC). The dataset covers dairy operations located in the states of Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont, New York, and New Jersey, and spans the 32-year period between 1980 and 2011. All farms in this dataset received a majority of their income from dairy activities.

Several dairy farms participate in the farm survey that is conducted annually by the NFC. However, in order to preserve confidentially the NFC, unfortunately, does not make the individual farm level data available. Instead, they aggregate and average the farm level information and report it on an annual basis for four different herd size

categories. Hence, the units of observation used in this article correspond to the four different farm size classes for each year in the data. Consequently, for the 32-year period between 1980 and 2011, we have 128 observations. The breakdown of the data according to farm size is as follows: farms with fewer than 90 cows are considered small; those with 90 to 149 cows are denoted as medium; farms with a herd size ranging from 150 to 299 cows are large; and those with 300 cows or more are considered to be very large. The number of individual farm units in the original dataset has ranged from a low of 391 in 1980 to a high of 789 in 1992.

The variables reported include the number of farms, average cows per farm, amount of milk sold per worker, total amount of milk sold in pounds, the cost of machinery per cow, feed and crop expenses per cow, cropland in acres per cow, and per worker, and milk prices. Descriptive statistics for variables in the data set are outlined in table 1. The quantity of concentrate feed was constructed by dividing the nominal figures for total feed expenses per cow by the nominal price for 16% feed concentrate for each year. Prices were obtained from the New England regional office of the NASS of the U.S. Department of Agriculture. The variable for labor is in worker equivalent hours collected and summarized by the NFC. All monetary values are converted into constant 2012-dollar values and all per cow figures are multiplied by the number of cows to obtain aggregate quantities.

The data is then augmented with estimates of a comprehensive index of pollution, constructed using EPA (2009) methodologies as detailed below, and a climatic variable consisting of averages of daily temperatures collected from the National Oceanic and Atmospheric Administration (NOAA). These average daily temperatures vary across

time, but not across farm size groups. The variable captures the effect of temperature variations and their impact on dairy activities in the Northeast United States. Mukherjee, Bravo-Ureta and De Vries (2013) find that temperature variations impact dairy production activities and hence temperature is included in the DODF below.

2.5.1 Construction of the undesirable output

As indicated, a novelty in this analysis is the method used to construct the undesirable output. The few farm level analyses available for dairy farms consider emissions as emanating only from nitrogen surplus (Reinhard, Lovell, and Thijssen 1999; Fernandez, Koop, and Steel 2002, 2005). We extend this variable construction by incorporating three major sources of pollution: 1) fuel based; 2) livestock based; and 3) fertilizer based. 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, and then carbon dioxide emission equivalents (CO_2e) are computed using the EPA greenhouse gas equivalencies calculator (EPA 2012).

The fertilizer-based emission is constructed using information on fertilizer expenditures and historical fertilizer prices from the NASS. This information is then the basis to calculate the total on farm fertilizer applications. The direct emission of nitrous oxide (N_2O) that is derived from nitrogen applied to the soil via fertilizers is calculated using formulations by Mosier (1994).

Livestock based emissions are constructed using methodologies outlined in EPA (2009) guidelines. Livestock 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), generated by the livestock in place at the dairy facility. Methane (CH_4) is a product of total volatile solids excreted per animal type, the fraction of volatile solids per animal type, and a methane conversion factor. 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. In the Northeast United States, they range from a low of 8.63 VS/day/1000 kg of animal mass in Massachusetts, to a high of 9.44 VS/day/1000 kg of animal mass in New Hampshire. Then, these estimates are multiplied by 21, which is the global warming potential of (CH_4).

Livestock based nitrous oxide (N_2O) is a product of the daily total nitrogen excreted per animal type, the fraction of total manure for each animal type, and the emissions factor. The daily total nitrogen excreted per animal type is a function of the average annual animal population in the facility and the typical animal mass, which by default is 604kg for dairy cows. The daily nitrogen excretion rate by animal type is state specific, and for the Northeast United States, this rate ranges from a low of 0.51 VS/day/1000 kg of animal mass in Massachusetts to a high of 0.54 kg of VS/day/1000 kg of animal mass in New Hampshire. These estimates are then multiplied by 310, which is the global warming potential of (N_2O). The combination of all three major sources of pollution is what gives us total emissions. Table 1 provides a summary of the variables used in this analysis.

2.6 Methodology

The theoretical foundation for modeling a multi-output technology is the Shephard (1970) output distance function. However, the output distance function is not appropriate for modeling polluting technologies because it radially expands both the desirable, and the undesirable output towards the frontier. The proportional expansion of all outputs, whether good or bad, undermines the goal of minimizing pollution.

2.6.1 The directional output distance function

An alternative to Shephard's output distance function is the directional distance function developed by Chambers, Chung and Färe (1996) and later extended as a technique for modeling polluting technologies by Chung, Färe and Grosskopf (1997). If the directional vectors for both inputs and outputs are allowed to vary, then we get a directional technology distance function (Färe 2010). The technology assumed in this article follows that of previous studies that restrict the input directional vector to zero (e.g. Chung, Färe, and Grosskopf 1997; Färe et al 2005; O'Donnell 2007; Färe et al 2012); hence, it is a directional output distance function or $DODF$. The $DODF$ makes two assumptions: 1) that in a multi-dimensional production frontier, the decision-making unit desires to simultaneously 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. The distance between the frontier and the observed output, in the direction that reduces the undesirable output while simultaneously expanding the desirable output, is the firm's environmental technical efficiency.

We begin by defining a technology set as a list of all feasible combinations of inputs and outputs. If $x \in \Re_+^k$ is a vector of k inputs, and $y \in \Re_+^m$ and $b \in \Re_+^i$ represent the desirable, and the undesirable output respectively, then the technology set can be defined as

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

An output set $P(x)$ is defined to be a multi-dimensional production possibility frontier that represents the combination of the desirable and the undesirable output (y, b) generated by the firm using the input vector x. More formally, $P(x) = \{(y, b): x\ can\ produce\ (y, b)\}$. The output set satisfies the following four properties (Färe et al. 2005): 1) it is closed and compact for each input vector $x \in \Re$. This means that finite amounts of inputs can generate finite amounts of outputs; 2) in the production of the desirable and the undesirable output, we assume null-jointness. That is, the good and the bad are produced jointly such that if output $b = 0$, then it is not possible to generate any of good *y*. Therefore, if $(y, b) \in P(x)$, and $b = 0$, then $y = 0$; and 3) following Shephard (1970), it is assumed that inputs are weakly disposable such that any proportional contraction of the good and the bad output is feasible. The weakly disposable property models the idea that disposing of the undesirable output is costly because some inputs must be redirected from producing the good output towards emission reduction. In other words, abatement requires a reduction in the firm's activity levels (Kuosmanen 2005). Equation 2 below defines the weak disposability property. Given a scalar $\theta \in (0,1)$, and inputs *x*, a proportional contraction of both the good and the bad output by θ is possible. Formally,

$$(y, b) \in P(x) \; and \; 0 \leq \theta \leq 1, then \; (\theta y, \theta b) \in P(x) \tag{2}$$

The final property, 4), is strong disposability, whereby given any feasible output vector $(y, b) \in P\,(x)$, then another vector with less of any of the goods is also feasible. That is, if $(y, b) \in P\,(x)$, and $(y', b) \leq (y, b)$, then $(y', b) \in P\,(x)$. In words, if the output set containing (y', b) is smaller than the output set containing (y, b), and if $(y, b) \in P\,(x)$, then it must also be the case that $(y', b) \in P\,(x)$.

Now, if $g = (g_y, -g_b)$ represents the directional vector then the $DODF$ is defined as:

$$\vec{D}o\,(x, y, b;\; g_y, -g_b) = \max\{\beta: (y + \beta g_y, b - \beta g_b) \in P(x)\} \tag{3}$$

where x, y, b are vectors of the inputs, the desirable output, and the undesirable output respectively as already noted. We define β to be a scaling factor, and the firms' objective is to expand production of the good output by βg_y while contracting the undesirable output by the factor βg_b.

The directional vector is exogenously determined and hence can take a variety of values. The properties of the $DODF$ are inherited from the output set and can be specified as follows: 1) The $DODF$ is non-negative for all feasible output vectors $(y, b) \in P\,(x)$; 2) It is concave in $(y, b) \in P\,(x)$; 3) It exhibits monotonicity, which can be represented as follows:

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

Equation 4 says that if a firm uses the same amount of inputs but generates more of the

good output and the same amount of the bad output, inefficiency does not increase. Conversely, when the firm raises production of the undesirable output, while holding production of the desirable output and inputs constant, inefficiency does not decrease. That is,

$$\vec{D}o\left(x,y,b';\ g_y,-g_b\right) \geq \vec{D}o\left(x,y,b;\ g_y,-g_b\right) for\ (y,b') \leq (y,b) \in P(x) \qquad (5)$$

The 5th property of the $DODF$ is weak disposability in both goods, that is:

$$\vec{D}o\left(x,\theta y,\theta b;\ g_y,-g_b\right) \geq 0\ for\ (y,b) \in P(x) and\ 0 \leq \theta \leq 1 \qquad (6)$$

The 6th and final property of the $DODF$ is the translation property, which is analogous to the homogeneity of degree one property of the Shephard (1970) output distance function. The translation property is expressed as

$$\vec{D}o\left(x,y+\beta g_y,b+\beta g_b;g_y,-g_b\right) = \vec{D}o\left(x,y,b;\ g_y,-g_b\right) - \beta, for\ \beta \in \Re \qquad (7)$$

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

Figure 2 provides a graphical illustration of the $DODF$. The representative firm described in this illustration is initially producing inside the output set, $P(x)$, at point $A = (y_1, b_1)$. The objective is to raise the firm's efficiency by simultaneously expanding production of the desirable output, and contracting production of the undesirable output. This can be accomplished by scaling the vector from point $A = (y_1, b_1)$ to point

$B = (y_1 + \beta g_y, b_1 - \beta g_b)$. The efficient combination of the desirable and the undesirable output is determined by the tangency between the price ratio (p_b/p_y) and the frontier of the output set $P(x)$, at point B. The vector $g = (g_y, -g_b)$ represents the directional vector, which is determined exogenously in this article. By the translation property, the scaling of the vector from point A to point B, parallel to the directional vector, towards the frontier, represents a solution to $\vec{D}o\ (x, y, b;\ g_y, -g_b) = \max\{\beta: (y + \beta g_y, b - \beta g_b) \in P(x)\}$. At the point of tangency, the representative firm has fully improved its environmental technical efficiency (ETE).

2.6.2 Empirical specification

A $DODF$ that models polluting technologies can be estimated using non-parametric or parametric approaches. Chung, Färe and Grosskopf (1997), Ball et al (1998), and Picazo-Tadeo et al (2005) are examples of studies that utilize non-parametric approaches. Färe et al (2005) implements both a non-parametric data envelopment analysis, and a parametric stochastic approach. O'Donnell (2007) estimates a stochastic quadratic $DODF$ with a Bayesian framework. Here we follow a parametric approach similar to that of Färe et al. (2005). A quadratic specification is utilized because it can be easily restricted to satisfy the translation property of the $DODF$. In addition, we are interested in estimating the shadow price of the undesirable output and since the quadratic specification is twice continuously differentiable it is suitable for this purpose.

Following Kumbhakar and Lovell (2000), we estimate a parametric stochastic frontier that takes on the form, $\vec{D}o\ (x, y, b;\ 1, -1) + \varepsilon = 0$, where $\varepsilon = \nu - u$, represent the statistical error and the inefficiency term respectively, that are independently and

identically distributed. As is customary, the statistical error is assumed to be normally distributed, $v \sim N(0, \sigma^2)$. The inefficiency component, on the other hand, can have a variety of distributional properties including: 1) a truncated half-normal distribution $N^+(0, \sigma^2)$ (Aigner, Lovell, and Schmidt 1977); 2) a one-sided exponential distribution (Meeusen and van den Broeck 1977); or 3) a general gamma distribution (Greene 1990).

A modified quadratic $DODF$ is implemented while imposing the values for the directional vector to be, $g = (1, -1)$. The choice of these values implies that equal weights are assigned to the desirable and the undesirable outputs. This choice is made because of analytical simplicity and the convenience of interpreting results. The model can be written as:

$$\vec{D}o\ (x, y, b;\ 1, -1) = \alpha_0 + \alpha_1 cows_{it} + \alpha_2 labor_{it} + \alpha_3 capital_{it} + \alpha_4 feed_{it} + \alpha_5 time_{it} + \alpha_6 temp_{it} + \varphi_1 milk_{it} + \gamma_1 emissions_{it} + \frac{1}{2}\varphi_2 milk_{it}^2 + \frac{1}{2}\gamma_2 emissions_{it}^2 + \mu(milk_{it})(emissions_{it}) + \frac{1}{2}\alpha_{11} cows_{it}^2 + \frac{1}{2}\alpha_{22} labor_{it}^2 + \frac{1}{2}\alpha_{33} capital_{it}^2 + \frac{1}{2}\alpha_{44} feed_{it}^2 + \frac{1}{2}\alpha_{55} time_{it}^2 + \frac{1}{2}\alpha_{66} temp_{it}^2 + (v_{it} + u_{it}) \tag{8}$$

From the translation property, the term $\vec{D}o\ (x, y, b;\ g_y, -g_b) - \beta$ can be substituted by $\vec{D}o(x, y + \beta g_y, b + \beta g_b; g_y, -g_b)$. As in Färe et al (2005), we assume that for the i^{th} observation, the scaling factor β^i is added to y^i and subtracted from b^i. In this article, we set $\beta^i = b^i$. Thus, we are able to obtain variation on the left hand side by choosing a β^i that is specific to each observation. The quadratic form given by equation 8 is:

$$-\beta^i = \vec{D}o\ (x^i, y^i + \beta^i, b^i - \beta^i; 1, -1) + (v_{i,t} + u_{i,t}) \tag{9}$$

In order for the translation property to hold, and to account for our choice of directional vector, we impose the following parameter restrictions, $\varphi_1 - \gamma_1 = -1$, and $\varphi_2 = \gamma_2 = \mu$ (Färe et al 2005).

2.6.3 The Bayesian framework

A Bayesian framework involves sampling from a posterior probability density function (Rossi, Allenby, and McCulloch 2006). The primary advantage of using a Bayesian framework is that it enables us to draw exact finite sample inferences concerning the unknown parameters (Fernandez, Osiewalski, and Steel 1997). Second, adopting the Bayesian approach can help us avoid problems associated with choosing instruments and also facilitates the imposition of monotonicity constraints (Fernandez, Koop, and Steel 2002; O'Donnell 2007). Third, we recognize that a sample of 128 observations is somewhat small, which makes the strong small sample properties of a Bayesian framework particularly helpful (Fernandez-Villaverde et al 2005).

Proper priors on the parameters of the frontier models are required to ensure the existence of the posterior density (Fernandez, Osiewalski, and Steel 1997). We assume natural conjugate priors, which is a joint density for the parameter space α and σ^2 that is proportional to the likelihood. A conjugate prior is one which when combined with the likelihood, yields a posterior in the same class of distributions (Koop 2003). Following Rossi, Allenby and McCulloch (2006) the conditional prior on α is:

$$p(\alpha|\sigma^2) \propto (\sigma^2)^{-\frac{k}{2}} \exp\left\{\frac{1}{2\sigma^2}(\alpha - \overline{\alpha})' A(\alpha - \overline{\alpha})\right\} \tag{10}$$

and that on σ is:

$$p(\sigma^2) \propto (\sigma^2)^{-\frac{v}{2+1}} \exp\left\{\frac{v s_0^2}{2\sigma^2}\right\} \tag{11}$$

Using the assumptions made about the distribution of the errors, the form of the likelihood of ε can be specified as:

$$p(\varepsilon|\sigma^2) \propto (2\pi)^{-\frac{n}{2}}(\sigma^2)^{-\frac{n}{2}} \exp\left\{-\frac{1}{2\sigma^2}\varepsilon'\varepsilon\right\} \quad (12)$$

and the joint likelihood for *(y, b)* is:

$$p(y, b|x, \alpha, \sigma^2) \propto \left\{\frac{1}{2\sigma^2}\left(Y - (x_{i,t})\alpha + u_i\right)'\left(Y - (x_{i,t})\alpha + u_i\right)\right\} \quad (13)$$

We assume a general gamma distribution for the inefficiency parameter, $u_i \sim Ga\ (\mu_u, \lambda)$, and set $\lambda = 1$, and center μ_u at one. The prior for the inefficiencies take the form $p(u|\lambda^{-1}) = f_G(u|1, \lambda^{-1})$. Setting up the inefficiency this way essentially reduces it to an exponential distribution (Greene 1990). Finally, the product of the likelihood and the normal conjugate priors yield the posterior shown below:

$$p(\alpha, \sigma^2|y, b, X) \propto p(y, b|X, \alpha, \sigma^2)p(\alpha, \sigma^2)p(u|\lambda^{-1}) \quad (14)$$

A simulation of equation 14 is conducted using a Gibbs sampler of 100,000 draws and, as alluded earlier, a burn-in of the initial 10,000 draws is done in order to draw from the full posterior conditional distribution for the parameter space (α, σ) and for the inefficiencies (u). We report the posterior estimates of the means, standard deviation, and numerical standard errors in table 2.

2.6.4 The shadow price

Undesirable outputs are not priced in markets; hence, the associated shadow prices are calculated. The shadow price is defined as the value of the undesirable output at the margin. In figure 2, the shadow price of the undesirable output is established by the tangency of the price-line (p_b/p_y) and the output frontier. Thus, we are looking for this dollar value by projecting the observed good output/bad output combination to the

frontier in a direction that expands the good output while simultaneously contracting the bad output. To accomplish this, based on Chambers, Chung and Färe (1998), we set up the revenue function:

$$R(p_y, p_b) = max_{y,b}\{p_y . y - p_b . b : \vec{D}o\ (x, y, b;\ g_y, -g_b)\} \geq 0 \tag{15}$$

where p_y and p_b are the prices of the good and the shadow price of the bad output respectively, and $\vec{D}o\ (x, y, b;\ g_y, -g_b)$ is the directional output distance function. The Lagrangian expression associated with the maximization of revenues subject to the $DODF$ is given as:

$$\mathcal{L} = max_{y,b}\ \left\{p_y . y - p_b . b + \lambda\left(0 - \vec{D}o\ (x, y, b;\ g_y, -g_b)\right)\right\} \tag{16}$$

In order to solve for the revenue function, we need to establish the value of λ. By making use of the translation property, the revenue function can be rewritten as:

$$R(p_y, p_b; \beta) =$$
$$max_{y,b}\{p_y(y + \beta g_y) - p_b(b + \beta g_b): \vec{D}o\ (x, y + \beta g_y, b + \beta g_b;\ g_y, -g_b) \geq 0\} +$$
$$\beta(p_y g_y + p_b g_b) \tag{17}$$

The short form of the above revenue function is $R(p_y, p_b;\ \beta) = R(p_y, p_b) - \beta\ (p_y g_y + p_b g_b)$, which implies that $\partial R(p_y, p_b; \beta)/\partial\beta = -\left(p_y g_y + p_b g_b\right)$. The translation property is incorporated into the Lagrangian expression, which leads to the following:

$\mathcal{L} = max_{y,b}\ \{p_y . y - p_b . b + \lambda(\beta - \vec{D}o\ (x, y, b;\ g_y, -g_b)\}$. Applying the envelope theorem,

$$\partial \mathcal{L}/\partial \beta = \partial R/\partial \beta = \partial/\partial \beta\{p_y.y - p_b.b + \lambda(\beta - \vec{D}o\,(x, y, b;\ g_y, -g_b))\} = \lambda \tag{18}$$

Using the initial values for the directional vector (1, -1), we solve for the revenue function:

$$R(p_y, p_b; 1, -1) = max_{y,b}\{p_y.y - p_b.b : (p_y.1 + p_b.1)\vec{D}o\,(x, y, b;\ 1, -1)\} \tag{19}$$

The first order conditions associated with the revenue function are:

$$\partial R/\partial y = p_y + (p_y.1 + p_b.1)\nabla y\,\vec{D}o(x, y, b; 1, -1) = 0 \tag{20}$$

and

$$\partial R/\partial b = -p_b + (p_y.1 + p_b.1)\nabla b\,\vec{D}o(x, y, b; 1, -1) = 0 \tag{21}$$

Now, given the parameterization of the $DODF$ in equation 8, we can express the first order conditions above as:

$$\partial \vec{D}o(x, y, b; 1, -1)/\partial b = (\gamma_1 + \gamma_2 b + \mu y) \tag{22}$$

and

$$\partial \vec{D}o(x, y, b; 1, -1)/\partial y = (\varphi_1 + \varphi_2 y + \mu y) \tag{23}$$

Finally, since the price of milk, p_y, is observable, we set up an equation with one unknown and then calculate the unknown shadow price of the undesirable output at the margin as:

$$p_b = -p_y(\gamma_1 + \gamma_2 b + \mu y)/(\varphi_1 + \varphi_2 y + \mu y) \tag{24}$$

2.7 Results

We report the posterior parameter estimates for the sample means, the standard deviations, and the numerical standard error in table 2. 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." As noted, these results are based on a Markov chain using a Gibbs sampler of 100,000 draws and a burn-in of the initial 10,000. Geweke's diagnostics are computed for part of the Markov chain and the resulting Z-scores are presented as diagnostic plots in figure 3. The horizontal dotted lines indicate the 95% confidence interval. A large number of the Z-scores fall within the interval, indicating convergence (Geweke 1992). The estimates of the sample means in table 2 are used in the subsequent analysis to compute the shadow price of the undesirable output, and the Morishima elasticities of substitution.

Regarding the shadow price of the undesirable 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 as shown in figure 2. Based on equation 24, shadow prices are reported for the four different farm sizes, for the years 1980, 1985, 1990, 1995, 2000, 2005 and 2010, and presented in table 3, and a graphical illustration in figure 3. Our results indicate that small farms face consistently higher shadow prices than larger dairy operations.

Another dimension stemming from this analysis is the measurement of Technical

Efficiency (TE). Other studies have defined TE as the ratio of observed to maximum feasible output along the frontier (e.g. Ahmad and Bravo-Ureta 1996; Bravo-Ureta et al. 2007; Mayen, Balgtas, and Alexander 2010). A major difference between conventional measures of TE and our approach is that we incorporate the environmental performance of the decision-making unit in the evaluation of TE. Hence, the measurement of TE in this article integrates the maximal unit expansion of the desirable output and the minimal unit reduction of the undesirable output subject to the directional vector. We refer to this as Environmental Technical Efficiency (ETE) following Färe et al. (2005). We report ETE estimates based on the arithmetic averages of farm sizes in table 3 for the years 1980, 1985, 1990, 1995, 2000, 2005 and 2010. Values of ETE are bounded between 0 and 1, which implies that the higher the estimates, the greater the level of ETE. The results we obtain indicate some variation across farm sizes.

