THE EFFECTS OF ENVIRONMENTAL REGULATION ON PLANT PRODUCTIVITY: A TEMPORAL INVESTIGATION OF PHASE ONE OF THE FEDERAL 1990 CLEAN AIR ACT AMENDMENTS

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CHAPTER 1

INTRODUCTION

Cost management is concerned with planning and controlling the costs of the resources consumed performing organizational activities. Specifically, cost management produces useful information by identifying, collecting, measuring, classifying, and reporting the cost of products and other objects to improve internal decision making and to promote continuous improvement (Hansen and Mowen, 2003, p. 2). One focus of cost management is to eliminate non-value added activities by reducing unnecessary inputs while at least maintaining valued added outputs. Thus, an underlying purpose of cost management is to improve efficiency. A particular set of costs gaining attention is environmental costs. Environmental costs have begun to play a major role in the policy-making decisions of firms because of growing compliance costs and a surge in social awareness. As a result, the environment is increasingly being used as a strategic tool to reduce cost and increase competitive advantage.

However, this idea has not been without its obstacles. The traditional approach to pollution control is guided by regulations that mandate both pollution reduction and the specific methods required to reduce the pollution. Under this approach, pollution reduction is often accompanied by a regress in productivity because valuable inputs are diverted from the production of good output. This causes either an increase in cost or a reduction of good output, either of which reduces efficiency. Therefore, the traditional approach views pollution reduction as having a direct and negative impact on efficiency.

Many firms have begun to search for a way to use environmental cost management as part of an alternative to the traditional pollution control model. A paradigm that has emerged is eco-efficiency. Eco-efficiency is a philosophy that encourages a search for and adoption of environmental improvements that allow a firm to become more environmentally responsible while at the same time becoming more profitable. The general premise of eco-efficiency is that firms can *voluntarily* adopt innovative and proactive pollution reduction methods that will reduce environmental degradation and lower costs. However, in order to accomplish this goal firms must have a solid understanding of their environmental cost function and how it is affected by actions taken to reduce pollution. Further, they must perceive that some benefit will emerge from adoption. Porter and Van de Linde (1991, 1995a, 1995b) have provided additional support for eco-efficiency by developing the Porter Hypothesis. The underlying principle of the Porter Hypothesis is that in general agents within firms may have limited rationality regarding the effects of eco-efficiency and consequently must be guided by an open intervention to make them understand how reductions in pollution promote efficiency. Thus, the Porter Hypothesis assumes: (1) pollution is a form of economic inefficiency; (2) environmental regulations provide a signal to companies to improve; and (3) that *properly* designed regulations trigger innovations that may partially offset or more than fully offset environmental costs. Therefore, the basis of the Porter Hypothesis is that environmental regulations can be used to induce firms to adopt eco-efficient behavior.

To date most of the evidence used to support eco-efficiency and the Porter Hypothesis has been anecdotal and based largely on the results of case studies [(Ditz et al (1995); Epstein (1996); De Simone and Popoff (1997); and Schmidheiny and Zorraquin (1996)]. To establish the validity of the Porter Hypothesis, properly crafted regulations must be present and there must be evidence that these regulations induce eco-efficient behavior. The Federal 1990 Clean Air Act Amendments (1990 CAAA) fit the definition of a properly crafted regulation. The 1990 CAAA require certain utilities to reduce their sulfur dioxide (SO_2) emissions but do not mandate how these reductions are to be achieved [U.S. Department of Energy, Energy Information Administration (1994) and (1997); EPA (2000); Swift (2001, p. 315)].

There has been some investigation of the 1990 CAAA and the results it has produced. Hughes (2000) studies firms affected by Phase One of the 1990 CAAA. His study examines the relationship between the market value of equity and SO_2 emissions for the period 1986 - 1993. He finds that SO_2 emissions have value relevance for the years 1989, 1990, and 1991 (there exists a significant negative relationship between market value and SO_2). This relationship disappears subsequent to 1991. Hughes (2000) suggests that the decline in the value relevance of SO_2 emissions may be attributable to endogenous changes in the firm's production processes. No direct evidence is provided to support this suggestion. Nor does the study provide any direct evidence about changes in productive efficiency attributable to the regulation.

1.1 Purpose of the Study

To date, no study has provided a *direct* test of the Porter Hypothesis. The 1990 CAAA provides an attractive opportunity to carry out this type of test. The purpose of this study is to evaluate the Porter Hypothesis by investigating how endogenous changes made by utilities in response to Phase One of the 1990 CAAA affect productive efficiency. The 1990 CAAA is useful because it represents a properly designed regulation that focuses on outcomes rather than methods and thus, provides a direct association between improved productivity and process improvements and innovation. If the Porter Hypothesis is valid, then utilities subject to the 1990 CAAA should engage in process improvement and process innovation, thus exhibiting an increase in productive efficiency relative to performance prior to the Act. Such an outcome will provide direct support for eco-efficiency and its position that firms can maintain or increase good output while simultaneously reducing environmental costs and bad output.