According to Blackorby and Russell (1989, p. 883), the Morishima elasticity of substitution (MES) is "..a measure of curvature, or ease of substitution". More recently, Färe et al (2005) define the MES as a measure of the change in the desirable-undesirable price ratio relative to changes in the desirable-undesirable output quantities, that is, $MES_{by} = \{\partial ln\,(p_b/p_y)/\partial ln\,(y/b)\}$. In other words, the MES is an indicator of the ability of the decision-making unit to trade reductions in milk for reductions in emissions. Following (Färe et al. 2005), and using parameter estimates obtained from equation 8, the MES can be expressed as:

$$MES_{by} = y^{*}\left\{\left(\frac{\mu}{\gamma_1 + \gamma_2 b + \mu y}\right) - \left(\frac{\varphi_2}{\varphi_1 + \varphi_2 y + \mu y}\right)\right\} \tag{25}$$

The MES estimates for the four different farm sizes in the sample are presented for the years 1980, 1985, 1990, 1995, 2000, 2005, and 2010, in table 4 and a graphical illustration is provided in figure 4. The more negative the MES estimate, the more difficult it is for the decision-making unit to trade reductions in milk for reductions in emissions. The results indicate that larger farms face less MES estimates than smaller farms. An implication of this finding is that larger farms have greater substitution possibilities than smaller farms. In addition, we find evidence that in general, the MES values for all farm sizes have trended downwards over time, indicating greater substitution possibilities in more recent years. Based on our definition of environmental efficiency, we conclude that the Northeast U.S. dairy farms represented in the dataset have exhibited an overall tendency towards improved environmental efficiency.

2.8 Concluding remarks

We use a $DODF$ to measure the environmental performance of a sample of dairy farms in the Northeast U.S. The primary advantage of the $DODF$ over other methods is that it allows for the simultaneous expansion of the desirable output while contracting the undesirable output. The method used to construct the undesirable output is one of the novelties in this analysis. Whereas previous analyses that model polluting technologies in dairy farming consider undesirable outputs only as emanating from excess application of fertilizer (Reinhard, Lovell, and Thijssen 1999; Fernandez, Koop and Steel 2002; 2005), this analysis relies on a more comprehensive measure based on EPA (2009) methodologies to construct Methane (CH_4) and Nitrous Oxide (N_2O) emissions from livestock. These values are then combined with CO_2 emissions from fuel combustion, and Nitrogen (N) emissions from the application of fertilizer to arrive at an overall measure

of emissions expressed as carbon dioxide equivalents (CO_2e). The estimated model is used to examine environmental technical efficiency, shadow prices, and Morishima elasticities of substitution (MES) in order to gauge the environmental performance of dairy farms differing in size.

The results indicate that, on average, smaller farms face a higher shadow price at the margin than larger farms suggesting that the smaller units would find it relatively costlier to project to their frontier in order to achieve environmental technical efficient. Furthermore, the MES estimates indicate that larger farms exhibit greater substitution possibilities than smaller farms. Conversely, smaller farms would face greater difficulties in trading reductions in milk production for reductions in emission.

In sum, the analysis reveals that, from an environmental efficiency perspective, larger dairy farms in the Northeast present and advantage over smaller operations. An important implication of these finding is that policy actions taken to curb emissions could have an adverse effect on the competitiveness of smaller dairy operations placing additional pressure on them. This finding compounds the relative competitive disadvantage of smaller farms in light of evidence that supports the presence of economies of size in U.S. dairy production (e.g. Mosheim and Lovell 2009). This poses a dilemma given the importance of small-scale dairy farms to the local economies, and to the preservation of agricultural landscapes in the Northeast (Abdalla 2001; Johnston 2002). From a policy prescription perspective, we advocate for public intervention to be directed towards smaller dairy farms in order to assist them to become environmentally sustainable. Such assistance could take on various forms including emphasis from extension services to provide expert opinion on pollution reduction methods available,

input subsidies, and tax breaks on pollution reduction equipment such as anaerobic digesters.

References

Abdalla, C. W. 2001. *Protecting Farmland at the Fringe: Do Regulations Work? Strengthening the Research Agenda*. Paper No. 7, Northeast Regional Center for Rural Development, The Pennsylvania State University.

Adams, R. M. 1989. Global Climate Change and Agriculture: An Economic Perspective. *American Journal of Agricultural Economics* 71(3): 1272-1279.

Ahmad, M., and B. E. Bravo-Ureta. 1996. Technical Efficiency Measures for Dairy Farms Using Panel Data: A Comparison of Alternative Model Specifications. *Journal of Productivity Analysis* 7(4): 399-415.

Aigner, D., C. A. K. Lovell, and P. Schmidt. 1977. Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics* 6(1): 21-37.

Atkinson, S. E., and J. H. Dorfman. 2005. Bayesian Measurement of Productivity and Efficiency in the Presence of Undesirable Outputs: Crediting Electric Utilities for Reducing Air Pollution. *Journal of Econometrics* 126(2): 445-468.

Ball, V. E., C. A. K. Lovell, R. Nehring, and A. Somwaru. 1994. Incorporating Undesirable Outputs into Models of Production: An Application to U.S. Agriculture. *Cahiers d'Economique et Sociologie Rurales* 31: 59-73.

Ball, V. E., R. Färe, S. Grosskopf, and R. Nehring. 1998. *Productivity of the U.S. Agricultural Sector: The Case of Undesirable Outputs*. Paper presented at

the 1998 Conference on Research in Income and Wealth, New Developments in Productivity Analysis.

Basset-Mens, C., S. Ledgard, and M. Boyes. 2009. Eco-Efficiency of Intensification Scenarios for Milk Production in New Zealand. *Ecological Economics* 68: 1615-1625.

Batie, S. 2003. The multifunctional attributes of Northeastern agriculture: A research agenda. *Agricultural and Resource Economics Review* 32(1): 1-8.

Blackorby, C., and R. R. Russell. 1989. Will the Real Elasticity of Substitution Please Stand Up? *American Economic Review* 79(4): 882-888.

Bravo-Ureta, B. E., D. Solis, V. H. Moreira, J. F. Maripani, A. Thiam, and T. Rivas. 2007. Technical Efficiency in Farming: A Meta-Regression Analysis. *Journal of Productivity Analysis* 27(1): 57-72.

Chambers, R. G., Y. Chung, and R. Färe. 1996. Benefit and Distance Functions. *Journal of Economic Theory* 70(2): 407-419.

Chambers, R. G., Y. Chung, and R. Färe. 1998. Profit, Directional Distance Functions, and Nerlovian Efficiency. *Journal of Optimization Theory and Applications* 98(2): 351-364.

Chib, S. 1995. Marginal Likelihood From the Gibbs Output. *Journal of the American Statistical Association* 90: 1313-1321.

Chung, Y. H., R. Färe, and S. Grosskopf. 1997. Productivity and Undesirable Outputs: A Directional Distance Function Approach. *Journal of Environmental*

Management 51(3): 229- 240.

Cuesta, R. A., C. A. K. Lovell, and J. Zofio. 2009. Environmental Efficiency Measurement with Translog Distance Functions: A Parametric Approach. *Ecological Economics* 68: 2232- 2242.

Färe, R., S. Grosskopf, C. A. K. Lovell, and C. Pasurka. 1989. Multilateral Productivity Comparisons When Some Outputs are Undesirable: A Nonparametric Approach. *Review of Economics and Statistics* 71(1): 90-98.

Färe, R., S. Grosskopf, C. A. K. Lovell, and S. Yaisawarng. 1993. Derivation of Shadow Prices for Undesirable Outputs: A Distance Function Approach. *Review of Economics and Statistics* 75(2): 374-380.

Färe, R., S. Grosskopf, and D. Tyteca. 1996. An Activity Analysis Model of the Environmental Performance of Firms - Application to Fossil-Fuel-Fired Electric Utilities. *Ecological Economics* 18: 161-175.

Färe, R., S. Grosskopf, D. Noh, and W. Weber. 2005. Characteristics of a Polluting Technology: Theory and Practice. *Journal of Econometrics* 126(2): 469-492.

Färe, R. 2010. Directional Distance Functions and Public Transportation: A Comment. *Transportation Research* Part D 15: 108-109.

Fernandez, C., J. Osiewalski, and M. F. J. Steel. 1997. On the use of Panel Data in Stochastic Frontier Models with Improper Priors. *Journal of Econometrics*

79(1): 169-193.

Fernandez, C., G. Koop, and M. F. J. Steel. 2002. Multiple-Output Production with Undesirable Outputs: An Application to Nitrogen Surplus in Agriculture. *Journal of the American Statistical Association* 97: 432-442.

Fernandez, C., G. Koop, and M. F. J. Steel. 2005. Alternative Efficiency Measures for Multiple-Output Production. *Journal of Econometrics* 126(2): 411-444.

Fernandez-Villaverde, J., F. Rubio-Ramirez, and M. Santos. 2005. *Convergence Properties of the Likelihood of Computed Dynamic Models*. Working Paper. National Bureau of Economic Research.

Geweke, J. 1992. Evaluating the Accuracy of Sampling Based Approaches to Calculating Posterior Moments. In *Bayesian Statistics 4* (ed. J. M. Bernado, J. O Berger, A. P Dawid and A. F. M Smith). Clarendon Press, U.K.

Greene, W. H. 1990. A Gamma-Distributed Stochastic Frontier Model. *Journal of Econometrics* 46(1): 141-163.

Iribarren, D., A. Hospido, M. T. Moreira, and G. Feijoo. 2011. Benchmarking Environmental and Operational Parameters through Eco-efficiency Criteria for Dairy Farms. *Science of the Total Environment* 409: 1786-1798.

Johnston, R. J. 2002. *Conserving Farm and Forest in a Changing Rural Landscape: Current and Potential Contributions of Economics*. Regional Rural Development Paper No. 11, Northeast Regional Center for Rural Development, The Pennsylvania State University, University Park.

Koop, G. 2003. *Bayesian Econometrics*. Wiley Series in Probability and Statistics.

Kumbhakar, S. C., and C. A. K. Lovell. 2000. *Stochastic Frontier Analysis*. Cambridge University Press, Cambridge, U.K.

Kuosmanen, T. 2005. Weak Disposability in Nonparametric Production Analysis with Undesirable Outputs. *American Journal of Agricultural Economics* 87(4): 1077-1082.

Macdonald, J. M., W. D. McBride, and E. J. O'Donoghue. 2007. Low Costs Drive Production to Large Dairy Farms. U.S. Department of Agriculture. Economic Research Service. Washington D.C. *Amber Waves* 5(4): 30-35.

Mayen, C. D., J. V. Balagtas, and C. Alexander. 2010. Technology Adoption and Technical Efficiency: Organic and Conventional Dairy Farms in the United States. American Journal of Agricultural Economics 92(1): 181-195.

Meeusen, W., and J. van den Broeck. 1977. Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *International Economic Review* 18(2): 435-444.

Mendelsohn, R., W. D. Nordhaus, and D. Shaw. 1994. The Impact of Global Warming on Agriculture: A Ricardian Analysis. *American Economic Review* 84(4): 753-771.

Mosheim, R., and C. A. K. Lovell. 2009. Scale Economies and Inefficiency of U.S. Dairy

Farms. *American Journal of Agricultural Economics* 91(3): 777-794.

Mosier, A. R. 1994. Nitrous Oxide Emissions from Agricultural Soils. *Fertilizer Research* 37(3): 191-200.

Mukherjee, D., B. Bravo-Ureta, and A. De Vries. 2013. Dairy Productivity and Climatic Conditions: Econometric Evidence from Southeastern United States. *Australian Journal of Agriculture and Resource Economics* 57(1): 123-140.

National Research Council. 2010. Advancing the Science of Climate Change. The National Academies Press, Washington D.C.

Nishimizu, M., and J. M. Page. 1982. Total Factor Productivity Growth, Technological Progress and Technical Efficiency Change: Dimensions of Productivity Change in Yugoslavia. 1967-1978. *Economic Journal* 92: 920-936.

O'Donnell, C. J. 2007. *Estimating the Characteristics of Polluting Technologies*. Presented at the 51st Annual Conference of the Australian Agricultural and Resource Economics Society, Queenstown, New Zealand.

Parry, M. L., O. F. Canziani, J. P. Palutikof, P. J. van der Linden, and C. E. Hanson. 2007. *Climate Change 2007: Impacts, Adaptation and Vulnerability*. Working group II. Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

Picazo-Tadeo, A. J., E. Reig-Martinez, and F. Hernandez-Sancho. 2005. Directional distance functions and environmental regulation. *Resource and Energy*

Economics 27(2): 131-142.

Pittman, R. W. 1983. Multilateral Productivity Comparisons with Undesirable Outputs. *Economic Journal* 93(372): 883-891.

Reinhard, S., C. A. K. Lovell, and G. Thijssen. 1999. Econometric Estimation of Technical and Environmental Efficiency: An Application to Dutch Dairy Farms. *American Journal of Agricultural Economics* 81(1): 44-60.

Rossi, P., G. Allenby, and R. McCulloch. 2006. Bayesian statistics and marketing. Wiley Series in Probability and Statistics.

Schmidheiny, S. 1992. Changing Course – A Global Business Perspective on Development and the Environment. World Business Council for Sustainable Development (WBCSD).

Shephard, R. W. 1970. Theory of Costs and Production Functions. Princeton University Press, Princeton, New Jersey.

Supreme Court Of The United States. 2007. Commonwealth of Massachusetts et al. vs. Environmental Protection Agency et al. Number 05-1120. Decided April 2, 2007.

Subak, S. 1999. Global Environmental Costs of Beef Production. *Ecological Economics* 30: 79-91.

Thoma, G., J. Popp, D. Nutter, D. Shonnard, R. Ulrich, M. Matlock, D. S. Kim, Z. Neiderman, N. Kemper, C. East, and F. Adom. 2013. Greenhouse Gas

Emissions from Milk Production and Consumption in the United States: A Cradle-to-Grave Life Cycle Assessment Circa 2008. *International Dairy Journal* 31(1): S3-S14.

Thomassen, M. A., M. A. Dolman, K. J. van Calker, and I. J. M. de Boer. 2009. Relating Life Cycle Assessment Indicators to Gross Value Added for Dutch Dairy Farms. *Ecological Economics* 68: 2278-2284.

Tietenberg, T. H. 2006. Emissions Trading: Principles and Practice. Resources For the Future.

Tietenberg, T. H., and L. Lewis. 2012. Environmental and Natural Resource Economics. Pearson.

U.S. Congress. 1990. *Clean Air Act Amendments of 1990*. Pub. L. No. 101-549, 104 Stat. 2399.

U.S. Department of Agriculture. 2010. Overview of the United States dairy industry. National Agricultural Statistics Service. Agricultural Statistics Board.

U.S. Department of Agriculture. 2012. Online at: http://www.nass.usda.gov/Statistics_by_Subject/Economics_and_Prices/index.asp. (Accessed August 21, 2012). National Agricultural Statistics Service.

U.S. Department of Agriculture. 2013. *Milk production, disposition, and income 2012 summary*. National Agricultural Statistics Service. ISSN: 1949-1506.

U.S. Environmental Protection Agency. 2009. *Mandatory Reporting of Greenhouse Gases; Final Rule*. Federal Register 74(209): 56337-56489.

U.S. Environmental Protection Agency. 2011. *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2009*. EPA 430-R-11-005. Washington D.C.

U.S. Environmental Protection Agency. 2012a. *U.S. Greenhouse gas emissions and sinks: 1990-2010.* Annex 2. Washington, DC, 430-R-12-001.

U.S. Environmental Protection Agency. 2012b. Greenhouse Gas Equivalencies Calculator, Online at: http://www.epa.gov/cleanenergy/energy-resources/calculator.html (Accessed August 21, 2012).

U.S. Environmental Protection Agency. 2012. U.S Anaerobic Digester Status: A 2011 Snapshot. Available at, *http:* //www.epa.gov/agstar/documents/2011digesterupdate.pdf (Accessed August 21, 2012). AgSTAR. Washington D.C.

Wilson, R. W. 1990. Climate Change-Factors and Forecasts. *Canadian Journal of Agricultural Economics* 38: 677-683.

Winsten, J. R., C. D. Kerchner, A. Richardson, A. Lichau, and J. M. Hyman. 2010. Trends in the Northeast dairy industry: Large-scale modern confinement feeding and management-intensive grazing. *Journal of Dairy Science* 93(4): 1759-1769.

Zaim, O. 2004. Measuring environmental performance of state manufacturing through

changes in pollution intensities: a DEA approach. *Ecological Economics* 18(48): 161-175.

2.9 Tables and Figures

Table 1: Descriptive Statistics

Variable (units)	Mean	Std. Dev	Min	Max
Milk (tons)	1,539.5	1,693.4	293.2	7,791.7
Emission (tons)	1,074.4	954.5	226.1	3,857.2
Cows (number)	170.5	159.9	46.0	712.0
Labor (hours)	4.2	2.9	1.7	14.2
Capital (dollars)	92,719.6	68,623.1	23,904.1	293,072.9
Feed (tons)	195,664.1	217,829.9	39,009.4	1,179,072.0
Temp (C^0)	8.2	0.6	7.3	9.7

Table 2: Summary of Posterior Results

Variable	Coefficient	Mean	Std. Dev	Num S.E	2.5%	97.5%
Constant(var1)	α_0	-3.2	9.7	0.033	-22.000	16.000
Cows(var2)	α_1	6.8	2.6	0.0086	1.800	12.000
Labor(var3)	α_2	-0.0042	0.0021	0.00068	-0.008	0.000
Capital(var4)	α_3	-0.00098	0.00094	0.00032	-0.001	0.003
Feed(var5)	α_4	0.085	10	0.036	0.094	0.076
Time(var6)	α_5	3.9	3.1	0.01	-2.100	9.900
Temp(var7)	α_6	-1.3	9.1	0.031	-19.000	17.000
Milk(var8)	φ_1	-0.35	0.54	0.0018	-0.460	-0.024
Emission	$\gamma_1 = \varphi_1 + 1$	0.65				
Milk*Emission(var9)	μ	0.00022	0.00016	0.001	-0.0001	0.0005
Milk^2(var10)	φ_2	-0.00046	0.00032	0.00001	-0.0011	0.00017
Emission^2(var11)	γ_2	0.00005	0.00013	0.00001	-0.00021	0.00031
Cows^2(var12)	α_{11}	-0.017	0.014	0.0005	-0.045	0.011
Labor^2(var13)	α_{22}	-0.0028	0.0002	0.0006	-0.0036	-0.0018
Capital^2(var14)	α_{33}	-0.00084	0.00019	0.03	-0.001	-0.00077
Feed^2(var15)	α_{44}	-0.024	10	0.032	-0.028	-0.019
Time^2(var16)	α_{55}	-0.14	0.45	0.0015	-1.000	0.760
Temp^2(var17)	α_{66}	1.5	6.5	0.021	-14.000	11.000

Table 3: Environmental Technical Efficiency and Shadow Prices

Year	1980	1985	1990	1995	2000	2005	2010
Average ETE	0.979	0.949	0.742	0.957	0.877	0.983	0.896
Average Milk Prices (p_y)	36.77	28.26	27.06	19.83	17.95	19.02	18.70
Average Shadow Prices (p_b)							
Small	17.29	13.08	15.69	9.58	6.29	6.25	5.98
Medium	9.30	6.48	9.56	6.42	3.81	4.04	3.89
Large	5.11	3.89	7.17	4.78	2.58	2.71	2.54
Very Large	2.48	1.48	4.62	2.73	1.81	1.78	1.52

Table 4: Morishima Elasticity of Substitution

Year	1980	1985	1990	1995	2000	2005	2010
Small	-1.115	-1.110	-1.121	-1.070	-0.963	-0.947	-0.945
Medium	-0.922	-0.892	-0.961	-0.942	-0.821	-0.819	-0.823
Large	-0.722	-0.717	-0.879	-0.859	-0.694	-0.692	-0.682
Very Large	-0.353	-0.162	-0.747	-0.683	-0.554	-0.523	-0.454

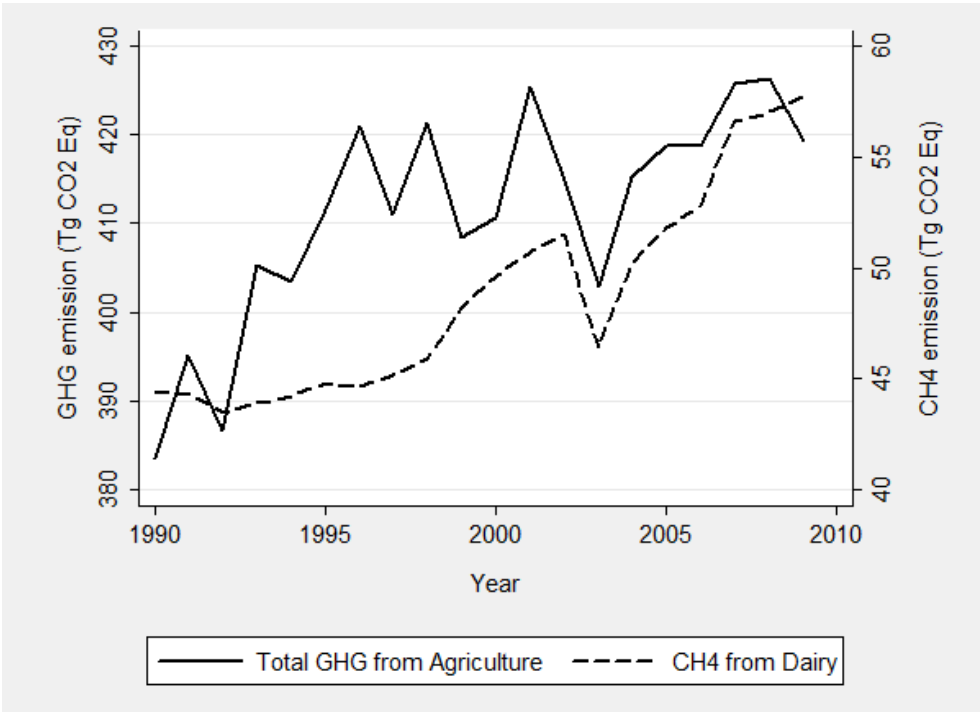


Figure 1: Trend in GHG emissions from the U.S. agricultural sector [Source: U.S. EPA 2011]