Finding evidence to support the Porter Hypothesis is important for several reasons. First, examining the effects of regulations on productive efficiency is particularly important because benchmarks can be established to evaluate how regulations impact profitability. Moreover, by concentrating on the relationship between environmental regulations and efficiency, smarter and finer trade-offs between business and environmental concerns will surface. Second, this evidence can serve to alter the attitudes and polices of management with respect to the environment. Third, evidence supporting eco-efficiency could also contribute to the potential reduction of the traditional adversarial relationship between the government and the business community relative to environmental issues. Fourth, it can be used to craft better environmental regulations and other public policies. Finally, this evidence would also establish the importance of a role for an environmental cost management system and thus, serves as a response to those who suggest the accounting profession should create a more accurate signal of how environmental performance affects firm value [Beets and Souther (1999, p. 129); Ilinitch et al. (1998, p. 384); Schmidheiny et al. (1996, p. 129); AICPA (2002, p. 3)].

The next chapter provides a literature review relative to environmental cost management, eco-efficiency, and the Porter Hypothesis. A discussion of the traditional and eco-efficient pollution control models is presented in Chapter Three. Hypotheses development and the approach to measuring relative efficiency is presented in Chapter Four. The research design is presented in Chapter Five. The empirical results are provided in Chapter Six. Finally, conclusions are presented in Chapter Seven.

CHAPTER 2

LITERATURE REVIEW

2.1 Environmental Cost Management

Cost management creates more value at a lower cost by integrating production, strategy, and management accounting into a discipline that focuses on value chain analysis, strategic positioning, and cost driver analysis (Shank, 1989, p. 47; Cooper and Slagmulder, 1998, p. 14). Creating more value at a lower cost suggests that increasing productive efficiency is a major objective of cost management. Process improvement and process innovation (business reengineering) are the principal sources of productivity improvements. Process improvements represent the elimination of technical inefficiencies whereas process innovations change the underlying production technology to achieve increased efficiency. Both approaches attempt to eliminate waste by finding better ways to produce (Hansen and Mowen, 2000, p. 376).

Environmental quality management is an area that may benefit from the use of cost management. The goal of environmental quality management is to reduce pollution and improve firm value by transforming existing practices (Bhat, 1998, p. 32). The marriage of environmental quality management with cost management is referred to as environmental cost management. Environmental costs are all the costs incurred by a firm to prevent, control, and clean up pollution. Environmental costs are important because of their magnitude. Wong (2001, p. 52) reports that environmental remediation is a $186 billion-dollar-a-year business industry. A recent analysis of the use of pollution control as a competitive weapon found that environmental costs could be as high as 20 percent of total operating costs (Bhat, 1996, p. 11). Further, a study by the World Resources Institute found that when the costs of labor, maintenance and operating activities were properly classified, the level of environmental costs went from 3 percent to 22 percent of the operating costs of an oil refinery (Ditz et al., 1995, p. 15). In another study, a small metal products manufacturer initially estimated its environmental costs at $50,000. An examination of direct and indirect costs and those imbedded in other accounts showed real annual environmental cost at about $1 million (Kunes, 2001, p. 72).

The emerging area of environmental cost management is receiving more attention not only because environmental costs are significant but also because there is increasing evidence to suggest that improving environmental performance can actually *reduce* environmental costs. For example, Baxter, a global pharmaceutical firm, established a proactive program to improve environmental performance. In 1994, the program reduced hazardous waste and produced cost avoidances of $23.4 million (Schmidheny et al., 1996, p.71). Similarly, Hyde Tool, a small manufacturer of industrial tools, established a pollution reduction program that reduced wastewater from 29 million to 1.25 million gallons while saving over $200,000 annually (Epstein, 1996, p. 157). Cracker Barrel likewise found that changes in production processes could bring significant savings. Working with suppliers to develop new ways to reduce trash, the company dramatically reduced the amount of disposable cardboard and saved more than $100,000 annually (Epstein, 1996, p. 47).

2.2 Eco-Efficiency

The above cases suggest that firms can use cost management to create opportunities to maintain or increase good outputs, reduce bad outputs, and improve performance by reducing costs. Thus, environmental cost management should focus on gaining insights about the environmental cost function and how it is affected by pollution reduction. Firms can use the behavior of the environmental cost function as a signal of when, where, and how to manage environmental performance by evaluating the *efficiency* with which inputs are used to create good as well as bad (i.e., pollution) outputs [Fare et al. (1996); Tyteca (1996); Tyteca (1997); and Tyteca, (1999)]. This link is a provocative concept because it has been argued that reductions in pollution actually increase productive efficiency and thereby reduce costs (King and Lenox, 2002, p. 289).