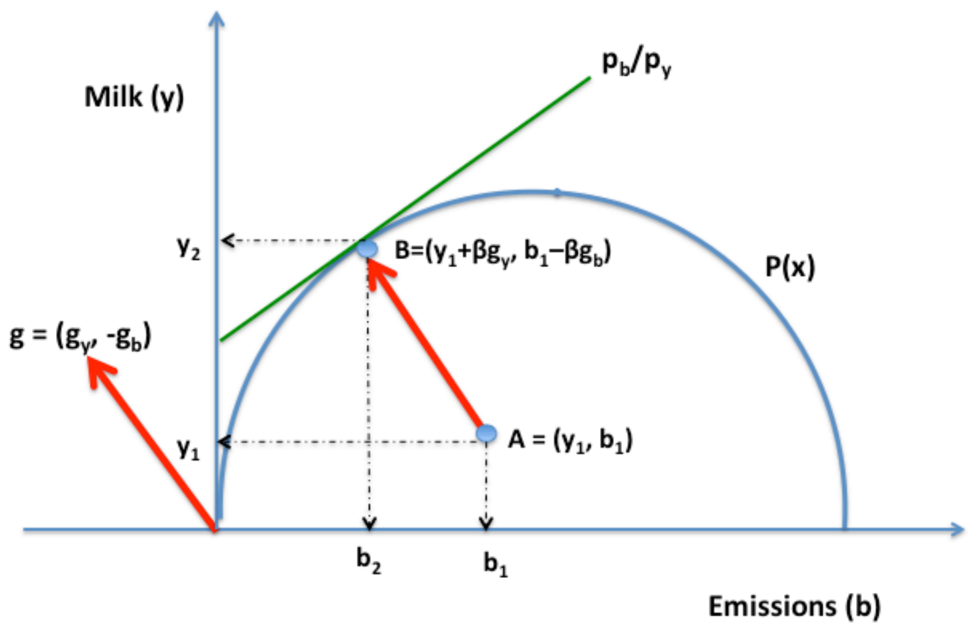


Figure 2: Graphical illustration of the directional output distance function

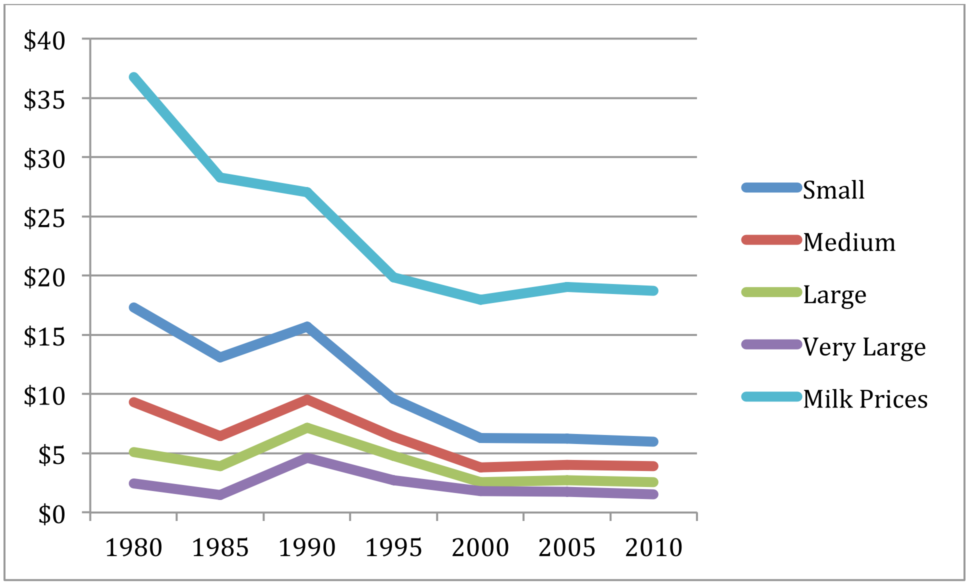


Figure 3: Average shadow prices by farm size

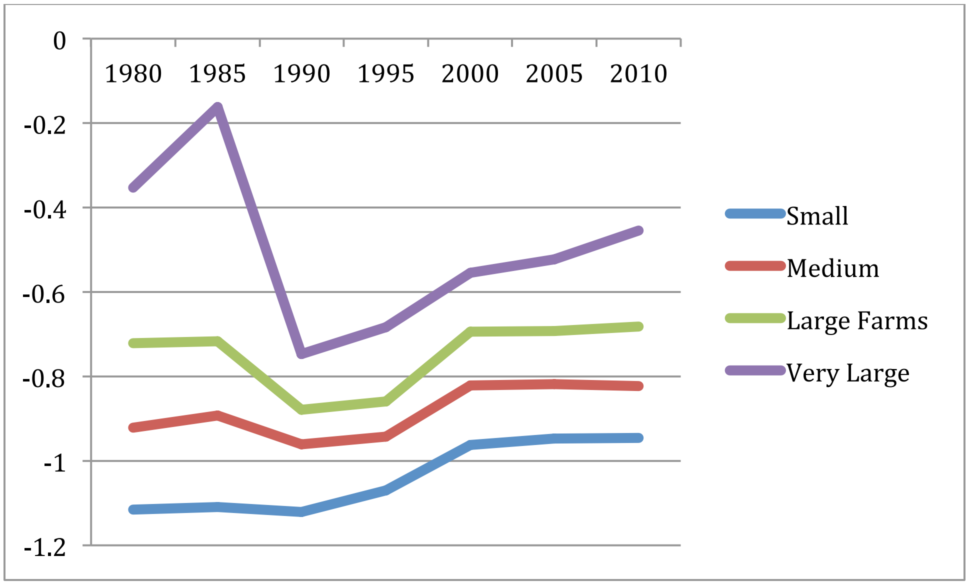


Figure 4: Morishima elasticity of output substitution by farm size

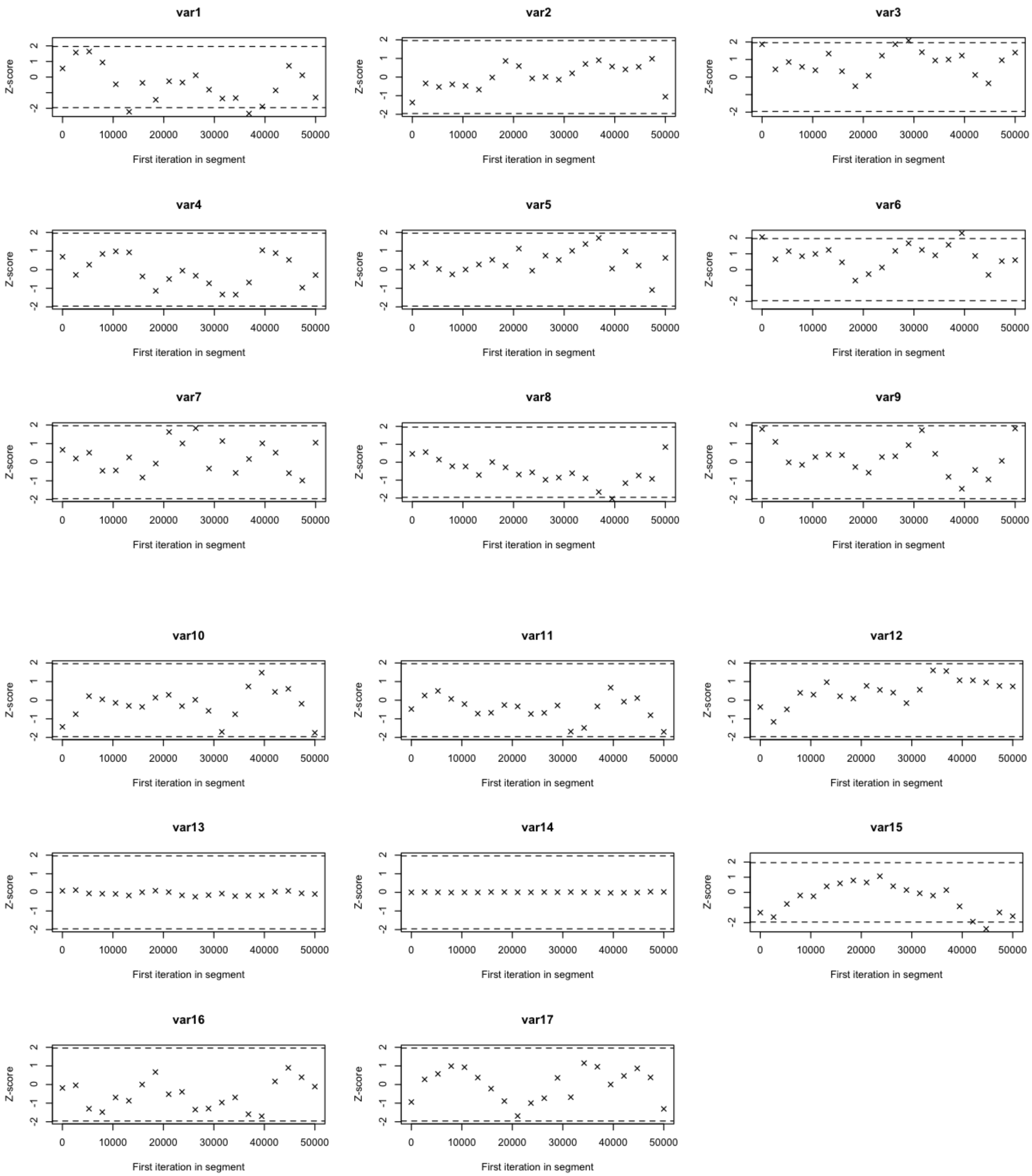


Figure 5: Geweke's diagnostic plot

Chapter 3

The Economic Costs of Environmental Regulation in U.S. Dairy Farming: A Directional Distance Function Approach[2]

3.1 Abstract

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. First, it 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

[2] The work in this chapter was partially funded by Grant # 2011-67024-30912, Agricultural Food Research Initiative of the National Institute of Food and Agriculture USDA.

3.2 Introduction

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.

3.3 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.

3.4 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

$$T = \{(x, y, b): x \in \Re_+^k, y \in \Re_+^m, b \in \Re_+^i\} \tag{1}$$

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 (Chung, Färe, and Grosskopf 1997), 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 $y = 0$.

3.4.1 *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

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

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

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

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

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

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

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

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:

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

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).

3.4.2 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,

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

3.4.3 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

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

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).

3.4.4 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:

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

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

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

From the translation property, the term $\vec{D}o\left(x, y, b;\ g_y, -g_b\right) - \beta$ can be substituted by $\vec{D}o\left(x, y + \beta g_y, b + \beta g_b; g_y, -g_b\right)$. As in Färe et al (2005), we assume that for the i^{th} observation, the scaling factor β^i is added to y^i and subtracted from b^i. In this article, we set $\beta^i = b^i$. Thus, we are able to obtain variation on the left hand side by choosing a β^i that is specific to each observation. The quadratic form given by equation 10 is:

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

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).

3.4.5 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):

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

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

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

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.

3.5 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

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

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 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).

3.5.1 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.

3.5.2 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:

$$\partial R/_{\partial y} = p_y + (p_y . g_y - p_b g_b)\nabla_y\, \vec{D}o\ (x, y, b;\ g_y, -g_b) = 0 \tag{15}$$

$$\partial R/_{\partial b} = -p_b + (p_y . g_y - p_b g_b)\nabla_b\, \vec{D}o\ (x, y, b;\ g_y, -g_b) = 0 \tag{16}$$

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.

3.5.3 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:

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

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.

3.5.4 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:

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

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

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

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

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

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

3.6 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 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

[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."

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).

3.7 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.

References

Anderson, T. W., and C. Hsiao. 1982. Formulation and Estimation of Dynamic Models Using Panel Data. *Journal of Econometrics* 18(1): 47-82.

Arimura, T. H., A. Hibiki, and H. Katayama. 2008. Is a Voluntary Approach an Effective Environmental Policy Instrument? A Case for Environmental Management Systems. *Journal of Environmental Economics and Management* 55(3): 281-295.

Atkinson, S. E., and J. H. Dorfman. 2005. Bayesian Measurement of Productivity and Efficiency in the Presence of Undesirable Outputs: Crediting Electric Utilities for Reducing Air Pollution. *Journal of Econometrics* 126(2): 445-468.

Ball, V. E., R. Färe, S. Grosskopf, and R. Nehring. 2001. Productivity of the U.S. Agricultural Sector: The Case of Undesirable Outputs. In: Hulten, C., Dean, E., Harper, M. (Eds.), *Studies in Income and Wealth*, vol. 63. University of Chicago Press, Chicago, pp. 541–586.

Bishop, C., and C. R. Shumway. 2009. The Economics of Dairy Anaerobic Digestion with Coproduct Marketing. *Review of Agricultural Economics* 31(3): 394-410.

Blackorby, C., and R. R. Russell. 1989. Will the Real Elasticity of Substitution Please Stand Up? *American Economic Review* 79(4): 882-888.

Brannlund, R., R. Färe, and S. Grosskopf. 1995. Environmental Regulation and Profitability: An Application to Swedish Pulp and Paper Mills. *Environmental*

and Resource Economics 6(1): 23-36.

Bravo-Ureta, B. E., D. Solis, V. H. Moreira, J. F. Maripani, A. Thiam, and T. Rivas. 2007. Technical Efficiency in Farming: A Meta-Regression Analysis. *Journal of Productivity Analysis* 27(1): 57-72.

Casella, G., and E. I. George. 1992. Explaining the Gibbs Sampler. *The American Statistician* 46(3): 167-174.

Chambers, R. G., Y. Chung, and R. Färe. 1996. Benefit and Distance Functions. *Journal of Economic Theory* 70(2): 407-419.

Chambers, R. G., Y. Chung, and R. Färe. 1998. Profit, Directional Distance Functions, and Nerlovian Efficiency. *Journal of Optimization Theory and Applications* 98(2): 351-364.

Chib, S. 1995. Marginal Likelihood from the Gibbs Output. *Journal of the American Statistical Association* 90, 1313-1321.

Chung, Y. H., R. Färe, and S. Grosskopf. 1997. Productivity and Undesirable Outputs: A Directional Distance Function Approach. *Journal of Environmental Management* 51(3): 229- 240.

Christainsen, G. B., and R. Haveman. 1981. The Contribution of Environmental Regulations to the Slowdown in Productivity Growth. *Journal of Environmental Economics and Management* 8(4): 381-390.

Conley, T., C. Hansen, R. McCulloch, and P. Rossi. 2008. A Semi-Parametric Bayesian

Approach to the Instrumental Variable Problem. *Journal of Econometrics* 144(1): 276-305.

Färe, R., and D. Primont. 1995. *Multi-Output production and duality: Theory and applications*. Kluwer Academic Publishers. Boston.

Färe, R., S. Grosskopf, D. Noh, and W. Weber. 2005. Characteristics of a Polluting Technology: Theory and Practice. *Journal of Econometrics* 126(2): 469-492.

Färe, R., S. Grosskopf, and C. Pasurka. 2007. Environmental Production Functions and Environmental Directional Distance Functions. *Energy* 32(7): 1055-1066.

Färe, R. 2010. Directional Distance Functions and Public Transportation: A Comment. *Transportation Research* Part D 15: 108-109.

Färe, R., S. Grosskopf, C. Pasurka, and W. Weber. 2012. Substitutability among Undesirable Outputs. *Applied Economics* 44(1): 39-47.

Fernandez, C., G. Koop, and M. F. J. Steel. 2002. Multiple-Output Production with Undesirable Outputs: An Application to Nitrogen Surplus in Agriculture. *Journal of the American Statistical Association* 97: 432-442.

Fernandez, C., J. Osiewalski, and M. F. J. Steel. 1997. On the use of Panel Data in Stochastic Frontier Models with Improper Priors. *Journal of Econometrics* 79(1): 169-193.

Geweke, J. 1992. Evaluating the Accuracy of Sampling Based Approaches to Calculating Posterior Moments. In *Bayesian Statistics 4* (ed. J.M. Bernado, J.O Berger, A.P

Dawid and A.F.M Smith). Clarendon Press, U.K.

Gollop, F., and M. Roberts. 1983. Environmental Regulations and Productivity Growth: The Case of Fossil-Fuel Electric Power Generation. *Journal of Political Economy* 91(4): 654-674.

Greene, W. H. 1990. A Gamma-Distributed Stochastic Frontier Model. *Journal of Econometrics* 46(1): 141-163.

Hart, R. 2008. The Timing of Taxes on CO_2 Emissions when Technological Change is Endogenous. *Journal of Environmental Economics and Management* 55(2): 194-212.

Hernandez-Sancho, F., A. J. Picazo-Tadeo, and E. Reig-Martinez. 2000. Efficiency and Environmental Regulation. *Environmental and Resource Economics* 15(4): 365-378.

Isik, M. 2004. Environmental Regulation and the Spatial Structure of the U.S. Dairy Sector. *American Journal of Agricultural Economics* 86(4): 949-962.

Jorgenson, D., and P. Wilcoxen. 1990. Environmental Regulation and U.S Economic Growth. *RAND Journal of Economics* 21(2): 314-340.

Key, N., and S. Sneeringer. 2012. Carbon Emissions, Renewable Electricity, and Profits: Comparing Policies to Promote Anaerobic Digesters in Dairies. *Agriculture and Resource Economics Review* 41(2): 139–157.

Kumbhakar, S. C., and C. A. K. Lovell. 2000. *Stochastic Frontier Analysis*. Cambridge

University Press, Cambridge, U.K.

Kuosmanen, T. 2005. Weak Disposability in Nonparametric Production Analysis with Undesirable Outputs. *American Journal of Agricultural Economics* 87(4): 1077-1082.

O'Donnell, C. J. 2007. *Estimating the Characteristics of Polluting Technologies*. Presented at the 51st Annual Conference of the Australian Agricultural and Resource Economics Society, Queenstown, New Zealand.

Picazo-Tadeo, A. J., E. Reig-Martinez, and F. Hernandez-Sancho. 2005. Directional Distance Functions and Environmental Regulation. *Resource and Energy Economics* 27(2): 131-142.

Mosier, A. R. 1994. Nitrous Oxide Emissions from Agricultural Soils. *Fertilizer Research* 37(3): 191-200.

Mukherjee, D., B. Bravo-Ureta, and A. De Vries. 2013. Dairy Productivity and Climatic Conditions: Econometric Evidence from Southeastern United States. *Australian Journal of Agriculture and Resource Economics* 57(1): 123-140.

Reinhard, S., C. A. K. Lovell, and G. Thijssen. 1999. Econometric Estimation of Technical and Environmental Efficiency: An Application to Dutch Dairy Farms. *American Journal of Agricultural Economics* 81(1): 44-60.

Rossi, P., G. Allenby, and R. McCulloch. 2006. *Bayesian Statistics and Marketing*. Wiley Series in Probability and Statistics.

Shephard, R. W., 1970. Theory of costs and production functions. Princeton University Press, Princeton, New Jersey.

Thoma, G., J. Popp, D. Nutter, D. Shonnard, R. Ulrich, M. Matlock, D. S. Kim, Z. Neiderman, N. Kemper, C. East, and F. Adom. 2013. Greenhouse Gas Emissions from Milk Production and Consumption in the United States: A Cradle-to-Grave Life Cycle Assessment Circa 2008. *International Dairy Journal* 31(1): S3-S14.

Shephard, R. W. 1970. *Theory of Costs and Production Functions*. Princeton University Press, Princeton, New Jersey.

Sneeringer, S., and R. Hogle. 2008. Variations in Environmental Regulations in California and Effects on Dairy Location. *Agricultural and Resource Economics Review* 27(2): 133-146.

Sneeringer, S., and N. Key. 2011. Effects of Size-Based Environmental Regulations: Evidence of Regulatory Avoidance. *American Journal of Agricultural Economics* 93(4): 1189-1211.

Sneeringer, S. 2011. Effects of Environmental Regulation and Urban Encroachment on California's Dairy Structure. *Journal of Agricultural and Resource Economics* 36(3): 590-614.

Supreme Court Of The United States. 2007. *Commonwealth of Massachusetts et al. vs. Environmental Protection Agency et al*. Number 05-1120, Decided April 2, 2007.

U.S. Congress. 1990. *Clean Air Act Amendments of 1990*. Pub. L. No. 101-549, 104 Stat. 2399.

U.S. Department of Agriculture. 2013a. *Dairy Market Statistics, 2012 Annual Summary*. Agriculture Marketing Service.

U.S. Department of Agriculture. 2013b. Agricultural Census Publications, Online at: *http* ://www.agcensus.usda.gov/Publications/2007/Full_Report/Census_by_State/(Accessed March 12th, 2013) National Agricultural Statistics Service.

U.S. Department of Agriculture. 2013c. *Climate Change and Agriculture in the United States: Effects and Adaptation*. Agricultural Research Service, Climate Change Program Office.

U.S. Environmental Protection Agency. 2008. *Revised National Pollutant Discharge Elimination System Permit Regulation and Effluent Limitations Guidelines for Concentrated Animal Feeding Operations; Final Rule*. Federal Register 73(225): 70418-70486.

U.S. Environmental Protection Agency. 2009. *Mandatory Reporting of Greenhouse Gases; Final Rule*. Federal Register 74(209): 56337-56489.

U.S. Environmental Protection Agency. 2013a. *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2011*. EPA Report 430-R-13-001, EPA Washington, D.C.

U.S. Environmental Protection Agency. 2013b. Greenhouse Gas Equivalencies

Calculator, Online at: http://www.epa.gov/cleanenergy/energy-resources/calculator.html (Accessed March 12, 2013).