This approach to environmental cost management is essentially equivalent to a pollution control strategy called eco-efficiency. Eco-efficiency is a management philosophy that encourages a search for and adoption of environmental improvements that allow a firm to become more environmentally responsible while at the same time becoming more profitable (WBCSD, 2000a, p. 4). The goal of eco-efficiency is to obtain economic and ecological efficiency through the optimal use of inputs. Thus, eco-efficiency differs from traditional environmental management because it uses a value chain approach to make a direct connection between environmental targets and firm profitability by including the efficient use of the environment as part of the strategic planning of the company [Cramer (1999, p. 54); President's Council on Sustainable Development (1996b, p. 1)]. Specifically, firms exhibit eco-efficient behavior when they adopt innovative and creative methods to produce more or the same level of useful goods and services while simultaneously reducing environmental degradation, resource consumption, and costs (WBCSD, 2000b, p. 7). In its purest form, eco-efficient behavior is *completely* voluntary and not encumbered by unyielding regulations. Thus, the best outcomes from adopting eco-efficiency are achieved when firms have a solid understanding of their environmental cost function and the benefits that accrue from pollution reduction.

2.3 The Porter Hypothesis

The productivity gains and innovation benefits associated with eco-efficiency have caused a number of firms to take the concept seriously and to reevaluate how to manage their interaction with the environment. However, many other firms have continued to guide their environmental activities using a traditional focus. Traditionally, the relationship between environmental quality and economic performance has been framed under the assumption that it is driven by regulations. This framework assumes that technology, products, and processes remain unchanged in the presence of regulation, and regulation thus inevitably raises costs and reduces productivity (Porter, 1991, p. 5). However, Porter (1991) and Porter and van der Linde (1995a, 1995b) take exception to this premise by assuming that pollution is a form of economic inefficiency and that environmental regulations provide a signal to companies to improve. Moreover, their research suggests, in what has become referred to as the Porter Hypothesis, that *properly* designed environmental regulations trigger innovations that may partially offset or more than fully offset environmental costs. Properly designed environmental regulations are those that emphasize outcomes and not methods and thereby encourage process improvements and process innovations. Thus, the objective of properly designed regulations is to promote economic efficiency while at the same time reducing environmental degradation. The Porter Hypothesis therefore maintains that properly designed environmental regulations are those that encourage eco-efficient behavior.

The need to craft a *properly* designed regulation is recognized by the President's Council on Sustainable Development. The Council concludes that traditional approaches to regulation are too inflexible and costly and suggests that while regulations should establish environmental standards they should also allow firms greater flexibility in achieving them (The President's Council on Sustainable Development, 1996a, p. 28). In return, companies can pursue technological innovations that will result in superior environmental protection at a lower cost. Moreover, by concentrating on the relationship between environmental regulations and efficiency, firms can identify smarter and finer trade-offs between business and environmental concerns (Walley and Whitehead, 1994, p. 47). Indeed, as noted by Epstein and Roy (1997, p. 26), although environmental improvements are often spurred by regulatory requirements, corporations can use these mandates as an impetus to voluntarily discover product and process innovations that can yield substantial benefits to both the environment and the firm.

Some theoretical support exists for the Porter Hypothesis. Mohr (2002) shows that regulations may be used to spur endogenous changes within a firm to create and make use of innovations that simultaneously alleviate pollution and increase productivity.

However, his model assumes that these results are achieved only when there is a single technology, the adoption of that technology is required, and that all market participants have full knowledge about the effects of adoption.

Xepapadeas and Zeeuw (1999) also theoretically examine the Porter Hypothesis by considering firms' reactions to regulations with respect to both the type and quantity of the equipment investments made in response to changes in production processes. Using a model in which firms are allowed to invest in machinery with different characteristics, they isolate both a productivity and a profit-emission effect. They find that although stricter environmental policies cannot always be expected to provide win-win situations in the sense of both reducing emissions and increasing profitability, it is reasonable to assume that trade-offs can be created such that the marginal decrease in pollution is increased and the marginal decrease in profits is reduced.

To date, most of the evidence used to support eco-efficiency and the Porter Hypothesis has been anecdotal and based largely on the results of case studies [(Ditz et al. (1995); Epstein (1996); De Simone and Popoff (1997); and Schmidheiny and Zorraquin (1996)]. Hirl (1998) criticizes this evidence, noting that it lacks a fair valuation of environmental parameters and does not include the reactions of standard setting bodies or the business community in its analyses. Indeed, as noted by Klaussen and McLaughlin (1996), while evidence suggests that there is a link between strong environmental performance and lower manufacturing costs, "...little empirical research has focused specifically on environmental management and firm financial performance" (Klaussen and McLaughlin, 1996, p. 1200). Even Porter and van de Linde admit that " ... a list of case studies…no matter how long, is not a complete substitute for careful empirical testing" (Porter and van der Linde, 1995a, p. 104).

One empirical study, Myer (1992), investigates the Porter Hypothesis by comparing states with strict environmental laws to states that have more lax standards to determine whether the pursuit of environmental quality hinders economic growth and development. He finds that "…there appears to be a moderate yet consistent association between environmentalism and economic growth" (Meyer, 1992, p.4). Jaffe et al. (1995) however, maintains that this correlation could be spurious, noting, "…the results are consistent with the hypothesis that poor states with no prospect of substantial growth will not enact tough environmental regulations" and that, "...the literature on the Porter Hypothesis remains one with a high ratio of speculation and an anecdote to systematic evidence" (Jaffe et al., 1995, p. 157). He further observes that "…there is little or no evidence supporting the revisionist hypothesis that environmental regulation stimulates innovation" (Jaffe et al., 1995, p. 157) and thus calls for more empirical investigations relative to the Porter Hypothesis.

CHAPTER 3

TRADITIONAL AND ECO-EFFICIENT POLLUTION MODELS

3.1 Traditional Economic Theory of Production

Traditional pollution control posits that a production possibilities frontier exists that describes all of the efficient combinations of outputs that can be generated given a finite set of resources and a given technology. The slope of the production possibilities frontier, known as the marginal rate of transformation (MRT), shows the rate at which the output of one good has to be sacrificed to increase the output of another. Relative to pollution control, outputs are classified as good or bad, where bad outputs correspond to pollutants.

Figure One illustrates a two-output production process where a firm produces a good product, X, with a bad product, Y, as a by-product, using a fixed amount of resources. Notice that to reduce the pollution from Y_2 to Y_1, good output must be reduced from X_2 to X_1. Reducing bad output causes a diversion of resources from the production of good output, a costly activity (revenues must be sacrificed). Alternatively, good output can be maintained at the X_2 level by acquiring additional resources to reduce Y_2 to Y_1, which is also a costly activity. Thus according to this model, a firm would have no incentive to reduce pollution.

3.2 Traditional Pollution Control Regulation

Because firms lack incentive to reduce pollution, the government has assumed an active role in pollution control (Kolstad, 2000, p.135 – 139). The traditional strategy of pollution control in the United States is command and control regulation (Pavetto and Bae, 1991, p. 27). Command and control regulations specify both the pollution output level allowed and the specific and strict methods of compliance (Kolstad, 2000, p. 139). Thus, command and control policies rely on the standardization of technologies and practices to achieve mandated environmental improvements. Moreover, results obtained under these methods usually become the benchmark for productive efficiency.

Usually, command and control methods change slowly and are unlikely to be improved, thus over time firms may find themselves controlling pollution with technologies that no longer fit or prohibit innovations that could achieve comparable environmental protection at a lower cost (DeSimone and Popoff, 1997, p. 18). However, if the traditional approach is lacking firms may be evaluating their use of resources incorrectly and thus may not be aware of any additional benefits that could emerge from innovations. In fact, there are many who contend that the command and control policies are ineffective. For example, Goodstein (1999, p. 265) refers to the command and control regulatory strategy as cost-ineffective and notes that uniform technological mandates are unlikely to provide the cheapest pollution control system. He suggests that a flexible system could result in the same goals of efficiency, safety, and ecological sustainability at a much lower cost. DeSimone and Popoff (1997, p. 18) observe that strict and unyielding command and control statutes"… require the installation of equipment when other options are available or pollutants have already been reduced using process change".

Kolstad (2000, p. 140) observes that the restriction of choice allowed a polluter might preclude any opportunity to combine reduced pollution and cost savings. All of these observations suggest the command and control regulatory approach discourages innovations that may lead to better environmental quality and lower costs. Furthermore, command and control methods may discourage firms from improving environmental quality by increasing productive efficiency.

Thus, the command and control approach has come under question because it does not encourage firms to improve processes or search for new and innovative methods to produce. Further, there is evidence to suggest that when actions taken beyond those mandated are encouraged, additional benefits are produced. For instance, Rockwell voluntarily implemented a plan to use resources more efficiently by redesigning products to improve environmental quality. Income from these programs offset the costs of disposing of hazardous wastes and returned over $300,000 to the business (Epstein, 1996, p. 46). Moreover, the 3M Corporation began running its pollution prevention pays program in 1975 with the aim of preventing pollution at its source. By improving process efficiency, the firm reduced emissions and netted more than $750 million in savings over the last two decades (DeSimone and Popoff, 1997, p. 4).

3.3 Eco-Efficiency Inducing Regulation

The aforementioned cases suggest the possibility that the traditional economic model of pollution control does not fully describe the benefits that firms can capture by reducing pollutants. For example, the model portrayed in Figure One does not consider technical inefficiency and changes in technology. Figure Two illustrates the presence of these two possibilities. In Figure Two, curve AC represents the production possibilities frontier given the current level of technology assuming no technical inefficiency. Curve AB represents the production possibilities frontier given the current level of technology assuming the existence of technical inefficiency. Curve AD represents the production possibilities frontier given that innovation has produced a new technology.