3.8 Tables and Figures

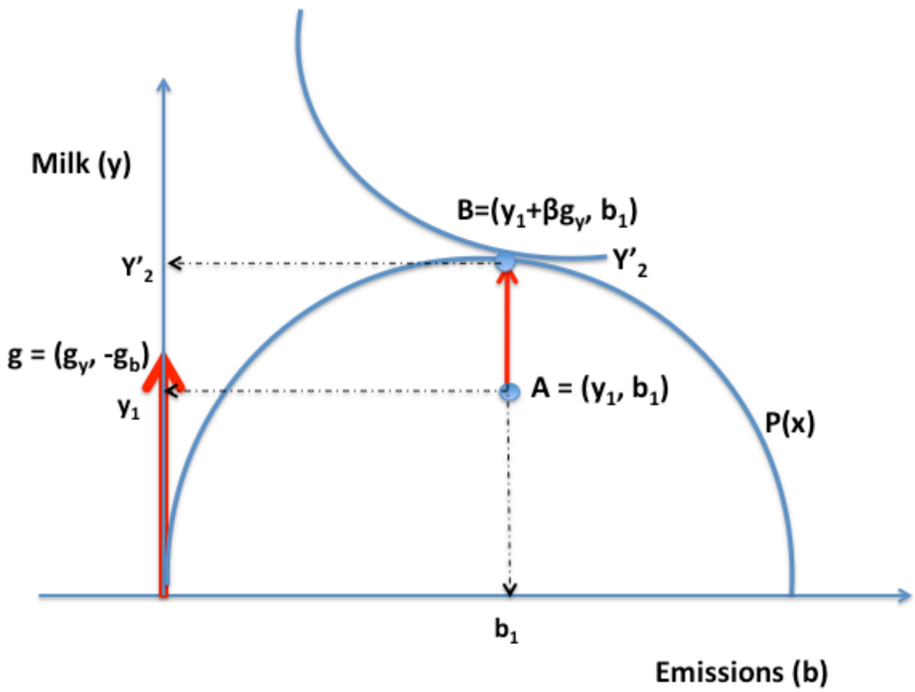


Figure 1: The directional output distance function for Case 1: No regulation

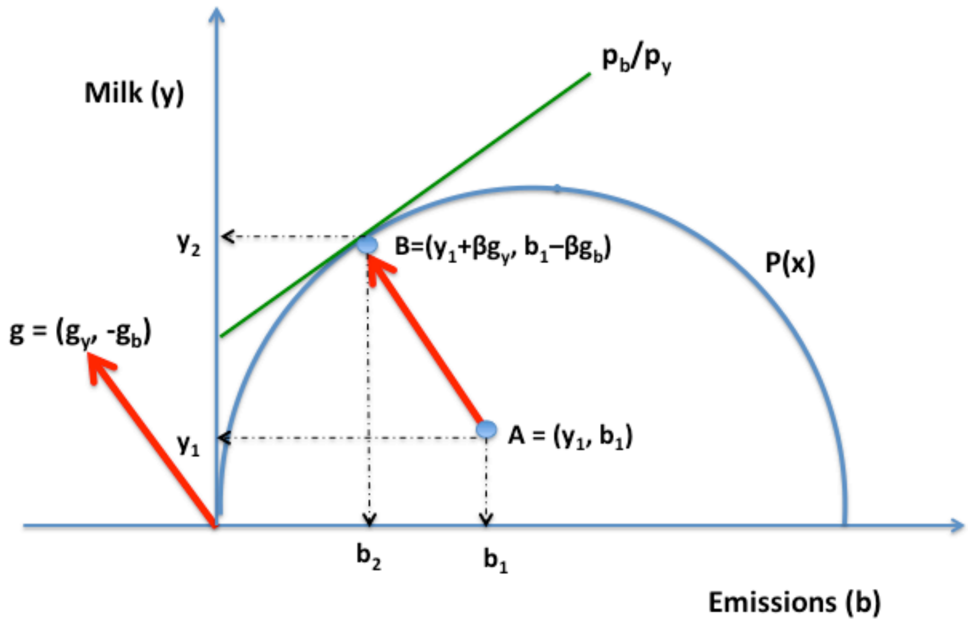


Figure 2: The directional output distance function for Case 2: Environmental regulation

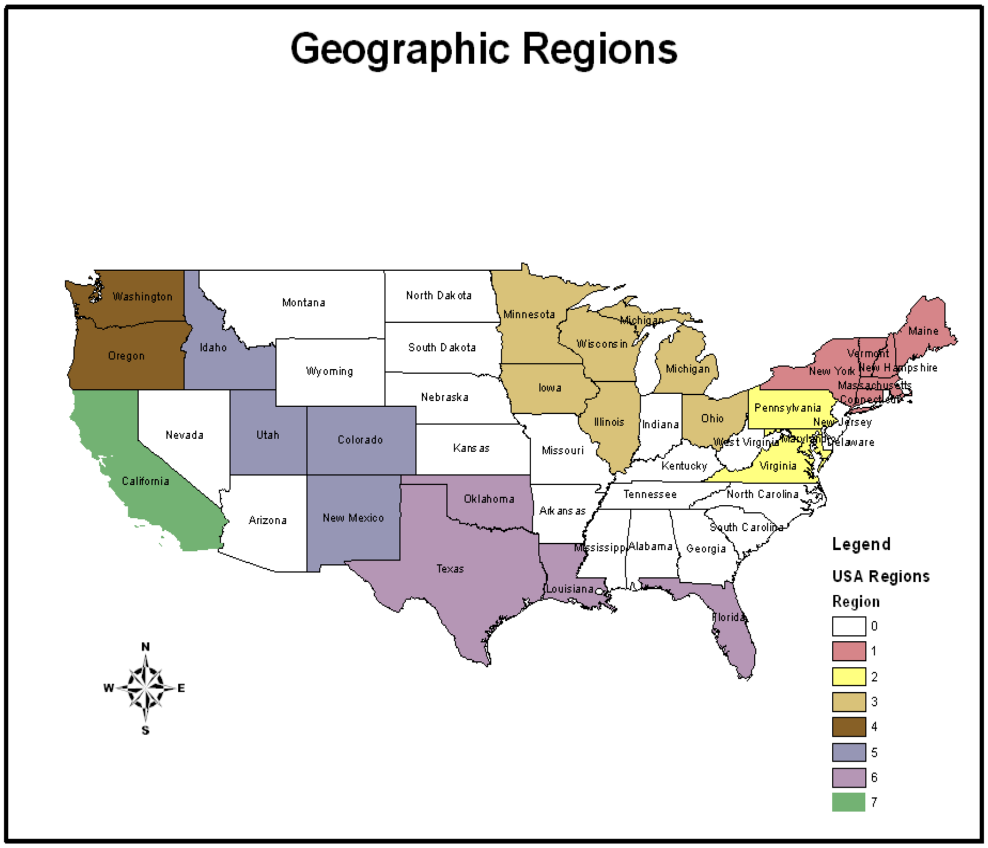


Figure 3: The geographic location of dairy counties

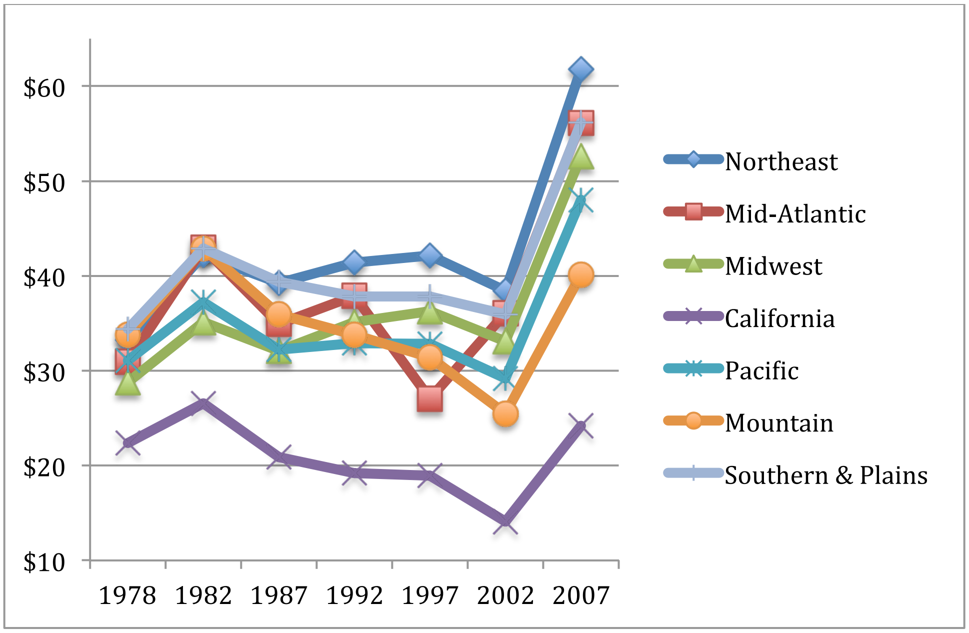


Figure 4: Average shadow prices

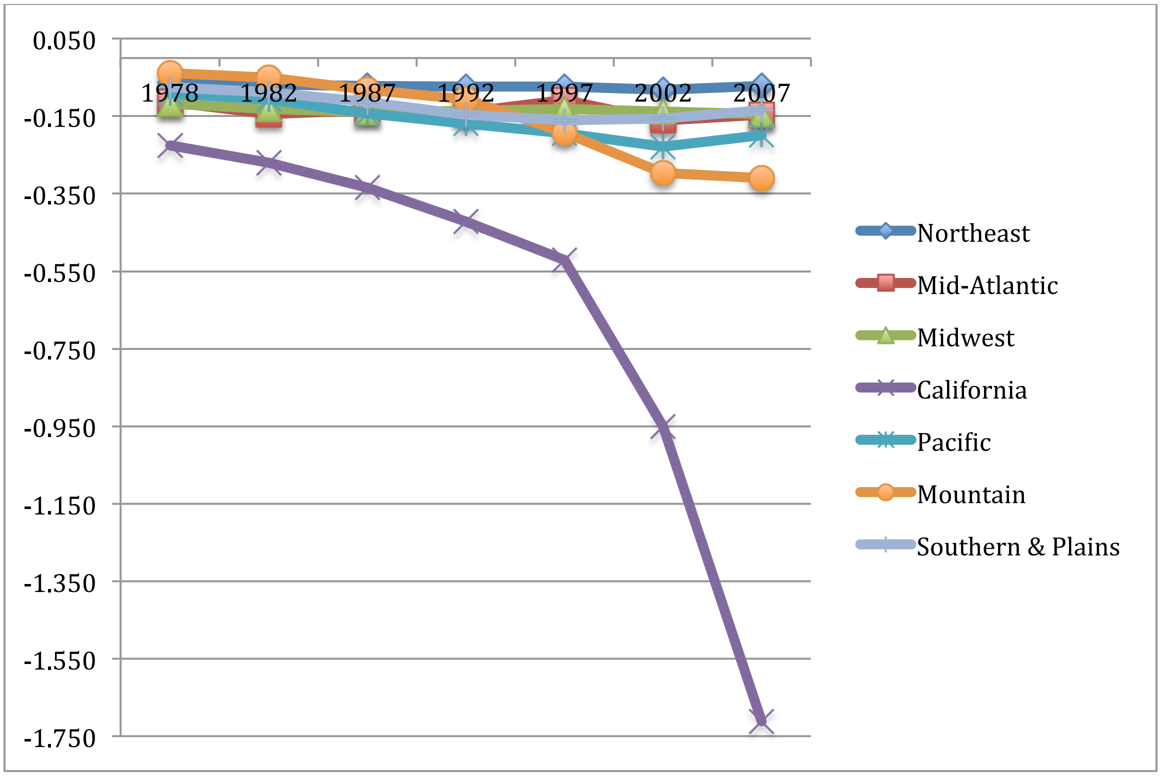


Figure 5: Morishima elasticity of substitution estimates

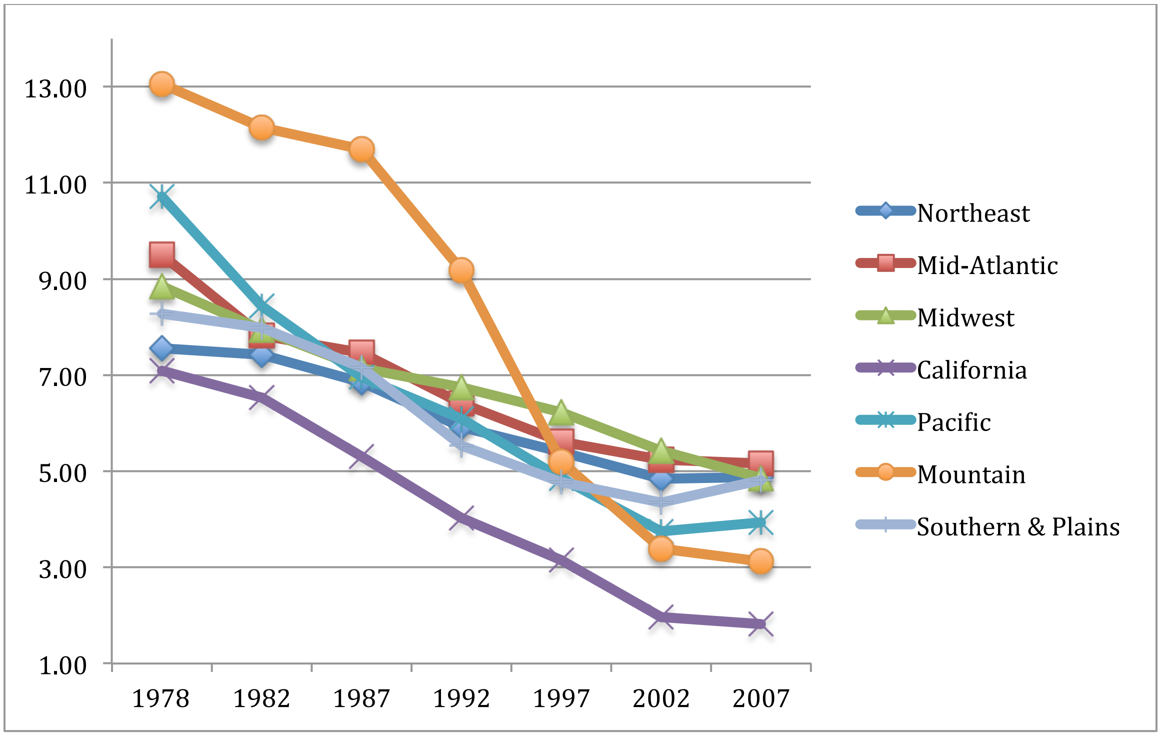


Figure 6: Percentage share of total output foregone

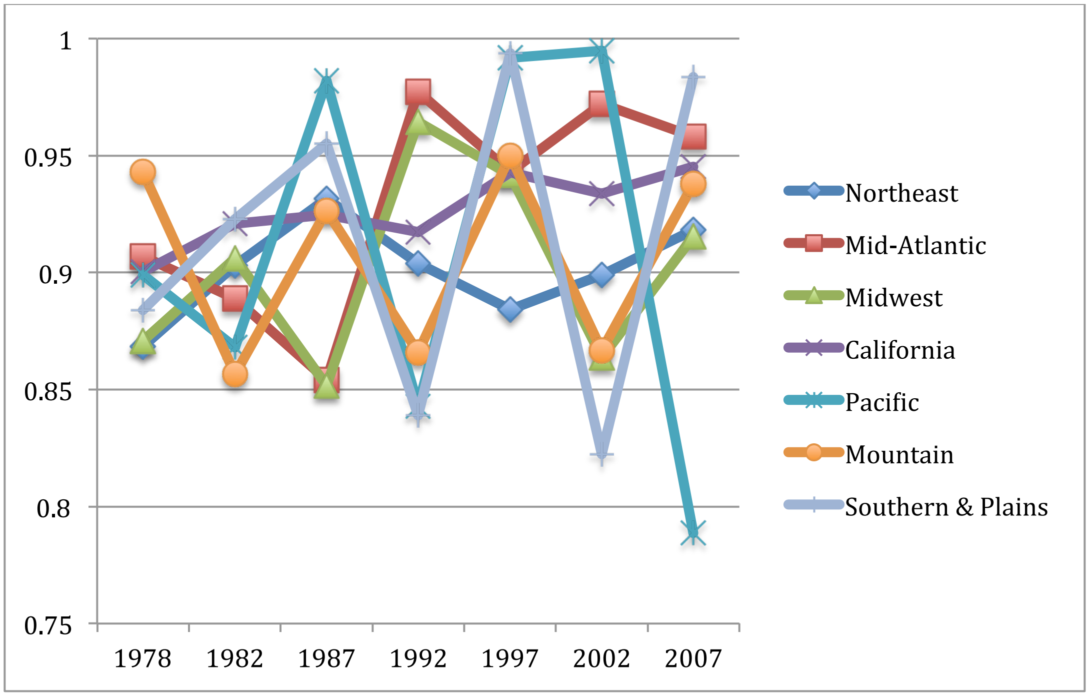


Figure 7: Average technical efficiency estimates for Case 1 (Unregulated) g = (1, 0)

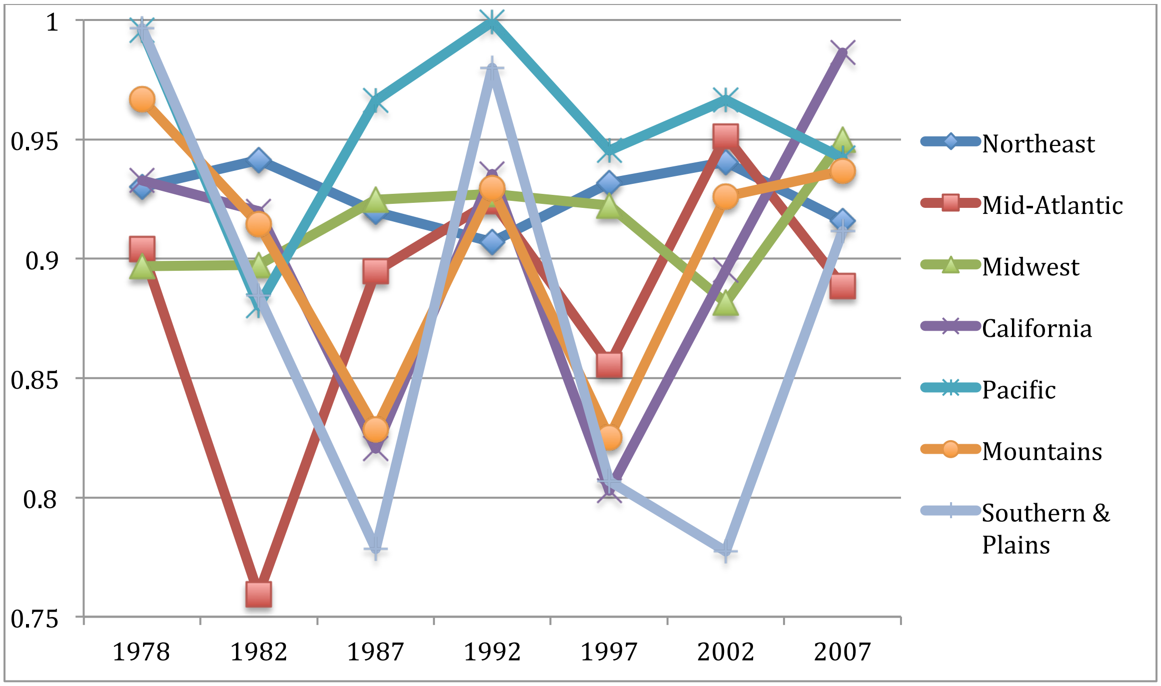
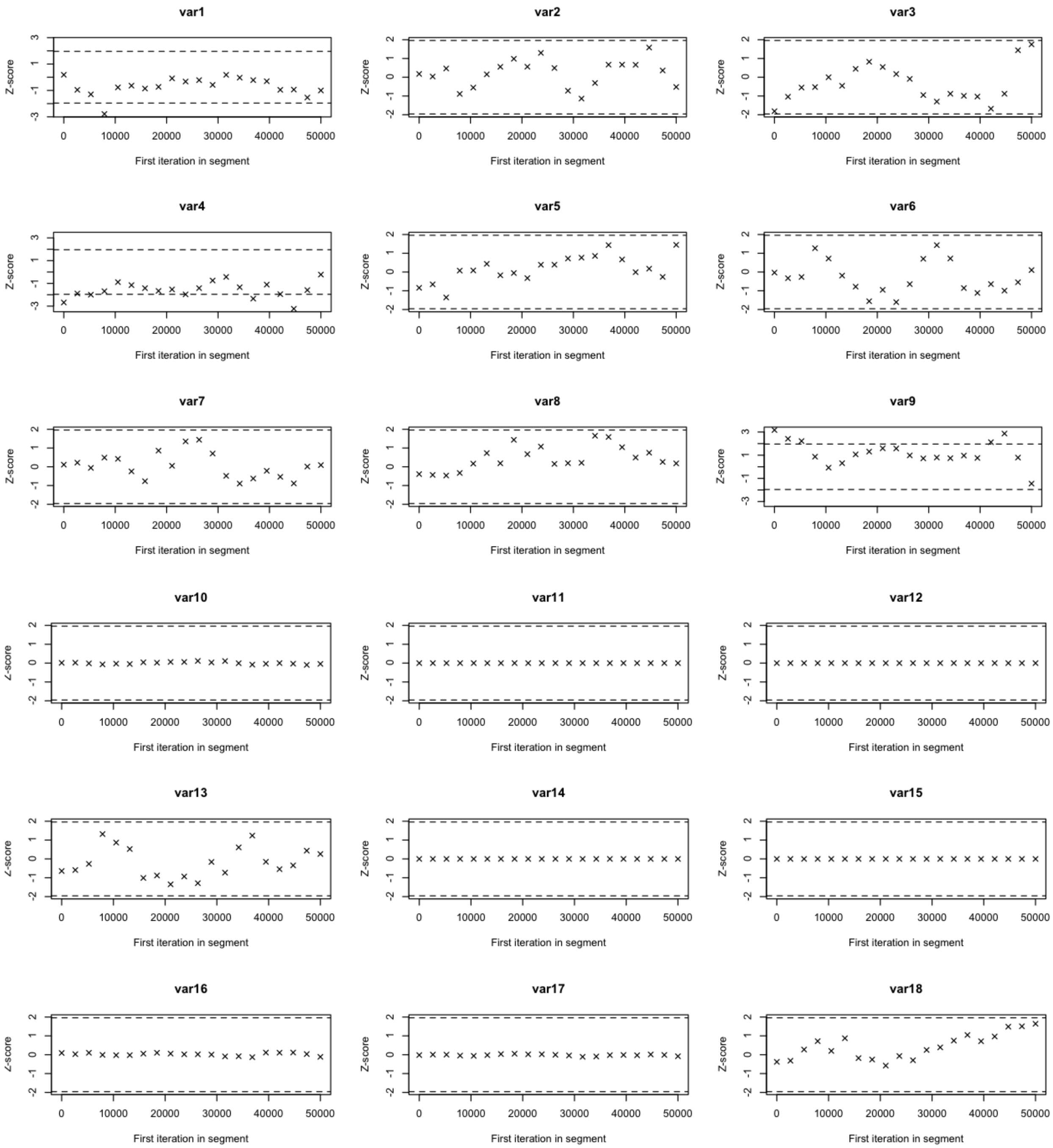


Figure 8: Average technical efficiency estimates for Case 2 (Regulated) g = (1, 1)


var1
var2
var3
var4
var5
var6
var7
var8
var9
var10
var11
var12
var13
var14
var15
var16
var17
var18
Z-score
First iteration in segment

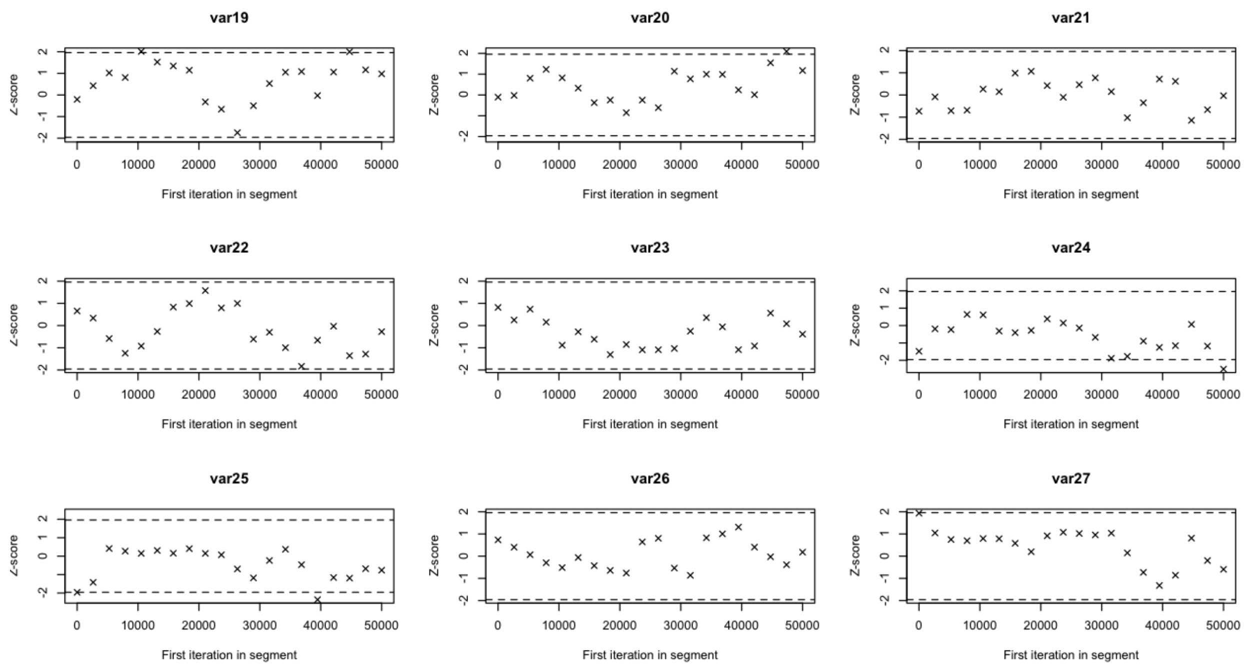


Figure A-1: Geweke's diagnostic plot

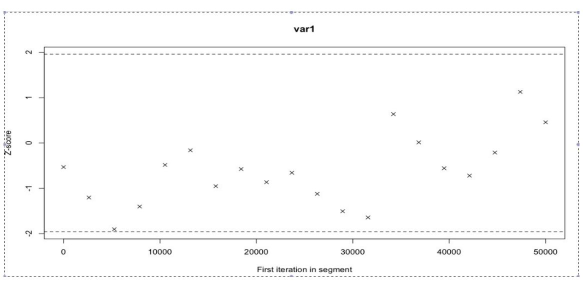


Figure A-2: Geweke's diagnostic plot for $milk_{(t-1)}$

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

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**	

Chapter 4

A New Look at the Decomposition of Agricultural Productivity Growth in the Face of Climate Change

4.1 Abstract

Climatic factors play an important role in agricultural output but this issue has not been addressed explicitly in the econometric analysis of total factor productivity growth (TFP). This article addresses this gap in the literature and makes two important contributions: 1) It utilizes a TFP index that satisfies key axiomatic and economic-theoretic approaches to constructing index numbers; and 2) It uses this index to evaluate TFP change in U.S. agriculture in the face of climatic variability. In addition to satisfying key economically-relevant axioms, this TFP index is multiplicatively complete. TFP growth is decomposed into climatic effect, technological progress, technical efficiency and scale efficiency. The climatic effect component, which combines temperature and precipitation, contributed positively to TFP growth in eight southern states, and negatively in the rest of the contiguous states in the U.S.

Keywords: total factor productivity, climate effects, Färe-Primont-O'Donnell index, production frontier, U.S. agriculture.

JEL Codes: D24, O47, Q10.

4.2 Introduction

This article makes two important contributions to the literature: 1) It utilizes a Total Factor Productivity (TFP) index that satisfies key axiomatic and economic-theoretic approaches to constructing index numbers; and 2) it takes into account the impact of climatic variability on TFP growth in U.S. agriculture. Both of these contributions enhance our understanding of the trends underlying U.S. agriculture in the face of increasing climatic variability. The analysis of the role that climatic factors play in total factor productivity growth has for the most part been ignored in the literature. Notable exceptions are Ball et al. (2004; 2005).

This article will incorporate temperature and precipitation into a stochastic production frontier model, as well as variables that facilitate adaptation to climatic change, namely irrigation and expenditures in research and development (R&D). Then, TFP indexes using data on outputs, inputs and output elasticities are constructed. Thereafter changes in productivity are decomposed into climatic effects, technological progress, technical efficiency, and scale efficiency changes. The argument is that for any given input levels, output levels will be affected by changes in the environment. Hence, TFP will be affected by these same environmental changes. Therefore, the contribution of this article is to isolate these climatic effects on TFP.

The TFP index employed in this article is a special case of an index that corresponds to a Cobb-Douglas output distance function that was first proposed by O'Donnell (2012b). In the absence of technological change and environmental change, the output and input change components are indexes similar to those found in Färe and

Primont (1995, p. 36, 38). Hence, here we refer to this TFP index as the Färe-Primont-O'Donnell (FPO) index.

The FPO index satisfies the basic economically relevant axioms of monotonicity, linear homogeneity, identity, commensurability, proportionality, and transitivity. Furthermore, it is multiplicatively complete. The term multiplicatively complete is used to refer to a TFP index that can be written in terms of aggregate input, and output quantities, and decomposed into several measures of efficiency change (O'Donnell 2008, 2012a).

The Laspeyres, Fisher, Paasche, Tornqvist and Hicks-Moorsteen indexes are commonly used productivity indexes that satisfy all the economically relevant axioms cited above, except for transitivity. The transitivity axiom states that a direct comparison of the TFP of two decision-making units (DMU) should yield the same estimate of TFP change as an indirect comparison through a third DMU (O'Donnell 2012c). Another key property is that of multiplicative-completeness. O'Donnell (2012a) demonstrated that all indexes that satisfy this property can be decomposed into measures of technical change, technical efficiency, and scale and mix efficiency change.

Therefore the key objective of this article is to present a methodology that yields TFP measures that account for climatic effects while exhibiting desirable axiomatic properties from index number theory. Using data prepared by the Economic Research Service (ERS) of the U.S. Department of Agriculture (USDA), we address the following research questions:

1. What are the key drivers of productivity growth in the face of climatic change?

2. What has been the impact of climatic variables on TFP growth in the U.S.?

3. To what extent has irrigation and expenditures on research and development (R&D), counteracted the adverse effects of climatic variability?

4.3 Climate Change and U.S. Agriculture

The sensitivity of U.S. agricultural productivity to climate variability is an important question given the significance of this country's role in world food markets (USDA 2013a) and the growing concern with climate change (Parry et al. 2007). Most studies conducted on this subject have adopted either a production function or a hedonic approach. Hedonic approaches are concerned about how climatic variability affects profitability whereas production function approaches measure output while accounting for environmental risk and are concerned with productivity growth[5].

In the presence of environmental change, hedonic approaches evaluate the effect of climatic variables on land values (e.g. Mendelsohn, Nordhaus, and Shaw 1994; Adams et al. 1995; Mendelsohn and Dinar 2003; Schlenker, Hanneman, and Fisher 2005, 2006; Deschenes and Greenstone 2007). In addition, they account for the responsiveness of profit-maximizing economic agents to changing climate patterns such as switching to more drought resistant crops or the adoption of improved irrigation systems in response to rising temperatures (e.g. Mendelsohn, Nordhaus, and Shaw 1994; Deschenes and Greenstone 2007). The results of these studies have yielded a wide range of predicted impacts on U.S. agriculture.

[5] O'Donnell (2012c) demonstrates why it is important to distinguish between profitability and TFP

The seminal paper by Mendelsohn, Nordhaus and Shaw (1994) was one of the first to report quantitative estimates of the economic effects of climate change on U.S. agriculture. That paper was also one of the first to present evidence that climate change might be beneficial to U.S. agriculture. The study specifies land value as a function of climatic factors, and economic and demographic variables. The analysis predicts regional adjustments in crop and livestock production, as well as resource use in order to mitigate the impacts of climate change. However, the study has been criticized in the literature for applying cross-sectional data while implicitly assuming perfectly elastic supply of irrigation water (Cline 1996), and for overstating the benefits of warm weather (Darwin 1999). In a different analysis, Kaufman (1998) questions the instability of the regression coefficients and the lack of consistency, and argues that this undermines the credibility of the results reported by Mendelsohn, Nordhaus and Shaw (1994).

Other studies have also predicted gains in U.S. agriculture due to climate change (e.g. Adams et al. 1995; Deschenes and Greenstone 2007). The argument is that U.S. agricultural productivity will be impacted primarily due to changing configurations of temperature and precipitation and that this would directly lead to changes in farming patterns, resource use (Mendelsohn, Nordhaus, and Shaw 1994) and a reliance on secondary sources for water such as irrigation (Mendelsohn and Dinar 2003; Schlenker, Hanneman, and Fisher 2006). It is also likely that long-run changes in climatic conditions might have smaller impacts because of the greater possibility for adaptation and mitigation (Schlenker, Hanneman, and Fisher 2005).

Most studies prior to Mendelsohn, Nordhaus and Shaw (1994) had predicted significant mid-continental warming in the U.S. brought about by increased

concentrations of atmospheric CO_2 (e.g. IPCC 1990). Adams et al. (1988) predict that climate change will impose additional costs on farmers, as they seek to mitigate its effects. In a different analysis, Adams (1989) projects significant yield reductions in agricultural commodities across the U.S. as a result of global warming. In addition, the study acknowledges the consensus among the scientific community that, a climate "signal" had yet to be detected. Short of urgent corrective measures "..the risk of transgressing critical thresholds increases strongly with ongoing climate change. Thus, waiting for higher levels of scientific certainty could mean that some tipping points will be crossed before they are recognized" (Allison et al. 2009, p.7).

Adams et al. (1995) use a general circulation model (GCM) that combines atmospheric and oceanic processes for simulating climate change. After accounting for crop water demand and irrigation, they predict that moderate warming will not be a threat to U.S. agriculture and net benefits are possible in some areas. Mendelsohn and Dinar (2003) assess the interaction between climate, water and agriculture, and predict mild marginal impact of global warming on U.S. agriculture. Schlenker and Roberts (2008) predict a mixture of results under different climate scenarios. Yields would increase gradually with temperatures up to 29-31° Celsius for corn, soybeans and cotton, the nation's most prevalent crops, then drop sharply at temperatures above these levels.

4.4 An Axiomatic Approach to Total Factor Productivity Analysis

The beginning of this article points out that a key missing link in the literature are studies

that satisfy axiomatic and economic-theoretic approaches. Notable exceptions are O'Donnell (2012a, 2012b, 2012c) who proposes an approach to TFP analysis that is compatible with economically relevant axioms. Accordingly, a TFP index must be the ratio of an output quantity index and an input quantity index, where each of these indexes satisfy the following: 1) Monotonicity - a requirement that the productivity index be non-decreasing in outputs and non-increasing in inputs (Feng and Zhang 2012); 2) Linear homogeneity - states that increasing inputs by a positive factor will cause outputs to increase by the same factor (Coelli et al. 2006); 3) Identity - ensures that if outputs and inputs remain unchanged, the productivity index should remain the same (O'Donnell 2012c); 4) Homogeneity of degree zero - states that the product of the comparison and the reference vector by the same scalar should leave the productivity index unchanged (O'Donnell 2012c); 5) Commensurability - a requirement that the TFP index be independent of the units of measurement (Coelli et al. 2006); 6) Proportionality - guarantees that if prices and quantities increase by the same proportion then the TFP index should increase by the same proportion (Coelli et al. 2006); and 7) Transitivity - a requirement that a direct comparison of two observations yield the same estimate of TFP change as an indirect comparison through a third observation (O'Donnell 2012b). The Laspeyres, Fisher, Paasche, Tornqvist and Hicks-Moorsteen are common productivity indexes that satisfy all of these axioms, except transitivity (O'Donnell 2012c).

If TFP indexes are expressed as ratios of aggregate outputs and inputs and the aggregator functions satisfy weak regularity conditions, then the index will satisfy all the axioms listed above. Moreover the associated TFP indexes will be multiplicatively complete (O'Donnell 2008). The technological change component measures shifts of the

production frontier, the technical efficiency change component measures movements towards or away from the frontier, whereas scale and mix efficiency change measures productivity gains linked to economies of scale and economies of scope respectively (O'Donnell 2012b). The Fisher, Paasche, Laspeyres, Tornqvist, and Hicks-Moorsteen are examples of indexes that can be decomposed this way (O'Donnell 2012a).

O'Donnell (2012a) examines the theory behind the TFP indexes that can be expressed as aggregator functions (e.g. Laspeyres, Fisher, Paasche, Tornqvist and Hicks-Moorsteen indexes). He argues that the Malmquist Productivity (MP) index, attributed to Caves, Christensen and Diewert (1982), and which has been used widely in the literature (e.g. Färe et al. 1994; Färe and Grosskopf 1998; Ball et al. 2001, 2005; Balk 2001; Orea 2002; Lovell 2003; Ball, Hallahan, and Nehring 2004), is neither additively nor multiplicatively complete, and hence may be an unreliable measure of TFP change. O'Donnell (2012b) demonstrates, in a multi-input multi-output framework, the econometric estimation and associated measures of TFP change using the Färe-Primont (FP) index. Using U.S. agricultural data from 1960-2004, the author computes and decomposes the FP index when only quantity data are available. This index satisfies all economically relevant axioms stated above and is appropriate when modeling environmental bads because output prices do not matter. However, a disadvantage of the FP index is that all input and output mixes are regarded as equally productive.

In a related paper, O'Donnell (2012c) proposes a new index, the Lowe index, that is multiplicatively complete, and that satisfies all the economically relevant axioms from index number theory. The Lowe index can be decomposed into measures of technological, technical efficiency, and scale and mix efficiency changes. In addition, the

Lowe index can be used to model polluting technologies, hence making it desirable for measuring productivity growth in the presence of undesirable outputs.

This article utilizes the FPO index, which is a special case of the Färe-Primont (FP) index that has been proposed recently as a robust measure of TFP (O'Donnell 2012b). This index satisfies the basic economically relevant axioms of monotonicity, linear homogeneity, identity, commensurability, proportionality, and transitivity. The following section demonstrates how this TFP index is constructed, and then proceeds to reveal how it can be decomposed into measures of technological, climatic effects, technical efficiency, and scale efficiency changes. The ability to decompose productivity into distinct components is crucial because when drivers of TFP growth can be identified, appropriate measures can be taken to reallocate resources appropriately in order to meet public policy objectives (Ahmad and Bravo-Ureta 1995; O'Donnell 2010).

4.5 The Choice of Total Factor Productivity Index

A brief chronological outline of productivity analysis, which connects directly with the objective of this article, is important in order to establish how we arrived at this point. Solow (1957) was one of the first to link the aggregate production function to productivity. In his seminal contribution, a theoretical link is developed between the production function, and the index number approach, which is now common in TFP studies. Using a Hicks-neutral aggregate production function with constant returns to scale, any increase in output, given inputs, represents TFP growth and this is referred to in the literature as the 'Solow Residual'. In other words, productivity growth is a gain in output that cannot be explained by increases in inputs. It is noteworthy to point out that if

the technology exhibits constant returns to scale and there are only two factors (e.g. capital and labor) then the Solow residual is a meaningful TFP index.

Jorgensen and Griliches (1967) postulate that if output and input quantities are measured accurately, then growth in total output can be explained by growth in total inputs. Under such conditions, they argue that the 'Solow Residual' is as a result of measurement errors, and that a careful approach to the measurement of all relevant variables can eliminate this residual. Using a Divisia productivity index, they introduce a number of innovations in measuring TFP growth in the U.S. in the post-war years going from 1945 to 1965. Their key innovation is the recognition that total output consists of both consumption goods as well as investment goods, and that by imposing a constant returns to scale assumption, the rental rate of capital can be estimated using the perpetual inventory method. A weakness in this approach is that it ignores any productivity effects associated with economies of scale and scope.

Christensen and Jorgenson (1970) propose a method that can separate revenue and expenses into their price and quantity components. Using U.S. data for the period 1929-1967, they develop a Tornqvist productivity (TP) index that can measure the responsiveness of output and input intensities to price changes. A limitation in the TP index approach is that it is intransitive (O'Donnell 2012c). In a subsequent study, Diewert (1976) demonstrates that when the production function is translog then the TP index is identical to the Divisia productivity index used in the Jorgenson and Griliches (1967) analysis.

An intertemporal comparison of productivity levels across countries, regions and

firms begun only a few decades ago. Jorgenson and Nishimizu (1978) derive a methodology using a translog production function and compare levels of growth in TFP between Japan and the U.S. during the 1952-1974 period. However, if the inputs or the outputs are strongly disposable then the production function cannot be translog (O'Donnell 2012c). This approach was further extended to include multiple comparisons of production units. Caves, Christensen and Diewert (1982) develop the Malmquist productivity (MP) index, which allows for a comparison of relative productivity levels between firms. This index can be defined in terms of distance functions, which is a very general representation of the production technology. In their framework, they demonstrate that when the technology is of the translog form, and under constant returns to scale, the MP index yields the same results as the TP index originally proposed by Christensen and Jorgensen (1970). A major limitation of the MP index is that it fails to satisfy transitivity. Furthermore, unless the technology exhibits constant returns to scale, and either the technology is homothetic or there is no technical change, then the MP index cannot be interpreted as a measure of TFP change (O'Donnell 2012a).

An alternative to the MP and TP indexes is the Fisher Ideal (FI) index, which was proposed by Färe and Grosskopf (1992). The FI index has minimal data and computational requirements and like the TP it can also be derived from MP indexes. In addition, the FI index is consistent with a flexible underlying technology, such as the translog distance function. The attractiveness of the FI index is its ability to exploit the duality of the distance function, and the cost and revenue functions, hence establishing a connection between the Malmquist and the Fisher ideal indexes. However, the FI index is intransitive (O'Donnell 2012c) and relies on a quadratic production function, which is an

incorrect approach when the input set is convex.

Chambers (1996) introduces another technique for measuring productivity growth, the Luenberger productivity (LP) index, which is based on a version of Luenberger's shortage function. This index is defined in terms of the directional distance function. A shortcoming of the LP index is that it requires information on all input and output prices. Furthermore, the LP index is an additive indicator, and these indicators take values that depend on units of measurement. When an index number depends on the units of measurement used, then it fails to satisfy the commensurability property (Coelli et al. 2006). An alternative to the LP index that does not require information on prices is the Malmquist-Luenberger (ML) productivity index that was proposed by Chung, Färe, and Grosskopf (1997). The ML index integrates properties of the MP index with the LP index. It does not require information on prices making it is suitable for modeling polluting technologies where prices of environmental effects are not available.

4.6 Productivity Indexes and U.S. Agriculture

A number of studies have been conducted that focus on TFP growth in U.S. agriculture including Jorgensen and Gollop (1992), who compare productivity growth between U.S. agriculture and the non-farm economy in the postwar era. The authors observe that in the period 1947-1985 productivity growth was a much more important source of economic growth in agriculture than it was in the private non-farm economy. They also report that productivity growth explains 82% of the expansion in U.S. agriculture, while it accounts for less than 13% in the private non-farm economy. Ball et al. (1997) derive index numbers of gross output, capital, labor and intermediate inputs in order to construct

indexes of total factor productivity in U.S. agriculture. In their analysis, output is defined as gross production leaving the farm, as opposed to real value added. Using this new definition, they observe that U.S. agricultural productivity increased on average 1.94% annually from 1948 to 1994.

Ball et al. (1999) move away from the aggregate nationwide TFP approach that was common then, to a state-specific and regional approach in order to determine whether the observed increase in aggregate productivity is due to productivity growth within states or due to shifts in agricultural production among states. The authors establish that productivity growth in the U.S. farm sector is wholly a function of productivity trends in individual states.

Ball et al. (2001) argue that productivity models for U.S. agriculture that ignore environmental effects are likely to overstate the social benefits of production. The authors observe that when undesirable outputs are accounted for, the average growth rates are markedly different. They demonstrate this by measuring productivity growth using two approaches. The first approach is based on desirable outputs alone using the MP index, whereas the second approach includes both desirable and undesirable outputs using a ML index, both of which fail the transitivity property.

Ball et al. (2004) construct transitive multilateral comparisons of outputs, inputs and TFP growth, using the *EKS* method attributed to Elteto and Koves (1964), and Szulc (1964). Within this framework, they test the hypothesis that the rate of growth of TFP for each individual state is inversely correlated with the level of productivity at the beginning of the period. They conclude that for states where TFP growth initially lagged behind, in

subsequent periods gained from the diffusion of technical information from the technology leaders, and thereafter recorded more rapid growth. However, the EKS approach does not satisfy the identity axiom (O'Donnell 2012c).

In Ball, Hallahan and Nehring (2004), the authors investigate productivity growth in U.S. agriculture between 1960 and 1996. Using the MP index, the authors find that when environmental impacts are incorporated, productivity growth is initially slower, and eventually much more rapid than conventionally measured productivity growth. Ball et al. (2005) use a Malmquist Cost Productivity (MCP) measure to estimate TFP growth in U.S. agriculture while accounting for environmental bads. The MCP represents an alternative to the ML index because it incorporates input price information, and secondly because it is based on a cost framework, a desirable way of representing production patterns.

4.7 The Production Technology

The following section presents the methodology that is used to analyze the production technology. The set of outputs $y \in \Re_+^m$ that can be produced using the input vector $x \in \Re_+^k$, and $z \in \Re_+^j$ exogenous variables that measure the characteristics of the production environment, is defined using the technology set

$$T = \{(x, y): x \in \Re_+^k, y \in \Re_+^m: h(y)^r \leq b(z)g(x)\} \tag{1}$$

where r is an unknown parameter to be estimated. Following O'Donnell (2012b), we assume the following properties regarding the output set: (1) $h: \Re_+^m \to \Re_+$ is nondecreasing, quasiconvex and homogeneous of degree 1/r with $h(0) = 0$ and

$h(y) > 0, \forall\, y \geq 0$; (2) $g: \Re_{+}^{K} \rightarrow \Re_{+}$ is nondecreasing, quasiconcave and homogeneous of degree *r* with $g(0) = 0$, and $g(x) > 0, \forall\, x \geq 0$: (3) $b: \Re_{++}^{J} \rightarrow \Re_{++}$ is nondecreasing and homogeneous of degree *k*. These properties ensure that the production possibility set exhibits free disposability in outputs and inputs. In addition, it is compact for each input vector $x \in \Re_{+}^{k}$, which also implies closedness of the output set. The parameter *r* conveniently provides a measure of the elasticity of scale.

The set of outputs that can be produced using input vector x_{it} and technology g_{it} in an environment characterized by z_{it} is $P\ (x_{it}, z_{it}, g_{it})$. If the production technology is regular then it can be represented using Shephard's (1970) output distance function as:

$$D_o\ (x_{it}, y_{it}, z_{it}, g_{it}) = \inf\left\{\delta > 0: \frac{y_{it}}{\delta} \in P(x_{it}, z_{it} g_{it})\right\} \tag{2}$$

For example, if there is only one output and the technology is Cobb-Douglas with Hicks-neutral technical change, which is the case in the analysis that follows, then

$$D_o\ (x_{it}, y_{it}, z_{it}, g_{it})\ \propto y_{it} g_{it}^{-\gamma_1} \prod_{j=2}^{J} z_{jit}^{-\gamma_j} \prod_{m=1}^{M} x_{mit}^{-\beta_m} \tag{3}$$

where $\beta_m \geq 0$ and $\sum_m \beta_m = r$

4.7.1 Total factor productivity change

Following O'Donnell (2012a), we define total factor productivity (TFP) as the ratio of an aggregate output to an aggregate input. More formally, the TFP of state *i* in year *t* is

$$TFP_{it} = \frac{Q_{it}}{X_{it}} \tag{4}$$

where $Q_{it} \equiv Q\ (y_{it})$ is an aggregate output, $X_{it} \equiv X\ (x_{it})$ *is* an aggregate input, and $Q: \Re_+^m \rightarrow \Re_+$, and $X: \Re_+^k \rightarrow \Re_+$. The aggregator functions $Q\ (y_{it})$ and $X\ (x_{it})$ are nonnegative, nondecreasing, and linearly homogeneous. The index that compares TFP in unit *i* in year *t* with TFP in unit *k* in year *s* is

$$TFPI_{ksit} = \frac{TFP_{it}}{TFP_{ks}} = \frac{QI_{ksit}}{XI_{ksit}} \tag{5}$$

where $QI_{ksit} \equiv Q_{it}/Q_{ks}$ and $XI_{ksit} \equiv X_{it}/X_{ks}$.