Assume that curve AB represents the production possibilities frontier at the point in time when the firm is mandated to reduce its level of pollution from Y_2 to Y_1. The current level of output is (X_2, Y_2). With the given level of inefficiency, and assuming no effort is made to increase productive efficiency, reducing Y_2 to Y_1 would produce a reduction in good output from X_2 to X_1. However, if the mandate stimulates process improvements that target the level of technical inefficiency, it is possible to reduce Y_2 to Y_1 while increasing good output from X_2 to X_3. On the other hand, assume that the mandate stimulates process innovation such that the production frontier becomes AD. This suggests the possibility of reducing pollution to Y_1 while increasing output from X_2 to X_4.

As demonstrated, both process improvements and process innovation can reduce pollution and increase good output. These outcomes are consistent with eco-efficient behavior. Eco-efficiency goes beyond making simple efficiency improvements that are required by regulations and encourages creativity and innovation to reduce resource use and pollutant release (OECD, 1998, p. 22 – 23). Thus, eco-efficiency expands traditional concepts by accepting the possibility that pollution can be reduced through process change and that less pollution will produce more value through improved efficiency and reduced costs (WBCSD, 1996, p.4).

However, unless there is a stimulus, firms may not voluntarily pursue eco-efficient outcomes.[1] A key economic assumption is that agents make rationale decisions using the best available and relevant information. However, because information may not readily available or cannot be easily interpreted, agents often have limited rationality. This is particularly true when evaluating environmental costs because they are often incorrectly reported. King and Lenox (2002, p. 290) provide an analysis of how firms may overlook or not pursue pollution control opportunities that extend beyond the traditional approach. They contend that because traditional models promote controlling pollution at the "end of the pipe-line", many firms devalue and underestimate the benefits of proactive waste prevention. Additionally, because the potential benefits of alternatives are uncertain, hard to observe, difficult to link to a particular source, and are often delayed or extended over time, information searches related to them might prove unprofitable. Given this, managers do not factor in the value of innovation as an unexpected benefit of waste prevention. Therefore, a profit-maximizing manager concerned about the marginal cost of reducing pollution is more likely to be influenced by the expected benefits of known pollution reduction methods.

These impediments to eco-efficiency have been noted in the literature. For example, Swift (2001) notes that "...in order to broadly support incentives for efficiency, innovation, and pollution prevention, environmental regulations must create a continuous driver for pollution reduction" (Swift, 2001, p. 410). Thus, eco-efficiency should be

[1] Evidence has shown that firms may use satisficing rather than optimizing behavior when complying with environmental regulations [Porter and Van der Linde (1995a) and Goodstein (1999, p.265]. For instance, firms may discover a better technique for pollution prevention at one location but opt not to adopt it because to do so might legally bind them to upgrade pollution control at other facilities which may not be cost effective.

encouraged by regulations that create economic incentives, allow greater use of market forces, and encourage innovative environmental technologies that are stimulated and maintained over time by continuous innovation [DeSimone and Popoff (1997, p. 153); Cramer (1997, p. 58); WBCSD (2000a); and OECD (1998, p. 10)].

3.4 The Federal 1990 Clean Air Act Amendments

To establish the validity of eco-efficiency and the Porter Hypothesis, two conditions must be met: (1) properly crafted regulations must be present and (2) there should be evidence that these regulations induce eco-efficient behavior. The Federal 1990 Clean Air Act Amendments (1990 CAAA) fit the definition of a properly crafted regulation. The 1990 CAAA is a properly crafted regulation because it requires certain entities to reduce pollution emissions but do not mandate how these reductions are to be achieved [U.S. Department of Energy, Energy Information Administration (1994) and (1997); EPA (2000); Swift (2001, p. 315)].

Among the numerous provisions of the 1990 CAAA is Title IV, which mandates that the Environmental Protection Agency (EPA) establish an Acid Rain Program to reduce the adverse affects of acidic deposition (acid rain)[2]. Acid rain is formed largely from emissions of sulfur dioxide (SO_2) and nitrogen oxides (NO_x). The objectives of Title IV were to be achieved primarily through domestic reductions of SO_2 and NO_x emissions by electric utilities. The electric utility industry was targeted under Title IV because its fossil fuel plants were the main source of SO_2 emissions and a major source of NO_x

[2] The majority of this discussion can be located in two reports prepared by the Energy Information Administration that discuss the initial plans and early results of complying with the 1990 CAAA. For more information, see US Department of Energy, Energy Information Administration (1994) and (1997).

emissions in the United States. Efforts to reduce these emissions were divided into two time periods: Phase One and Phase Two. The 1990 CAAA identified 110 large plants known to be especially dirty and then mandated specified reductions in SO_2 and NO_x output that these plants had to achieve by 1995. These mandated levels of SO_2 and NO_x output had to be maintained by these 110 plants through 1999. This period of 1995 to 1999 defines what is referred to as Phase One. Thus, plants affected by Phase One are referred to as Phase One plants. Phase Two, which began in the year 2000, tightened the total annual emissions limits imposed on Phase One plants and, in addition, expanded the lower mandated levels to all other (i.e., non-Phase One) electric utility plants.