If the technology is given by (3) and we choose $X\ (x_{it})$ as the aggregate input, then

$$TFPI_{ksit} = \frac{y_{it}}{y_{ks}} \left[\prod_{m=1}^{M} \left(\frac{x_{mit}}{x_{mks}} \right)^{\beta_m} \right]^{-1/r} \tag{6}$$

Equation (3) can be rewritten as

$$y_{it} \propto g_{it}^{\gamma_1} \prod_{j=2}^{J} z_{jit}^{\gamma_j} \prod_{m=1}^{M} x_{mit}^{\beta_m} \exp(-u_{it}) \exp(-v_{it}) \tag{7}$$

where $\exp(-u_{it}) = D_o\ (x_{it}, y_{it}, z_{it}, g_{it}) \leq 1$. Thus,

$$TFPI_{ksit} = \left(\frac{g_{it}}{g_{ks}} \right)^{\gamma_1} \prod_{j=2}^{J} \left(\frac{z_{jit}}{z_{jks}} \right)^{\gamma_j} \prod_{m=1}^{M} \left(\frac{x_{mit}}{x_{mks}} \right)^{\beta_m \left(\frac{r-1}{r} \right)} \frac{\exp\ (-u_{it})}{\exp\ (-u_{ks})} \frac{\exp\ (-v_{it})}{\exp\ (-v_{ks})} \tag{8}$$

We take the logs of both sides of (7) to obtain

$$y_{it} = x_{it}'\beta + v_{it} - u_{it} \tag{9}$$

where $y_{it} \equiv lnq_{it}$, is log-output, $x_{it} = (1, g_{it}, z_{2it}, \ldots, x_{Mit})'$, is log-inputs and v_{it} accounts for approximation errors (i.e. the possibility that the technology is not Cobb-

Douglas) and other sources of noise (i.e. omitted variables). We assume that the error terms are $v_{it} \sim iid\ N(0, \sigma_v^2)$ and $u_{it} \sim Ga\ (\mu_u, \lambda)$, and estimate the model in a standard stochastic frontier framework.

4.8 Data and Econometric Specification

The data consists of indices of farm output and input at the state level across the 48 contiguous states of the U.S. This data come from the Economic Research Service (ERS) of the U.S. Department of Agriculture and it has been used previously by several authors to analyze different productivity issues in the United States (e.g. Ball et al. 1997; Ball, Hallahan, and Nehring 2004; O'Donnell 2012b, 2012c). This article utilizes the 45-year period between 1960 and 2004 comprising 2,160 observations.

The index for output, which is compiled by the ERS, is constructed by combining both livestock and crops sold off the farm. It involves disaggregating quantities and market prices of commodities sold. The index for the capital input is calculated from data on capital stocks and rental prices for each asset type and state. ERS utilizes the perpetual inventory method to develop stocks of depreciable capital. Under this approach, the capital stock at the end of each period is measured as the sum of all past investments, weighted by its relative efficiency (USDA 2013b). The index of the land input is prepared by first constructing an intertemporal price index for land in farms. The stock of land is then considered to be the ratio of the value of land in farms to the intertemporal price index. Land is considered to be homogeneous at the county level, and this is the level at which aggregation is done. The index for labor is constructed by incorporating demographic characteristics (e.g. gender, age, education) at the state level from the

decennial census conducted by the U.S. Census Bureau, and compensation data for each demographic group consistent with USDA hours worked and compensation totals. Labor hours with higher marginal productivity are thus accorded higher weights (USDA 2013b).

According to USDA (2013b), 17 states account for nearly 75% of U.S. irrigated agriculture. These states include Arizona, California, Colorado, Idaho, Kansas, Montana, Nebraska, Nevada, New Mexico, North Dakota, Texas, Utah, Washington State and Wyoming. Irrigation in the other 31 states occurs largely for supplemental purposes. Data on irrigation is an index prepared by the ERS based on information collected from the U.S. Geological Services (USGS), the National Agricultural Statistics Services (NASS) and the Farm and Ranch Irrigation Survey (FRIC).

Data on R&D is an index prepared by ERS based on federal data from the national science foundation, state-level data from USDA's current research information systems, and various private sector data. The data is then adjusted for inflation using a research deflator based on the methodology of Pardey et al. (1987).

Temperature variations impact some agricultural production activities and hence an index for temperature ought to be included in the production function (Mukherjee, Bravo-Ureta, and De Vries 2013). In this regard, the ERS data is augmented with average annual temperature and precipitation data obtained from the Western Regional Climate Center (WRCC), which is a repository of historical climate data and information and one of six regional climate centers in the United States. The National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA) administers

the data.

4.8.1 Stochastic production frontier

We estimate a stochastic production frontier assuming a Cobb-Douglas (C-D) functional form. The C-D specification is selected over other functional forms (e.g. translog) because it satisfies certain desirable properties. First, it is strongly disposable in inputs and outputs, which means that inputs can be increased without reducing output (Färe, Grosskopf, and Lovell 1994). Second, the C-D is also closed and bounded in inputs (O'Donnell 2012b), which implies that it is closed in outputs (Färe and Primont 1995). This means that finite amounts of inputs can only produce finite amounts of outputs. The empirical model estimated is:

$$lny_{it} = \beta_0 + \beta_1 lnx_{1it} + \beta_2 lnx_{2it} + \beta_3 lnx_{3it} + \beta_4 lnx_{4it} + \gamma_1 lnz_{1it} + \gamma_2 lnz_{2it} + \gamma_3 lng_{it} + \delta_1 R_1 + \delta_2 R_2 + \exp\,(v_{it} - u_{it}) \quad (10)$$

The left-hand side variable y_{it} is output, whereas the right hand side comprises four conventional inputs, x_{1it}, x_{2it}, x_{3it} and x_{4it}, representing land, labor, capital and irrigation, respectively. The variables z_{1it} and z_{2it} denote temperature and precipitation respectively. The variable g_{it} represents expenditures in R&D and is included to capture technological progress, which is an improvement over the common practice of measuring technological change using a time trend (e.g. Ball et al. 1999; Lovell 2003; O'Donnell 2012b). Finally, the data are grouped into 3 regions, and R_1 and R_2 represent the dummy variables to be estimated. Figure 1 illustrates regional groupings.

4.8.2 The Bayesian framework

Equation 10 is estimated using a Bayesian framework. This involves sampling from a posterior probability density function. The primary advantage of using a Bayesian structure is that it enables us to draw exact finite sample inferences concerning the unknown parameters e.g. 95% posterior credible intervals (Fernandez, Koop, and Steel 2002). In addition, the Bayesian approach facilitates the imposition of monotonicity constraints (O'Donnell 2007). Following Rossi, Allenby and McCulloch (2006), we begin by stating the conditional likelihood for y as,

$$p(y|x,\beta,\sigma^2) \propto \left\{\frac{1}{2\sigma^2}\left(y-(x_{i,t})\beta+u_i\right)'\left(y-(x_{i,t})\beta+u_i\right)\right\} \tag{11}$$

Proper priors for the parameters of the production frontier model are required to ensure the existence of the posterior density (Fernandez, Osiewalski, and Steel 1997). We assume natural conjugate priors, which is a joint density for the parameter space β and σ^2 that is proportional to the likelihood. The conjugate conditional prior on β is

$$p(\beta|\sigma^2) \propto (\sigma^2)^{-\frac{k}{2}} \exp\left\{\frac{1}{2\sigma^2}\left(\beta-\overline{\beta}\right)'A\left(\beta-\overline{\beta}\right)\right\} \tag{12}$$

and that on σ

$$p(\sigma^2) \propto (\sigma^2)^{-\frac{v}{2+1}} \exp\left\{\frac{vs_0^2}{2\sigma^2}\right\} \tag{13}$$

Following Rossi, Allenby and McCulloch (2006), $\bar{\beta}$ in (12) represents the mean of β, whereas A is a positive definite square matrix that is a product of a lower triangular matrix and its conjugate transpose. In (13), vs_0^2 in represents the sum of square errors.

We assume a general gamma distribution for the inefficiency parameter, $u_i \sim Ga\ (\mu_u, \lambda)$, and set $\lambda = 1$, and center μ_u at one. The prior for the inefficiencies take the form $p(u|\lambda^{-1}) = f_G(u|1, \lambda^{-1})$. Setting up the inefficiency this way essentially reduces it to an exponential distribution (Greene 1990). Finally, the product of the likelihood function and the normal conjugate priors yield the following:

$$p(\beta, \sigma^2|y, X) \propto p(y|X, \beta, \sigma^2)p(\beta, \sigma^2)p(u|\lambda^{-1}) \tag{14}$$

The posterior stated in equation (14) is in the same class of distributions as the priors. Posterior inference is conducted using a Gibbs sampler (see Casella and George 1992) that was programed using the R software. A total of 100,000 draws are made with a burn-in of the initial 10,000 draws. The posterior estimates of the means, standard deviation, numerical standard errors and 95% posterior density interval limits are reported in table 2.

4.8.3 Decomposing TFP change

The index that compares the TFP of firm *i* in period *t* with the TFP of firm *k* in period *s* is given by $TFPI_{ksit} = TFP_{it}/TFP_{ks}$. This index can be decomposed as:

$$TFPI_{ksit} = \prod_{m=1}^{M} \left(\frac{X_{mit}}{X_{mks}}\right)^{\beta_m\left(\frac{r-1}{r}\right)} \times \left[\left(\frac{z_{1it}}{z_{1ks}}\right)^{\gamma_1} \left(\frac{z_{2it}}{z_{2ks}}\right)^{\gamma_2} \left(\frac{g_{it}}{g_{ks}}\right)^{\gamma_3}\right] \times \prod_{m=1}^{M} \frac{\exp\ (-u_{it})}{\exp\ (-u_{ks})} \tag{15}$$

Equation (15) is the FPO index, which satisfies all the economically relevant axioms from index number theory. The first right-hand term is a measure of scale efficiency change. If the technology exhibits constant return to scale, then r = 1 and this component drops out of the equation. The second term in the square brackets on the right-hand side

measures respectively temperature, rainfall and the stock of scientific knowledge. Collectively, these three components capture climatic effects and technological change. The last component measures the output-oriented technical efficiency change. Mix efficiency, a measure of the potential change in productivity is not present in this decomposition because the aggregator functions are proportional to the output and input distance functions (O'Donnell 2012b).

4.9 Results

As indicated above, the model in equation 10 is estimated using a Bayesian framework and the resulting parameters are reported in table 2. The estimation yields a total of 100,000 sets of parameters and the initial 10,000 are discarded. Geweke (1992) proposed a convergence diagnostic test that evaluates whether mean estimates drawn from the same stationary distribution have converged. Therefore, from the remaining 90,000 sets of parameters, Geweke's diagnostics are computed for the first 10% and the last 50% of the Markov chain and the resulting Z-scores are presented as diagnostic plots in figure A-1. The horizontal dotted lines indicate the 95% confidence interval. A large number of the Z-scores fall within the interval signifying convergence of the Markov chain (Geweke 1992).

The coefficient estimates for the conventional inputs, land, labor, capital and irrigation, can be interpreted as partial output elasticities. They are nonnegative, which is consistent with inputs being strongly disposable. The sum of the coefficients indicates that the estimated elasticity of scale is $\hat{r} = 1.044$ revealing slightly increasing returns to scale. The coefficient for temperature is positive, signifying that, ceteris paribus,

increasing temperatures have a positive effect on output. Conversely, the coefficient for precipitation is negative, showing that increases in rainfall result in a drop in output. The estimated coefficient for $R\&D\ is$ 0.898 indicating that investments in research and development lead to substantial increases in output. This finding is consistent with many other studies that have examined R&D expenditures in U.S. agriculture (e.g. Fuglie et al. 1996; Alston et al. 2010; Pardey and Alston 2010).

4.9.1 Total factor productivity change

Table 3 presents estimates of TFP change in 2004 relative to 1960 for the 48 contiguous states and the U.S., as well as the state rankings. Recall that TFP change is the product of technological progress, technical efficiency, climatic effect, and scale efficiency changes. We find that, on average, TFP growth is rising albeit at different rates.

These indexes are normalized so that the TFP level for Alabama (AL) in 1960 is unity. Each index number in table 3 makes a comparison of the performance of a particular state in a particular year with the performance of Alabama in 1960. For example, the row corresponding to Arkansas (AR) reveals that in 1960 its productivity level was 28.3% lower than that of Alabama. Similarly, in 1960, California (CA) experienced a productivity level 25.7% greater than Alabama's. Another way of interpreting these index numbers is as follows. The first row corresponding to Alabama reveals that between the years 1960-2004, TFP in that state improved at an annual pace of 2.8%[6]. During the same period, California reported a 3.8% per year increase in productivity.

---

[6] Following O'Donnell (2012b, p. 14) these estimated average annual rates of TFP are calculated as arithmetic averages of the estimated growth rates.

Total factor productivity growth in the U.S. is estimated to have averaged 1.4% per year between 1960 and 2004. This rate is lower than TFP growth rates reported in previous studies. Ball et al. (1997) found a 1.94% annual TFP growth rate during the period 1948 and 1994. Findings from Jorgenson, Ho and Stiroh (2005) show a TFP growth rate of 1.9% in U.S. agriculture over the 1977 to 2000 period. Ball, Wang and Nehring (2011) use a bilateral Fisher index, which is intransitive, and they report a 1.76% average growth rate over the period 1960 to 2004. In a more recent study, O'Donnell (2012c) shows a growth rate of approximately 1.7% during the period 1960-2004. A point to note is that none of these studies included climatic variables in their analysis.

A state-by-state analysis reveals that Delaware (DE) recorded the largest increase in TFP between 1960 and 2004, with an estimated average of 9.3% change per year. A total of eight states recorded negative TFP change over the same period: Montana (MT), New Hampshire (NH), New Jersey (NJ), Nevada (NV), Oklahoma (OK), Tennessee (TS), West Virginia (WV) and Wyoming (WY), where the latter had the lowest change in TFP at 0.89% decrease per year.

Figure 2 presents an illustration of components of total factor productivity change in the U.S. during the period 1960-2004. It is evident from figure 2 that technological progress was the main driver behind productivity growth in U.S. agriculture during this period. Ball, Hallahan and Nehring (2004) attribute this rapid TFP growth in part, to the "the industrialization of agriculture, characterized by the expanding presence of large vertically integrated firms" (p. 1317). Figure 3 illustrates TFP change across the U.S. The states with the highest TFP changes are marked in green, whereas the states with the lowest changes are marked in red. The states that exhibit the fastest growth are found in

the Midwest, the Southeast, and the Pacific coast.

The proposition that the rate of productivity growth tends to be inversely related to initial levels of productivity has been noted in previous studies (e.g. Abramovitz 1986; Ball, Hallahan, and Nehring 2004). In Ball, Hallahan and Nehring (2004), they argue that TFP growth in U.S. agriculture is inversely correlated with the level of productivity for each individual state at the beginning of the period of study. Our findings regarding TFP growth appear to run counter to this proposition. We find that in 1960, a total of 25 states had TFP growth rates below the national average of 1.4%. Of these states, only eight had matched or surpassed the national average in 2004.

4.9.2 Technological progress

One of the key variables in our model is R&D, which captures changes in output as a result of expenditures in research and development. In the TFP decomposition, this variable accounts for technological progress (TP). Table 4 presents the estimates of TP in the U.S., as well the rankings of the 48 contiguous states. Average annual change in the U.S. was 0.85% between the years 1960 and 2004. Florida (FL) experienced the highest annual TP equal to 1.56%. Figure 4 presents the same results in a spatial format. We observe that states in the southern portion of the U.S. experienced rapid TP, whereas states in the northern portion of the U.S. experienced slower TP. The rapid growth in the south can be attributed to technological catch-up as these states gained the most from the diffusion of technical knowledge (Ball, Butault, and Nehring 2002). Wang et al. (2012) use a variable cost function to assess the benefits of R&D investments in U.S. agriculture over the years 1980 to 2004. They find that investment in R&D has the highest impact in

the Appalachian, Delta regions, Mountain, Northeast and the Southeast. In a study of the returns to public agricultural R&D investments, Plastina and Fulginiti (2012) find a social rate of return of 29% across the U.S. between the years 1949-1991, which translates into about an average annual growth of 0.67%.

4.9.3 Climatic effects

A key research objective of this article is to establish the impact of climatic variables on TFP growth in the U.S. The climatic effect (CE) component of TFP change is captured by the inclusion of temperature and precipitation in the production frontier, and then in the TFP growth decomposition. Table 5 below presents estimates of the CE component for the 48 contiguous states and the U.S., as well as the rankings. Our findings indicate that in 2004 relative to Alabama in 1960, the CE component contributed an average of 13.01% decline in TFP in the U.S. as a whole. Furthermore, only eight states recorded a positive CE: Arizona (AZ), Alabama (AL), Florida (FL), Georgia (GA), Louisiana (LA), Mississippi (MS), South Carolina (SC) and Texas (TX), with changes ranging from 0.79% (AZ) to 8.78% (FL). In contrast, 40 states recorded a negative CE with the largest decrease, 33.04%, exhibited by Maine (ME). Figure 5 provides a color-coded spatial illustration of the CE component. A salient feature is that the eight states that benefit positively from the CE are all located in the southern portion of the U.S., whereas the states that are impacted negatively are all located in the northern portion of the country.

4.9.4 Technical efficiency change

Table 6 presents estimates of Technical Efficiency Change (TEC) and rankings for the 48 contiguous states and the U.S. The TEC component measures movements towards or

away from the frontier. The average TEC for the U.S. in 2004 relative to Alabama in 1960 has risen by 12.4%. Delaware (DE) recorded the highest TEC, a 207.3% increase, while the lowest was -35.8% for Tennessee (TS). There were 17 states that recorded negative TEC during the period under review. Figure 6 presents a color-coded spatial illustration of TEC across the U.S. The states marked in a dark shade of green recorded the highest scores whereas states in red recorded the lowest.

4.9.5 Scale efficiency change

The last component of TFP change that is considered is Scale Efficiency Change (SEC). The SEC is defined as "… a measure of the potential productivity gains that can be achieved through economies of scale" (O'Donnell 2010, p. 534). The estimated production frontier exhibits slightly increasing returns to scale. The results of SEC in each state and across the U.S. are presented in table 7. The largest gain in SEC in 2004 relative to Alabama in 1960 was 6.7% recorded in Texas (TX), whereas the lowest was a 17.5% decrease in Rhode Island (RI). Figure 7 presents a spatial illustration of SEC across the U.S. We observe that all the New England states recorded negative SEC. On the other hand, Northwestern states recorded moderate change whereas Midwestern states, California (CA), and Texas (TX) experienced the largest SEC.

4.10 Concluding Remarks

This article builds upon previous studies that have sought to understand underlying TFP trends in U.S. agriculture (e.g. Ball et al. 2001; Ball, Butault, and Nehring 2002; Ball, Hallahan, and Nehring 2004; Ball, Wang, and Nehring 2011; O'Donnell 2012b, 2012c).

The article goes a step further by explicitly introducing into the modeling, irrigation as a factor of production. In addition, we include climatic variables, namely rainfall and precipitation, in order to understand the impact of climatic variability, as well as R&D in order to capture technological change in lieu of the traditional time trend. We make two important and innovative contributions to the literature: 1) we utilize the Färe-Primont-O'Donnell (FPO) index, which satisfies all economically relevant axioms; and 2) we exploit this index to measure productivity growth while incorporating climatic variables. This has led to new results relating to the evolution of TFP growth in U.S. agriculture in the face of climatic change.

The findings reveal that temperature and irrigation have a significantly positive effect on agricultural output, whereas changes in precipitation have a negative but statistically insignificant effect. The main long-term driver of TFP change is technological progress. The only other study that we have found that incorporates climatic variables in TFP decomposition is by Hughes et al. (2011). These authors, in a study for the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES), use rainfall from two crop growing seasons, summer (November to March) and winter (April to October), and average monthly temperatures in their model. They observe a strong positive relationship between rainfall and output, and a negative relationship between temperature extremes and output.

In addition, we find that 40 out of 48 states exhibited positive TFP growth over the period 1960-2004. However, there was considerable variance and some states exhibited significantly faster growth than others. And, although technological progress was the primary driver of TFP growth in U.S. agriculture, its pace slowed down markedly

beginning in the mid-1990s. The proposition that productivity growth rates tend to be inversely related to initial levels of productivity (Abramovitz 1986; Ball, Hallahan, and Nehring 2004) is not borne in our empirical results. We observe that some states started out with slow TFP growth rates below the national average and in 2004 most of them still lagged behind. The climatic effect (CE) component and its contribution to TFP growth provide additional insights. On average, CE contributed negatively to TFP growth during the period 1960 to 2004. However, a state-by-state analysis reveals considerable variance. Only eight states in the southern portion of the U.S. recorded a positive CE whereas the rest of the contiguous states recorded a negative CE.

It is evident from these results that regional impacts due to climatic variability are wide-ranging. Our findings are consistent with the IPCC (2007) report that predicts increasing temperatures will cause snowpack to melt resulting in increased runoff and precipitation. In addition, warming may benefit food production, albeit with strong regional differences. Moreover, Hatfield et al. (2008) predict annual precipitation will increase over much of the eastern U.S. and across the middle to high latitudes of central and western U.S. They forecast that temperature effects would vary depending on species. Horticultural crops are more sensitive than grains to temperature stresses; similarly, dairy production is more prone to heat stress than beef production.

In another analysis, Malcolm et al. (2012) predict that the impact of climate change will vary widely and across regions. Their analysis goes on to underscore the lack of consensus on the impact of precipitation across the U.S. They apply four different climate prediction models and find that the only consensus comes from the Pacific Northwest region, where they expect an increase in precipitation, and the

Texas/Louisiana region, where they expect a decline in precipitation.

The ability to respond appropriately and in a timely fashion to adverse effects from climate change is expected to have a significant impact on future productivity (FAO 2008). Hence, analyzing TFP indexes in terms of key components is crucial from a policy perspective in order to craft appropriate responses. Currently, the Federal and State governments provide multiple policy measures (e.g. price support mechanisms, input subsidies, and various tax schemes) aimed at raising productivity. Hence, policy interventions ought to be targeted towards meeting the challenge of climate change by directing support towards mitigation and adaptation efforts.

The amount of support provided to R&D, extension, and climate change adaptation need to be recalibrated to adequately respond to the threat of climate change. We propose that such a response be directed to three key areas: 1) technological developments, particularly on drought resistant crop varieties; 2) investments in early warning systems to improve information gathering on weather patterns and seasonal changes, and dissemination of this information to key stakeholders in order to adjust farming practices accordingly; and 3) extension support, to provide tailored advise on best managerial and farming practices in the face of climatic variability.