The 1990 CAAA approach to reducing SO_2 was especially noteworthy because it represented the first large-scale attempt to establish overall emissions levels through a market structure that used allowances to govern how much SO_2 an electric utility was permitted to emit. Each allowance authorizes an electric utility to emit one ton of SO_2. The total allowances provided to a utility define the SO_2 output limits. Thus, to be in compliance with the law, an electric utility could not emit more SO_2 than the allowances held. Electric utilities that reduced their emissions below the number of allowances held could elect to trade allowances within their system, bank them for future use, or sell them to other utilities. The 1990 CAAA approach to controlling SO_2 was a radical departure from the traditional "command and control" approach because it allowed electric utilities to choose any method they deemed appropriate to meet environmental standards. Thus, for the first time electric utilities had a real opportunity to use process improvements and innovations to reduce emissions and improve efficiency (EPA, 2000, p.3).

Two events occurred subsequent to the passage of the 1990 CAAA that had an effect on Phase One. First, 54 additional plants were brought into Phase One [U.S. Department of Energy, Energy Information Administration (1994, p. 38) and (1997, p. vii); Swift (2001, p.321)]. Thus, in 1995 164 plants underwent the annual reconciliation process administered by the EPA to determine compliance with Phase One (EPA, 1996a, p.1). Second, the initial rules governing Phase One NO_x reductions were vacated in 1994 and not replaced until early 1995 (U.S. Department of Energy, Energy Information Administration, 1997, p. 39). Therefore, NO_x emissions reductions were not required until 1996 (EPA, 1996b, p. 5).[3]

There has been some empirical investigation of the reaction to the 1990 CAAA and the outcomes it has produced. Hughes (2000) studies firms affected by Phase One of the 1990 CAAA. His study examines the relationship between the market value of equity and SO_2 emissions for the period 1986 - 1993. He finds that SO_2 emissions have value relevance for the years 1989, 1990, and 1991 (there exists a significant negative relationship between market value and SO_2). This relationship disappears subsequent to 1991. Hughes (2000) suggests that the decline in value relevance of SO_2 emissions may be attributable to *endogenous* changes in the firm's production processes made in response to the Act. However, no direct evidence is provided to support this suggestion. Nor does the study provide any direct evidence about changes in productive efficiency attributable to the regulation.

[3] Because reductions in NO_x are not required until 1996, neither the calculation of the change in NO_x emissions nor the effect of any such change on efficiency is included as a part of this study.

CHAPTER 4

STATEMENT OF HYPOTHESES AND METHODOLOGY

4.1 Operational Hypotheses

The traditional pollution control model assumes that reductions in pollution reduce efficiency because additional costs are incurred or inputs are diverted from the production of good to bad outputs. Pure eco-efficiency assumes that firms are rational and understand that reducing pollution will improve efficiency. Therefore, they will *voluntarily* seek out and adopt innovative ways to create benefits that outweigh the costs incurred to reduce the pollution. However, given the lack of information about environmental costs, the connection between pollution reduction and improvements in efficiency is not always made. Thus, intervention induced eco-efficiency, which is the underlying base of the Porter Hypothesis, assumes that regulations are required to guide firms to the understanding that pollution reductions improve efficiency.

Phase One of the 1990 CAAA offers an attractive opportunity for testing the validity of the Porter Hypothesis. It mandates reduced levels of SO_2 for a specific subset of electric utility plants without indicating how to achieve the reductions while exempting all other plants from this mandate. The Act thus identified two groups of plants: those that have a relatively high level of pollution and those that have a relatively lower level of pollution. Dividing plants into high and low polluting categories at a particular point in time creates the ability to execute a cross-sectional test of Porter's claim that pollution is equivalent to economic inefficiency (Porter and van der Linde, 1995a and 1995b). Thus, the first hypothesis, pertaining to *cross-sectional* relative efficiency, can be stated in the alternative form as:

> H_1: Plants with lower pollution will be relatively more efficient than plants with higher pollution.

Cross sectional relative efficiency will be evaluated in 1990 and 1995. Investigating cross sectional relative efficiency in 1990 is a test of pure eco-efficiency. Its purpose is to see if eco-efficiency initially holds prior to intervention. If no such evidence exists, there is support for the assumption that the traditional pollution model is present in 1990 and thus, provides a benchmark for evaluating efficiency after intervention. Therefore, the null hypothesis pertaining to the 1990 cross sectional relative efficiency assumes that the efficiency of the Phase One plants will be greater than the efficiency of the Non-Phase One plants.

In 1995, an eco-efficient inducing regulation has been introduced. If the traditional view holds, then the Phase One firms will become less efficient because they are required to reduce pollution. However, the Porter Hypothesis would say that since the requirements of the 1990 CAAA to reduce pollution leaves open the question of how to achieve these reductions, eco-efficient behavior will be triggered and improvements in efficiency will occur. Thus, investigating cross sectional relative efficiency in 1995 is a test of eco-efficiency with intervention that uses 1990 as a base. The objective is to determine if intervention of the right kind (i.e., eco-efficient inducing) will reduce pollution and thus cause the efficiency of those subject to the Act to increase relative to those not subject to the Act. In addition, if the Phase One plants were more efficient in 1990 and if Porter is right, then in 1995 they should stay more efficient relative to Non-Phase One plants even though they have been required to reduce pollution. Thus, the null hypothesis pertaining to the 1995 cross sectional efficiency assumes that the efficiency of the Non-Phase One plants will be greater than the efficiency of the Phase One plants.

Another aspect of the Porter Hypothesis is that government intervention induces plants to increase productive efficiency subsequent to an intervening event. Thus, the grouping of plants into two categories also allows the development of a longitudinal analysis. A longitudinal analysis provides a more complete assessment of the Porter Hypothesis because it simultaneously evaluates the assumptions that: (1) pollution is a form of economic inefficiency; (2) environmental regulations provide a signal to improve; and (3) properly designed regulations trigger innovations that may partially offset or more than fully offset environmental costs.

Because of the 1990 CAAA, Phase One plants will have lower pollution during Phase One than pre-Phase-One. Again, if pollution is equivalent to economic inefficiency, then productive efficiency for the Phase One plants should increase over time. Essentially, if productive efficiency is measured prior to Phase One years and then measured during the Phase One years, the relative efficiency of Phase One plants should increase. A natural control group (non-Phase One plants) exists to determine whether a change in relative productive efficiency for Phase One plants is specifically attributable to the Act's mandate. Thus, the second hypothesis, pertaining to *longitudinal* relative efficiency, can be stated in the alternative form as:

H_2: Plants that have been mandated to reduce pollution will be relatively more efficient after the mandate than before the mandate.

Both Phase One and Non-Phase One longitudinal relative efficiency will be evaluated. The null hypothesis pertaining to the longitudinal relative efficiency of the Phase One plants assumes that the efficiency of the 1990 Phase One plants will be greater than the efficiency of the 1995 Phase One plants. The null hypothesis of the relative efficiency of the Non-Phase One plants assumes that the efficiency of the 1995 Non-Phase One plants will be greater than the efficiency of the 1990 Non-Phase One plants.

4.2 The Data Envelopment Analysis Methodology

4.2.1 Measuring Relative Efficiency

In general, efficiency is best measured in relative terms where one firm is compared to another. A firm can also be compared to itself at different times to obtain a trend of how well the firm has performed over a period of time. Relative comparisons are especially important to environmental management because they provide a baseline to set improvement goals based on external environmental regulations, internal business practices, and emerging technological implications (Ruch and Roper, 1992, p.15).

Data envelopment analysis (DEA) is an empirical method used to estimate the relative efficiency of a group of decision-making units (DMU) with similar goals and objectives (e.g., DMUs operating in the same industry). DEA computes these relative measures of efficiency using all of the inputs and outputs of all of the DMUs in the reference group. Thus, DEA uses input-output quantity data to estimate a DMU's production function using linear approximations to map the envelope (frontier) of the input-output data (Callen,1991). DMUs operating on the frontier are relatively more efficient than those operating off the frontier. Figure Three portrays a one-input, one-output production frontier, assuming variable returns to scale. As can be seen, DEA estimates a discrete piecewise frontier by enveloping the data to reveal relative efficiency relationships. DMUs C, F, M, D, and I form the efficient production frontier because given their input levels, they are able to produce more output relative to any other DMU. DMUs L, G, E, and H are less efficient and thus, all fall within the interior, off the frontier.

DEA uses linear programming to measure the relative efficiency of each DMU in the reference group. Each time an optimization is carried out, a set of weights is produced. This set of weights defines a hypothetical composite DMU using the outputs and inputs of all DMUs within the reference group. Constraints in the linear programming model require outputs of the composite DMU to be *greater than or equal* to the outputs of the DMU being evaluated. If the inputs for the composite DMU can be shown to be *less than* the inputs for the DMU being evaluated, the composite DMU will thus produce the *same, or more, output* for *less input*. In this case, DEA indicates that the composite DMU is *more efficient* than the DMU being evaluated. Moreover, because the composite DMU is based on all DMUs in the reference group, the DMU being evaluated can be judged *relatively inefficient* to all other DMUs in the group.