Finally, future research should consider the use of micro-level data (e.g. farm or county level) in order to capture salient characteristics within each individual state including analysis for different crops and livestock systems. Such an approach would be enhanced by the expansion of satellite and remote-sensing capabilities to provide localized climatic information necessary for accurate estimation of micro effects. This

combined information would significantly enhance the analysis of the interaction between productivity growth and climatic variability.

References

Abramovitz, M. 1986. Catching Up, Forging Ahead, and Falling Behind. *Journal of Economic History* 46(2): 385-406.

Adams, R. M., B. A. McCarl, D. J. Dudek, and J. D. Glyer. 1988. Implications of Global Climate Change for Western Agriculture. *Western Journal of Agricultural Economics* 13(2): 348-356.

Adams, R. M. 1989. Global Climate Change and Agriculture: An Economic Perspective. *American Journal of Agricultural Economics* 71(3): 1272-1279.

Adams, R. M., R. A. Fleming, C. Chang, B. A. McCarl, and C. Rosenzweig. 1995. A Reassessment of the Economic Effects of Global Climate Change on U.S. Agriculture. *Climatic Change* 30(2): 147-167.

Ahmad, M., and B. Bravo-Ureta. 1995. An Econometric Decomposition of Dairy Output Growth. *American Journal of Agricultural Economics* 77(4): 914-921.

Allison, I., N. L. Bindoff, R. A. Bindschadler, P. M. Cox, N. de Noblet, M. H. England, J. E. Francis, N. Gruber, A. M. Haywood, D. J. Karoly, G. Kaser, C. Le Quéré, T. M. Lenton, M. E. Mann, B. I. McNeil, A. J. Pitman, S. Rahmstorf, E. Rignot, H. J. Schellnhuber, S. H. Schneider, S. C. Sherwood, R. C. J. Somerville, K. Steffen, E. J. Steig, M. Visbeck, and A. J. Weaver. 2009. *Updating the World on the Latest Climate Science*. Climate Change Research Centre (CCRC). The University of New South Wales, Sydney, Australia.

Alston, J. M., M. A. Anderson, J. S. James, and P. G. Pardey. 2010. *Persistence Pays: U.S. Agricultural Productivity Growth and the Benefits from Public R&D Spending*. Series: Natural Resources Management and Policy Vol. 34. Springer, London, U.K.

Ball, V. E., J. Bureau, R. Nehring, and A. Somwaru. 1997. Agricultural Productivity Revisited. *American Journal of Agricultural Economics* 79(4): 1045-1063.

Ball, V. E., R. Färe, S. Grosskopf, and R. Nehring. 1998. *Productivity of the U.S. Agricultural Sector: The Case of Undesirable Outputs*. Paper presented at the 1998 Conference on Research in Income and Wealth, New Developments in Productivity Analysis.

Ball, V. E., F. M. Gollop, A. Kelly-Hawke, and G. P. Swinand. 1999. Patterns of State Productivity Growth in the U.S. Farm Sector: Linking State and Aggregate Models. *American Journal of Agricultural Economics* 81(1): 164-179.

Ball, V. E., R. Färe, S. Grosskopf, and R. Nehring. 2001. Productivity of the U.S. Agricultural Sector: The Case of Undesirable Outputs. In: Hulten, C., Dean, E., Harper, M. (Eds.), *Studies in Income and Wealth*, vol. 63. University of Chicago Press, Chicago, p. 541–586.

Ball, V. E., J. P. Butault, and R. Nehring. 2002. U.S. agriculture, 1960–1996: A Multilateral Comparison of Total Factor Productivity. In: Ball, V.E., Norton, G. (Eds.), *Agricultural Productivity: Measurement and Sources of Growth*. Kluwer Academic Publishers, Boston, p. 257–276.

Ball, V. E., C. A. K. Lovell, H. Luu, and R. Nehring. 2004. Incorporating Environmental Impacts in the Measurement of Agricultural Productivity Growth. *Journal of Agricultural and Resource Economics* 29(3): 436-460.

Ball, V. E., C. Hallahan, and R. Nehring. 2004. Convergence of Productivity: An analysis of the catch-up hypothesis within a panel of states. *American Journal of Agricultural Economics* 86(5): 1315-1321.

Ball, V. E., R. Färe, S. Grosskopf, and O. Zaim. 2005. Accounting for Externalities in the Measurement of Productivity Growth: The Malmquist Cost Productivity Measure. *Structural Change and Economic Dynamics* 16(3): 374-394.

Ball, V. E., S. L. Wang, and R. Nehring. 2011. *Agricultural Productivity in the U.S.* Economic Research. U.S. Department of Agriculture, Washington D.C.

Balk, B. M. 2001. Scale Efficiency and Productivity Change. *Journal of Productivity Analysis* 15(3): 159-183.

Casella, G., and E. I. George. 1992. Explaining the Gibbs Sampler. *The American Statistician* 46(3): 167-174.

Caves, D. W., L. R. Christensen, W. E. Diewert. 1982. The Economic Theory of Index Numbers and Measurement of Input, Output and Productivity. *Econometrica* 50(6): 1393-1413.

Chambers, R. G. 1996. A New Look at Input, Output, Technical Change and Productivity Measurement. University of Maryland WP 96-05.

Christensen, L. R., and D. Jorgenson. 1970. U.S. Real Product and Real Factor Input, 1927-1969. *Review of Income and Wealth* 16: 19-50.

Chung, Y. H., R. Färe, and S. Grosskopf. 1997. Productivity and Undesirable Outputs: A Directional Distance Function Approach. *Journal of Environmental Management* 51(3): 229- 240.

Cline, W. R. 1996. The Impact of Global Warming on Agriculture: Comment. *American Economic Review* 86(5): 1309-1311.

Coelli, T. J., D. S. P. Rao, C. J. O'Donnell, and G. E. Battese. 2006. *An Introduction to Efficiency and Productivity Analysis*. 2nd ed. Springer.

Darwin, R. 1999. The Impact of Global Warming on Agriculture: A Ricardian Analysis: Comment. *American Economic Review* 89(4): 1049-1052.

Dean, E., M. Harper, and M. Sherwood. 1996. *Productivity Measurement with Changing-Weight Indexes of Outputs and Inputs*. Presented at the OECD Expert Workshop on Productivity: International Comparison and Measurement Issues, Paris, May 2-3, 1996.

Deschenes, O., and M. Greenstone. 2007. The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather. *American Economic Review* 97(1): 354-385.

Diewert, W. E. 1976. Exact and Superlative Index Numbers. *Journal of Econometrics* 4(2): 115-145.

Färe, R., and S. Grosskopf. 1992. Malmquist Productivity Indexes and Fisher Ideal Indexes. *The Economic Journal* 102: 158-160.

Färe, R., S. Grosskopf and C. A. K. Lovell. 1994. *Production Frontiers*. Cambridge University Press, U.K.

Färe, R., S. Grosskopf, M. Norris, and Z. Zhang. 1994. Productivity Growth, Technical Progress and Efficiency Change in Industrialized Countries. *American Economic Review* 84(1): 66-83.

Färe, R., and D. Primont. 1995. *Multi-Output production and duality: Theory and applications*. Kluwer Academic Publishers. Boston.

Färe, R., and S. Grosskopf. 1998. Malmquist Productivity Indexes: A Survey of Theory and Practice. In R. Färe, S. Grosskopf, and R. R. Russell (eds.). *Index Numbers: Essays in Honour of Sten Malmquist*. Boston/London/Dordrecht: Kluwer Academic Publishers.

Feng, G., and X. Zhang. 2012. Productivity and Efficiency at Large and Community Banks in the US: A Bayesian True Random Effects Stochastic Distance Frontier Analysis. *Journal of Banking and Finance* 36(7): 1883-1895.

Fernandez, C., G. Koop, and M. F. J. Steel. 2002. Multiple-Output Production with Undesirable Outputs: An Application to Nitrogen Surplus in Agriculture. *Journal of the American Statistical Association* 97: 432-442.

Fernandez, C., J. Osiewalski, and M. F. J. Steel. 1997. On the use of Panel Data in

Stochastic Frontier Models with Improper Priors. *Journal of Econometrics* 79(1): 169-193.

Fuglie, K O., N. Ballenger, K. Day, C. Klotz, M. Ollinger, J. M. Reilly, U. Vasavada, and J. Yee. 1996. *Agricultural Research and Development: Public and Private Investments Under Alternative Markets and Institutions.* Agricultural Economics Report 735, U.S. Department of Agriculture, Economic Research Service.

Geweke, J. 1992. Evaluating the Accuracy of Sampling Based Approaches to Calculating Posterior Moments. In *Bayesian Statistics 4* (ed. J.M. Bernado, J.O Berger, A.P Dawid and A.F.M Smith). Clarendon Press, U.K.

Greene, W. H. 1990. A Gamma-Distributed Stochastic Frontier Model. *Journal of Econometrics* 46(1): 141-163.

Hatfield, J., K. Boote, P. Fay, L. Hahn, C. Izaurralde, B. A. Kimball, T. Mader, J. Morgan, D. Ort, W. Polley, A. Thomson, and D. Wolfe. 2008. Agriculture. In: *The effects of climate change on agriculture, land resources, water resources, and biodiversity.* A Report by the U.S. Climate Change Science Program and the Subcommittee on Global Change Research. Washington, D.C.

Hughes, N., K. Lawson, A. Davidson, T. Jackson, and Y. Sheng. 2011. Productivity Pathways: Climate Adjusted Production Frontiers for the Australian Broadacre Cropping Industry; ABARES Research Report 11.5, Canberra.

Houghton, J. T., G. J. Jenkins, and J. J. Ephraums (eds). 1990. *Climate Change: The*

IPCC Scientific Assessment. Report Prepared for the Intergovernmental Panel on Climate Change by Working Group I. Cambridge University Press, U.K.

Jorgenson, D. W., and Z. Griliches. 1967. The Explanation of Productivity Change. The *Review of Economic Studies* 34(3): 249–283.

Jorgenson, D. W., and M. Nishimizu. 1978. U.S. and Japanese Economic Growth, 1952-1974: An International Comparison. *The Economic Journal* 88: 707-726.

Jorgenson, D. W., and F. M. Gollop. 1992. Productivity Growth in U.S. Agriculture: A Postwar Perspective. *American Journal of Agricultural Economics* 74(3): 745-750.

Jorgenson, D. W., M. Ho, and K. Stiroh. 2005. *Productivity: Information Technology and the American Growth Resurgence*. The MIT Press, Cambridge.

Kaufman, R. K. 1998. The Impact of Climate Change on U.S. Agriculture: A Response to Mendelsohn et al. (1994). *Ecological Economics* 26(2): 113-119.

Lovell, C. A. K. 2003. The Decomposition of Malmquist Productivity Indexes. *Journal of Productivity Analysis* 20(3): 437-458.

Malcolm, S., E. Marshall, M. Aillery, P. Heisey, M. Livingston, and K. Day-Rubenstein. 2012. *Agricultural Adaptation to a Changing Climate: Economic and Environmental Implications Vary by U.S. Region.* U.S. Department of Agriculture. Economic Research Service, ERR-136.

Mendelsohn, R., W. D. Nordhaus, and D. Shaw. 1994. The Impact of Global Warming on

Agriculture: A Ricardian Analysis. *American Economic Review* 84(4): 753-771.

Mendelsohn, R., and A. Dinar. 2003. Climate, Water, and Agriculture. *Land Economics* 79(3): 328-341.

Mukherjee, D., B. Bravo-Ureta, and A. De Vries. 2013. Dairy Productivity and Climatic Conditions: Econometric Evidence from Southeastern United States. *Australian Journal of Agriculture and Resource Economics* 57(1): 123-140.

O'Donnell, C. J. 2008. *An aggregate quantity-price framework for measuring and decomposing productivity and profitability change*. Center for Efficiency and Productivity Analysis. Working Papers Series, No. WP07/2008.

O'Donnell, C. J. 2010. Measuring and Decomposing Agricultural Productivity and Profitability Change. *Australian Journal of Agricultural and Resource Economics* 54(4): 527-560.

O'Donnell, C. J. 2011. *The Sources of Productivity Change in the U.S. Economy.* Center for Efficiency and Productivity Analysis. Working Paper Series, No. WP07/2011.

O'Donnell, C. J. 2012a. An Aggregate Quantity Framework for Measuring and Decomposing Productivity Change. *Journal of Productivity Analysis* 38(3): 255-272.

O'Donnell, C. J. 2012b. Econometric Estimation of Distance Functions and Associated Measures of Productivity and Efficiency Change. *Journal of Productivity*

Analysis DOI: 10.1007/s11123-012-0311-1.

O'Donnell, C. J. 2012c. Nonparametric Estimates of the Components of Productivity and Profitability Change in U.S. Agriculture. *American Journal of Agricultural Economics* 94(4): 873-890.

Orea, L., 2002. Parametric Decomposition of a Generalized Malmquist Productivity Index. *Journal of Productivity Analysis* 18(1): 5-22.

Pardey, P. G., and J. M. Alston. 2010. *U.S. Agricultural Research in a Global Food Security Setting*. A Report for the Center for Strategic and International Studies Task Force on Food Security.

Pardey, P. G., B. Craig, and M. L. Hallaway. 1987. *U.S. Agricultural Research Deflators*. Institute of Agriculture, Forestry and Home Economics. University of Minnesota. Staff Paper P87-25.

Parry, M.L., O. F. Canziani, J. P. Palutikof, P. J. van der Linden, and C. E. Hanson. 2007. Climate Change 2007: Impacts, Adaptation and Vulnerability. Working Group II, *Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press.

Plastina, A., and L. Fulginiti. 2012. Rates of Return to Public Agricultural Research in 48 U.S. States. *Journal of Productivity Analysis* 37(2): 95-113.

Reinhard, S., C. A. K. Lovell, and G. Thijssen. 1999. Econometric Estimation of Technical and Environmental Efficiency: An Application to Dutch Dairy Farms.

American Journal of Agricultural Economics 81(1): 44-60.

Rossi, P., G. Allenby, and R. McCulloch. 2006. *Bayesian Statistics and Marketing*. Wiley Series in Probability and Statistics.

Shephard, R. W. 1970. *Theory of Costs and Production Functions*. Princeton University Press, Princeton, New Jersey.

Solow, R. 1957. Technical Change and the Aggregate Production Function. *Review of Economics and Statistics* 39(3): 312-320.

Schlenker, W., W. M. Hanneman, and A. C. Fisher. 2005. Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach. *American Economic Review* 95(1): 395-406.

Schlenker, W., W. M. Hanneman, and A. C. Fisher. 2006. The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions. *The Review of Economic and Statistics* 88(1): 113-125.

Schlenker, W., and M. Roberts. 2009. Nonlinear Temperature Effects Severe Damages to U.S. Crop Yields Under Climate Change. *Proceedings of the National Academy of Sciences* 106(37): 15594-15598.

United Nations Food and Agricultural Organization. 2008. *Climate Change and Food Security: A Framework Document*. Rome.

U.S. Department of Agriculture. 2013a. *World Agricultural Supply and Demand Estimates*. Economic Research Service. ISSN: 1554-9089.

U.S. Department of Agriculture. 2013b. *Agricultural Productivity in the U.S.* Online at: http://www.ers.usda.gov/data-products/agricultural-productivity-in-the-us.aspx#28250 (Accessed June 3rd, 2013) Economic Research Service.

Wang, S. L., V. E. Ball, L. E. Fulginiti, and A. Plastina. 2012. Accounting for the Impact of Local and Spill-in Public Research, Extension and Roads on U.S. Regional Agricultural Productivity, 1980-2004. In K. O. Fuglie, S. L. Wang, and V. E. Ball (eds.). *Productivity Growth in Agriculture: An International Perspective*. Economic Research Service. U.S. Department of Agriculture.

4.11 Tables and Figures

Table 1: Descriptive Statistics

Variable (Units)	No. of Observations	Mean	Std. Dev.	Min	Max
Total Output	2160	2.27	52.76	0.01	2453.83
Land	2160	4.19	97.35	0.01	4527.25
Capital	2160	3.74	86.86	0.02	4040.08
Labor	2160	5.24	121.65	0.02	5658.11
R&D Expenditure	2160	1739	526.83	821.92	2350.67
Irrigation	2160	3034	6019.58	0.03	41433.34
Temperature (Celsius)	2160	11.11	4.24	2.51	22.55
Precipitation (mm)	2160	76.64	31.67	11.37	170.56

Table 2: Parameter Estimates

Variables	**Mean**	**Std. Dev**	**Num. Se**	**2.50%**	**97.50%**
Intercept (var1)	-3.5940	0.2640	0.0009	-4.1070	-3.0735
Land (var2)	0.0800	0.0560	0.0002	-0.0310	0.1903
Capital (var3)	0.4000	0.0790	0.0003	0.2470	0.5547
Labor (var4)	0.5140	0.0740	0.0002	0.3680	0.6596
Irrigation (var5)	0.0500	0.0120	0.0000	0.0270	0.0734
R&D (var6)	0.8980	0.0790	0.0003	0.7410	1.0518
Temperature (var7)	0.3180	0.0920	0.0003	0.1370	0.498
Precipitation (var8)	-0.0100	0.0830	0.0003	-0.1720	0.1519
R1 (var9)	-0.0690	0.0310	0.0001	-0.1300	-0.0076
R2 (var10)	-0.0310	0.0320	0.0001	-0.0940	0.0315

Table 3: Total Factor Productivity Change and State Rankings, 1960-2004

	Total Factor Productivity				
State	1960	2004	Δ	%Δ	Rank
US	**0.817**	**2.449**	**1.632**	**1.40**	
AL	1.000	3.260	2.260	2.80	11
AR	0.717	3.198	2.481	3.29	7
AZ	1.510	3.240	1.729	1.62	21
CA	1.257	3.970	2.713	3.81	5
CO	0.814	2.628	1.815	1.81	18
CT	0.805	2.179	1.374	0.83	30
DE	1.296	6.491	5.195	9.32	1
FL	1.526	3.073	1.547	1.22	25
GA	0.936	3.680	2.744	3.88	4
IA	1.268	4.805	3.537	5.64	3
ID	0.699	2.650	1.952	2.12	14
IL	1.277	3.560	2.283	2.85	10
IN	0.941	3.293	2.353	3.01	9
KS	0.841	2.679	1.838	1.86	17
KY	0.842	2.192	1.350	0.78	33
LA	0.514	2.051	1.537	1.19	26
MA	0.757	1.936	1.179	0.40	38
MD	0.831	2.983	2.152	2.56	13
ME	0.941	2.312	1.371	0.82	31
MI	0.639	2.244	1.605	1.34	23
MN	1.062	3.256	2.194	2.65	12
MO	0.897	1.945	1.048	0.11	40
MS	0.646	3.324	2.678	3.73	6
MT	0.609	1.332	0.723	-0.62	47
NC	0.907	4.535	3.628	5.84	2
ND	0.701	2.332	1.631	1.40	22
NE	0.848	3.283	2.435	3.19	8
NH	0.634	1.569	0.935	-0.14	44
NJ	1.059	2.039	0.981	-0.04	42
NM	0.677	2.058	1.381	0.85	29
NV	0.774	1.763	0.989	-0.02	41
NY	0.940	2.309	1.369	0.82	32
OH	0.803	2.743	1.941	2.09	15
OK	0.810	1.650	0.839	-0.36	45
OR	0.480	1.862	1.382	0.85	28
PA	0.822	2.167	1.345	0.77	35

RI	0.752	2.098	1.346	0.77	34
SC	0.695	2.481	1.786	1.75	19
SD	0.879	2.786	1.907	2.02	16
TN	0.737	1.575	0.838	-0.36	46
TX	0.688	1.882	1.194	0.43	37
UT	0.595	1.664	1.069	0.15	39
VA	0.638	2.190	1.552	1.23	24
VT	0.871	2.194	1.323	0.72	36
WA	0.601	2.382	1.780	1.73	20
WI	0.880	2.267	1.387	0.86	27
WV	0.504	1.475	0.971	-0.06	43
WY	0.598	1.196	0.598	-0.89	48

Table 4: Technological Change and State Rankings, 1960-2004

	Technological Change				
State	1960	2004	Δ	%Δ	Rank
US	**0.854**	**2.236**	**1.382**	**0.85**	
AL	1.000	2.594	1.594	1.32	7
AR	0.974	2.533	1.559	1.24	9
AZ	0.997	2.576	1.579	1.29	8
CA	0.980	2.533	1.553	1.23	10
CO	0.778	2.046	1.267	0.59	36
CT	0.823	2.134	1.311	0.69	34
DE	0.909	2.376	1.467	1.04	16
FL	1.078	2.780	1.703	1.56	1
GA	1.009	2.615	1.606	1.35	4
IA	0.796	2.123	1.327	0.73	31
ID	0.747	2.013	1.266	0.59	37
IL	0.867	2.276	1.409	0.91	23
IN	0.865	2.268	1.403	0.90	24
KS	0.900	2.362	1.462	1.03	17
KY	0.913	2.402	1.489	1.09	14
LA	1.037	2.690	1.653	1.45	2
MA	0.816	2.081	1.264	0.59	38
MD	0.895	2.353	1.458	1.02	18
ME	0.712	1.712	1.000	0.00	48
MI	0.749	1.948	1.199	0.44	41
MN	0.676	1.784	1.109	0.24	45
MO	0.907	2.356	1.450	1.00	19
MS	1.006	2.603	1.597	1.33	5
MT	0.718	1.921	1.203	0.45	40
NC	0.957	2.495	1.539	1.20	12
ND	0.654	1.733	1.079	0.18	47
NE	0.819	2.186	1.367	0.82	28
NH	0.744	1.897	1.153	0.34	44
NJ	0.881	2.295	1.414	0.92	22
NM	0.903	2.337	1.434	0.96	20
NV	0.871	2.242	1.371	0.82	27
NY	0.775	1.987	1.212	0.47	39
OH	0.853	2.227	1.374	0.83	26
OK	0.968	2.512	1.544	1.21	11
OR	0.825	2.189	1.364	0.81	29
PA	0.825	2.141	1.316	0.70	33

RI	0.844	2.166	1.321	0.71	32
SC	0.998	2.592	1.594	1.32	6
SD	0.753	2.043	1.290	0.64	35
TN	0.939	2.457	1.518	1.15	13
TX	1.031	2.656	1.626	1.39	3
UT	0.842	2.178	1.336	0.75	30
VA	0.914	2.385	1.471	1.05	15
VT	0.736	1.819	1.084	0.19	46
WA	0.813	2.194	1.382	0.85	25
WI	0.729	1.894	1.166	0.37	42
WV	0.860	2.275	1.415	0.92	21
WY	0.727	1.890	1.163	0.36	43

Table 5: Climatic Effects and State Rankings, 1960-2004

	Climatic Effect				
State	1960	2004	Δ	%Δ	Rank
US	**0.854**	**0.870**	**0.016**	**-13.01**	
AL	1.000	1.015	0.015	1.50	6
AR	0.974	0.991	0.017	-0.90	10
AZ	0.997	1.008	0.010	0.79	8
CA	0.980	0.991	0.011	-0.88	9
CO	0.778	0.800	0.022	-19.97	36
CT	0.823	0.835	0.012	-16.51	33
DE	0.909	0.930	0.021	-7.02	16
FL	1.078	1.088	0.010	8.78	1
GA	1.009	1.023	0.014	2.30	4
IA	0.796	0.831	0.034	-16.94	34
ID	0.747	0.787	0.041	-21.25	38
IL	0.867	0.890	0.024	-10.96	22
IN	0.865	0.887	0.023	-11.28	24
KS	0.900	0.924	0.024	-7.57	17
KY	0.913	0.940	0.027	-6.03	14
LA	1.037	1.052	0.016	5.24	2
MA	0.816	0.814	-0.002	-18.60	35
MD	0.895	0.921	0.026	-7.95	19
ME	0.712	0.670	-0.042	-33.04	48
MI	0.749	0.762	0.013	-23.79	40
MN	0.676	0.698	0.022	-30.20	46
MO	0.907	0.922	0.015	-7.81	18
MS	1.006	1.018	0.013	1.84	5
MT	0.718	0.752	0.034	-24.83	41
NC	0.957	0.976	0.020	-2.37	12
ND	0.654	0.678	0.024	-32.20	47
NE	0.819	0.855	0.036	-14.47	29
NH	0.744	0.742	-0.002	-25.78	42
NJ	0.881	0.898	0.017	-10.22	21
NM	0.903	0.914	0.011	-8.56	20
NV	0.871	0.877	0.006	-12.30	25
NY	0.775	0.777	0.003	-22.26	39
OH	0.853	0.871	0.018	-12.86	26
OK	0.968	0.983	0.015	-1.72	11
OR	0.825	0.856	0.031	-14.35	28
PA	0.825	0.837	0.013	-16.25	32
RI	0.844	0.847	0.003	-15.26	31

SC	0.998	1.014	0.016	1.42	7
SD	0.753	0.799	0.046	-20.07	37
TN	0.939	0.961	0.022	-3.88	13
TX	1.031	1.039	0.009	3.91	3
UT	0.842	0.852	0.010	-14.78	30
VA	0.914	0.933	0.019	-6.67	15
VT	0.736	0.712	-0.024	-28.83	45
WA	0.813	0.858	0.046	-14.15	27
WI	0.729	0.741	0.012	-25.89	43
WV	0.860	0.890	0.030	-11.00	23
WY	0.727	0.739	0.012	-26.07	44

Table 6: Technical Efficiency Change and State Rankings, 1960-2004

	Technical Efficiency Change				
State	1960	2004	Δ	%Δ	Rank
US	**0.954**	**1.124**	**0.169**	**12.36**	
AL	1.000	1.283	0.283	28.28	19
AR	0.723	1.256	0.533	25.59	20
AZ	1.566	1.307	-0.259	30.69	16
CA	1.196	1.472	0.276	47.24	7
CO	1.031	1.291	0.260	29.10	18
CT	1.039	1.125	0.086	12.49	26
DE	1.567	3.073	1.506	207.31	1
FL	1.420	1.098	-0.322	9.80	28
GA	0.915	1.415	0.499	41.46	10
IA	1.498	2.199	0.701	119.91	2
ID	0.928	1.322	0.394	32.21	14
IL	1.406	1.524	0.118	52.39	5
IN	1.050	1.440	0.391	44.04	9
KS	0.891	1.102	0.210	10.17	27
KY	0.908	0.911	0.003	-8.85	36
LA	0.494	0.783	0.289	-21.74	42
MA	0.970	1.023	0.053	2.33	30
MD	0.952	1.337	0.385	33.72	13
ME	1.394	1.482	0.088	48.23	6
MI	0.821	1.141	0.320	14.14	24
MN	1.495	1.774	0.278	77.38	4
MO	0.949	0.801	-0.148	-19.86	40
MS	0.627	1.297	0.670	29.72	17
MT	0.842	0.695	-0.148	-30.53	44
NC	0.917	1.819	0.902	81.86	3
ND	1.050	1.341	0.291	34.10	12
NE	0.990	1.458	0.468	45.76	8
NH	0.927	0.941	0.014	-5.92	34
NJ	1.241	0.948	-0.293	-5.19	33
NM	0.768	0.906	0.139	-9.36	37
NV	0.974	0.864	-0.110	-13.56	38
NY	1.177	1.167	-0.010	16.71	23
OH	0.902	1.221	0.319	22.07	21
OK	0.816	0.646	-0.170	-35.43	47
OR	0.571	0.849	0.278	-15.13	39
PA	0.969	1.002	0.033	0.18	31
RI	1.024	1.175	0.151	17.46	22

SC	0.697	0.993	0.296	-0.75	32
SD	1.142	1.359	0.217	35.90	11
TN	0.771	0.642	-0.130	-35.83	48
TX	0.618	0.664	0.047	-33.56	45
UT	0.725	0.798	0.073	-20.25	41
VA	0.685	0.932	0.247	-6.84	35
VT	1.246	1.317	0.071	31.65	15
WA	0.723	1.076	0.352	7.56	29
WI	1.144	1.166	0.022	16.56	24
WV	0.605	0.699	0.093	-30.15	43
WY	0.847	0.660	-0.187	-33.96	46

Table 7: Scale Efficiency Change and State Rankings, 1960-2004

	Scale Efficiency Change				
	1960	2004	Δ	%Δ	Rank
US	**1.003**	**0.980**	**-0.023**	**-1.98**	
AL	1.000	0.980	-0.020	-2.05	31
AR	1.018	1.005	-0.013	0.53	17
AZ	0.967	0.962	-0.005	-3.77	35
CA	1.072	1.064	-0.007	6.43	2
CO	1.014	0.995	-0.019	-0.47	27
CT	0.942	0.908	-0.034	-9.21	45
DE	0.910	0.889	-0.021	-11.12	46
FL	0.997	1.007	0.010	0.67	16
GA	1.013	0.995	-0.018	-0.52	28
IA	1.064	1.029	-0.035	2.92	6
ID	1.008	0.996	-0.012	-0.40	25
IL	1.049	1.026	-0.022	2.64	9
IN	1.037	1.008	-0.028	0.83	15
KS	1.048	1.029	-0.018	2.92	5
KY	1.016	1.001	-0.014	0.13	21
LA	1.004	0.974	-0.029	-2.59	32
MA	0.956	0.909	-0.047	-9.06	44
MD	0.975	0.948	-0.027	-5.19	38
ME	0.948	0.911	-0.037	-8.88	42
MI	1.039	1.009	-0.030	0.92	13
MN	1.051	1.029	-0.022	2.88	7
MO	1.042	1.030	-0.012	2.98	4
MS	1.024	0.984	-0.039	-1.56	30
MT	1.008	0.998	-0.010	-0.21	24
NC	1.034	0.999	-0.034	-0.06	22
ND	1.021	1.003	-0.017	0.34	19
NE	1.047	1.030	-0.017	3.01	3
NH	0.919	0.879	-0.040	-12.08	47
NJ	0.968	0.937	-0.031	-6.28	39
NM	0.977	0.971	-0.005	-2.86	33
NV	0.911	0.910	-0.002	-9.04	43
NY	1.031	0.996	-0.035	-0.44	26
OH	1.043	1.009	-0.034	0.91	14
OK	1.027	1.017	-0.010	1.71	10
OR	1.020	1.002	-0.018	0.21	20
PA	1.029	1.011	-0.018	1.06	11
RI	0.870	0.825	-0.045	-17.53	48

SC	0.999	0.964	-0.035	-3.58	34
SD	1.023	1.004	-0.019	0.35	18
TN	1.018	0.999	-0.018	-0.07	23
TX	1.081	1.067	-0.014	6.66	1
UT	0.974	0.958	-0.016	-4.21	37
VA	1.019	0.986	-0.033	-1.43	29
VT	0.950	0.916	-0.034	-8.39	41
WA	1.023	1.009	-0.014	0.92	12
WI	1.056	1.027	-0.029	2.66	8
WV	0.968	0.928	-0.040	-7.16	40
WY	0.971	0.958	-0.013	-4.16	36

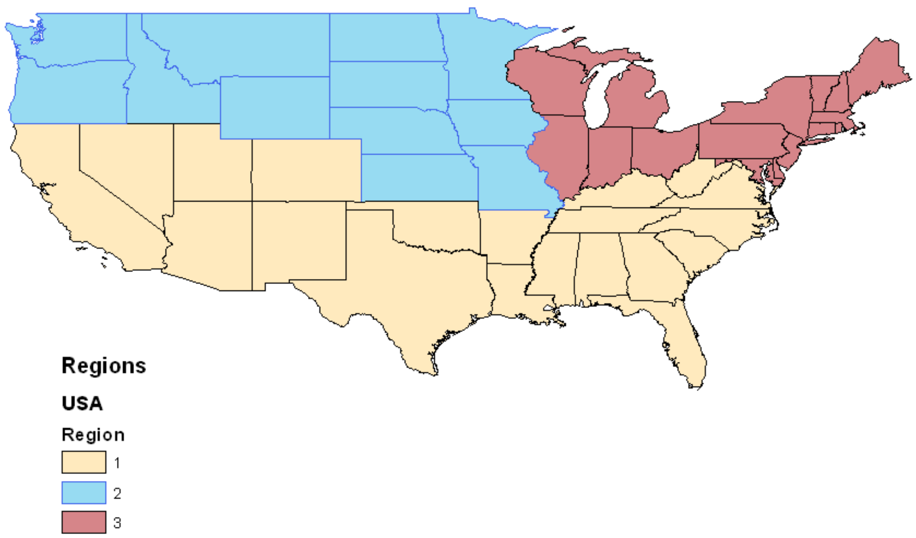


Figure 1: U.S. Regions

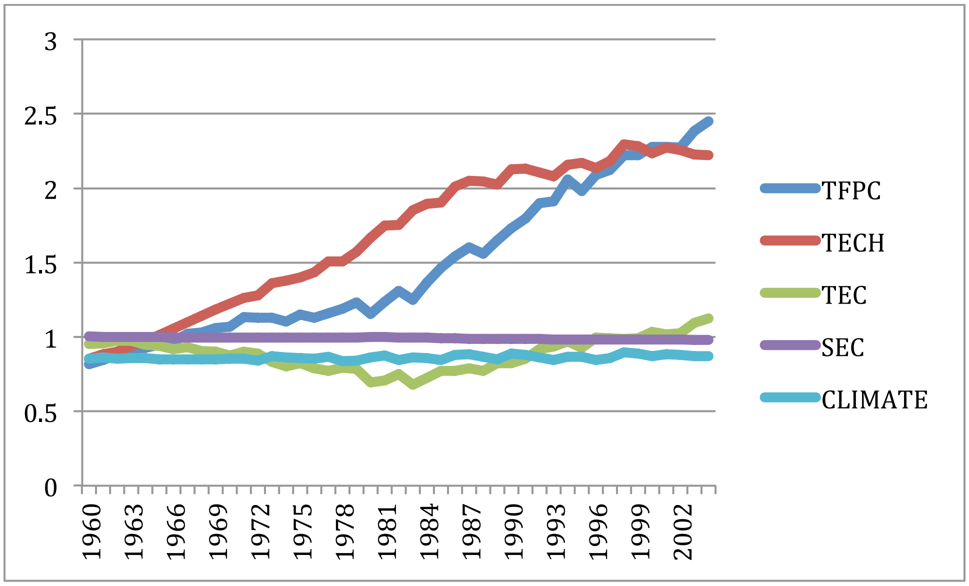


Figure 2: TFP Change in the U.S. 1960-2004 (cf. AL in 1960)

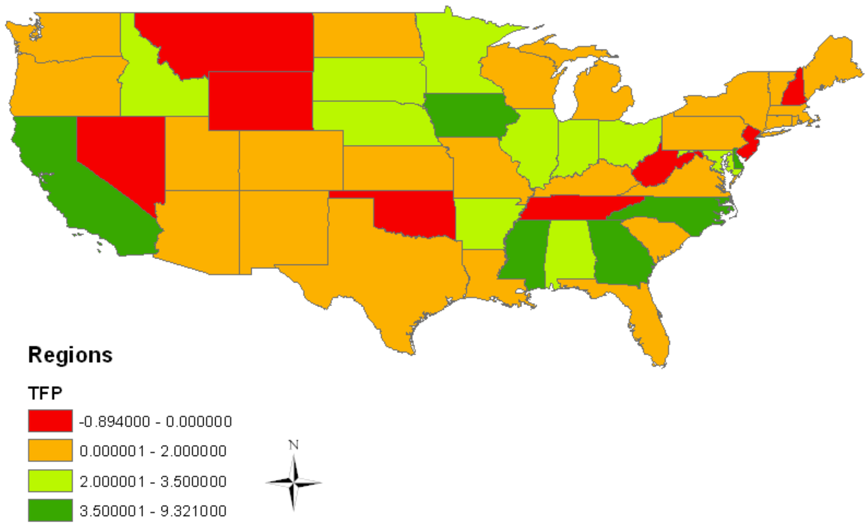


Figure 3: U.S. Total Factor Productivity

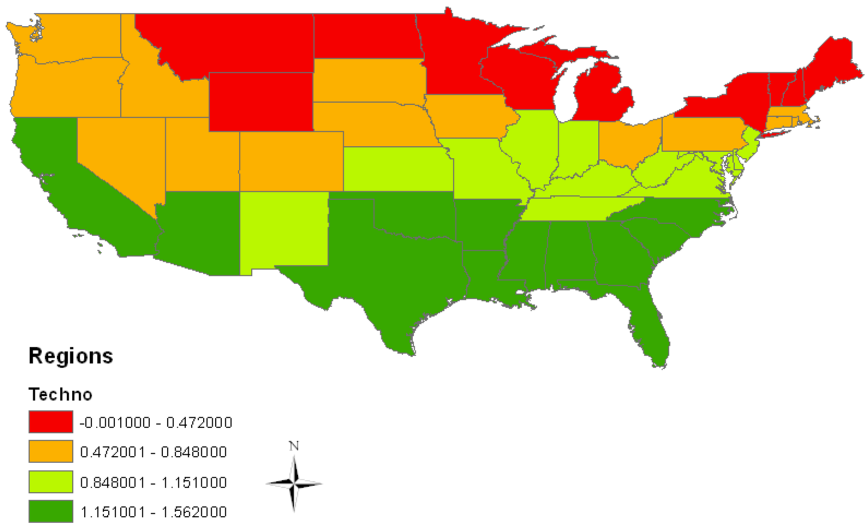


Figure 4: U.S. Technological Change, 1960-2004

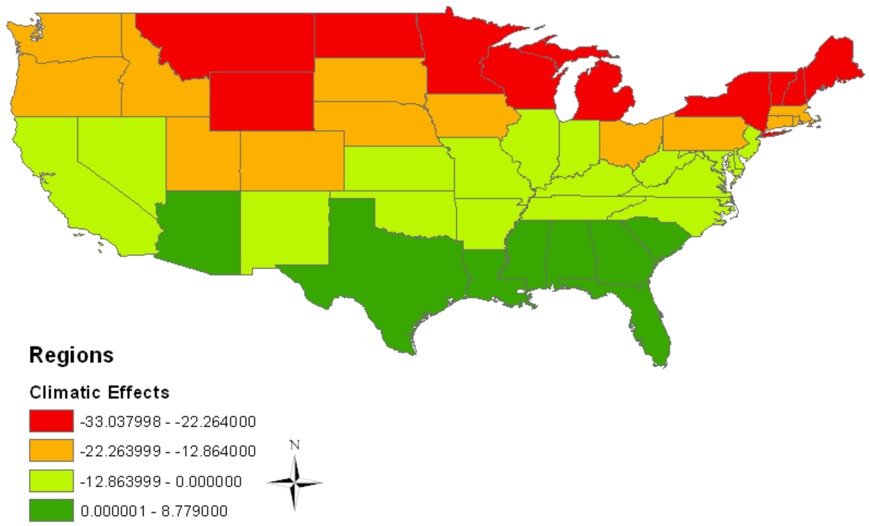


Figure 5: U.S. Climatic Effect, 1960-2004

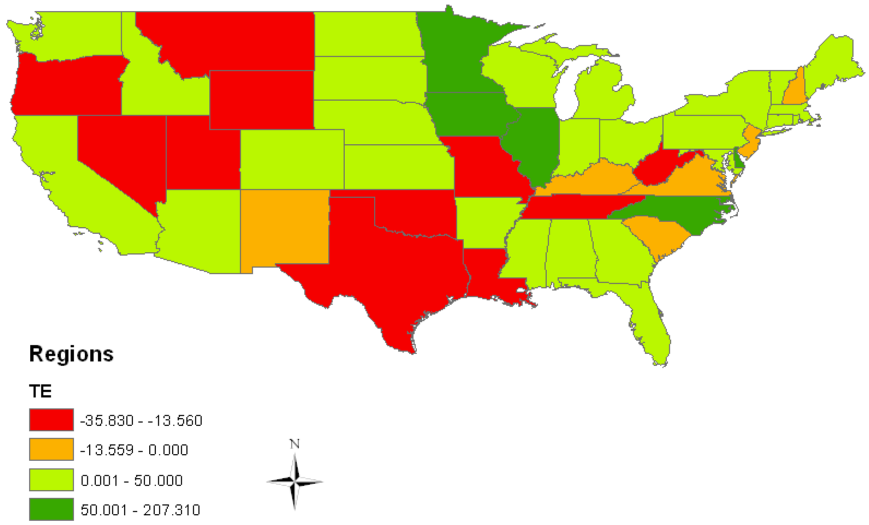


Figure 6: U.S. Technical Efficiency Change, 1960-2004

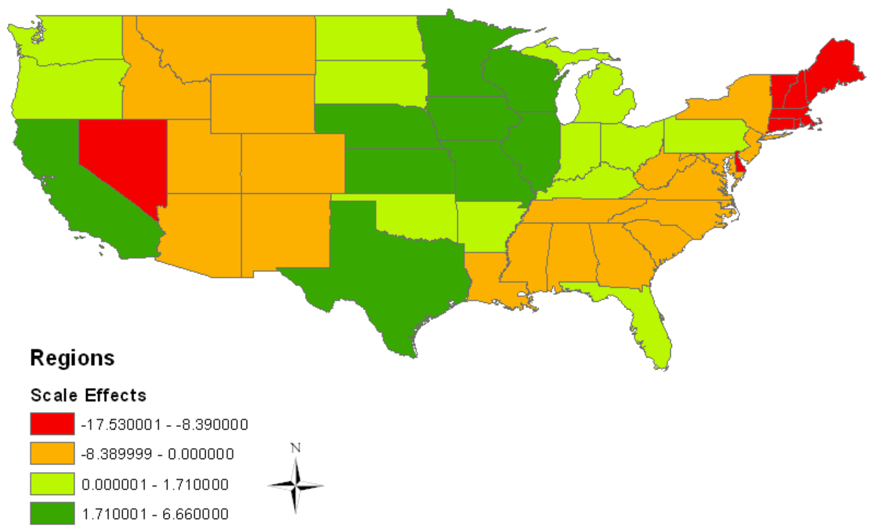


Figure 7: U.S. Scale Efficiency Change, 1960-2004

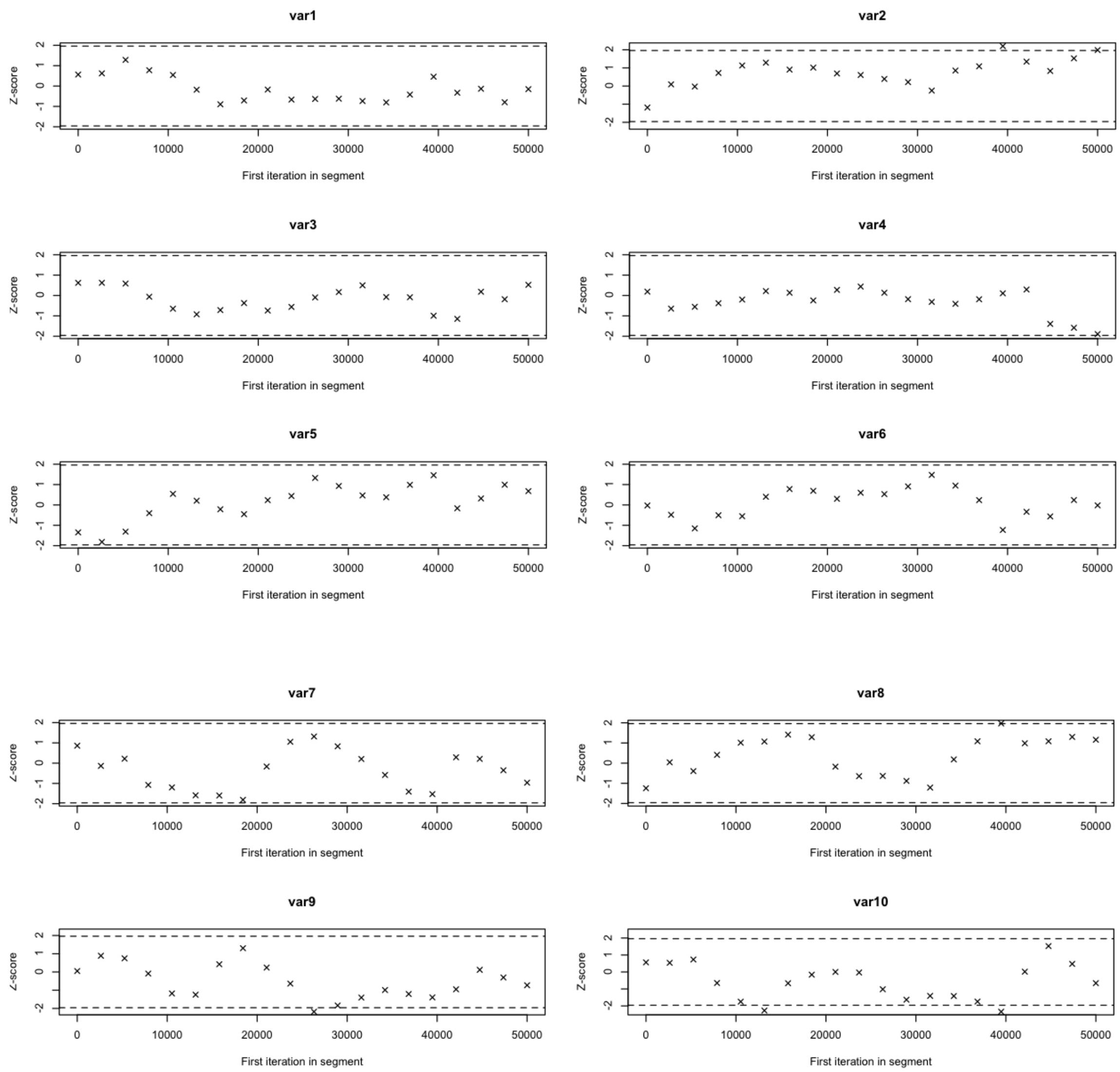


Figure A-1: Geweke's diagnostic plot