Program A offers a DEA model that illustrates these relationships for n DMUs, m outputs, and p inputs:

$$\text{Min}\ \varepsilon$$

subject to:

$$\sum_{i=1}^{n} w_i O_{ij} \geq O_{kj},\ \ j = 1,2,\ldots m \qquad \text{(A)}$$

$$\sum_{i=1}^{n} w_i I_{ir} \leq \varepsilon I_{kr},\ \ r = 1,2,\ldots p$$

$$\sum_{i=1}^{n} w_i = 1$$

where

ϵ = the efficiency or "DEA " scores assigned by DEA

O_{ij} = output j for DMU i

I_{ir} = input r for DMU i

O_{kj} = the output j for DMU k

I_{kr} = input r for DMU k, where k denotes the DMU being evaluated for its efficiency relative to all others (target DMU)

w = the weight assigned by DEA

The model selects a set of weights that minimize ϵ. This is equivalent to minimizing the input resources required by the composite DMU. Since the target DMU is one of the n DMUs, it is possible that the target DMU could be selected as the composite DMU by setting $w_k = 1$. The value of ϵ lies between zero and one. If $\epsilon < 1$, indicating that the composite DMU requires *less* input resources, the target DMU is judged as *relatively inefficient.* If $\epsilon = 1$, this indicates that the target DMU uses no more inputs than those required by the composite DMU. In this instance, the target DMU is on the efficient frontier.

DEA has several characteristics that make its use attractive. First, it accepts that inefficiencies are real, assigns a value to them, and focuses on the impact of these inefficiencies on performance. Thus, DEA directs attention to the potential benefits from increasing outputs and/or decreasing inputs (Turner and DePree, 1991, p. 3). Second, the DEA model is Pareto optimal, meaning that any input variable reduction or output augmentation can be effected without worsening other model variables (Bowlin, 1999, p. 292). Third, DEA identifies the best performing DMUs and provides a valid and meaningful scalar measure of performance for each DMU under evaluation by comparing them to the best performing DMU (Bowlin, 1995, p. 541). Fourth, DEA creates its frontier based on the observed behavior of the best performing organizations using an approach free of *a priori* specifications. Thus, the weights assigned by the DEA model are obtained as part of the solution of a mathematical programming problem that is free of potential biases that might accompany traditional benchmarking methodologies (Bowlin, 1999, p. 292). Finally, DEA does not require a specified functional form and therefore allows flexibility in the type of production function used by each DMU under investigation. As a result, a DMU is given the best possible rating based on its actual production function. This characteristic of DEA is significant because it recognizes the many and diverse ways firms can combine resources to produce output. This is an important feature because it simultaneously considers all resource inputs and outputs, allows interdependence and trade-offs among these variables, and promotes the inclusion of effects that might be intangible and otherwise excluded (Kleinsorge et al., 1992, p. 360).

4.2.2 DEA for the Plant Setting

Program A serves as the model for measuring relative efficiency at the power plant level. For the cross-sectional analysis, each power plant corresponds to a DMU. For the longitudinal analysis, each power plant in a different year defines a DMU (thus a DMU is a plant-year combination). The plant DEA reference group is composed of both high polluting and low polluting plants. To measure relative efficiency, outputs and inputs must be selected and defined. Prior studies have generally advocated the identification and measurement of variables deemed most relevant for a particular set of DMUs [Majumdar (1998, p. 816); Nunamker (1985, p. 56)]. Four variables will be selected for use in the plant-level DEA model. For electric utility plants, output is **Kilowatt-hours** (H). Three inputs will be used in the computation of DEA scores: **Capital** (K), **Fuel Costs** (F), and **Operating Costs** (C). With these definitions, relative efficiency for a plant based DMU is measured by the following program:

$$\text{Min}\,\varepsilon$$

subject to:

$$\sum_{i=1}^{n} w_i H_i \geq H_k \tag{B}$$

$$\sum_{i=1}^{n} w_i F_i \leq \varepsilon F_k$$

$$\sum_{i=1}^{n} w_i K_i \leq \varepsilon K_k$$

$$\sum_{i=1}^{n} w_i C_i \leq \varepsilon C_k$$

$$\sum_{i=1}^{n} w_i = 1$$

Program B uses only good output and does not include bad output. Bad output is exogenous to the plant-level DEA model and is used to ensure that the reference group includes DMUs with significantly different levels of pollution. Traditional economic theory assumes that reducing pollution requires either a reduction in good output or an increase in cost, either of which will reduce efficiency. The Porter Hypothesis assumes that reducing pollution will induce a plant to maintain or improve good output while using relatively less inputs and costs. Thus, the above plant-level DEA model allows a direct evaluation of whether or not lower levels of pollution bring about greater relative efficiency.

The DEA inputs were identified in several ways. First, they are the inputs most widely used for performance measurement in the electric utility industry [Christensen and Greene (1976, p. 663); Cowing et al. (1981, p. 169)]. In addition, they are the most often identified inputs in the literature related to the calculation of DEA scores for the electric utility industry [Goto and Tsutsui (1998); Athanassopoulos et al. (1999); Fare et al. (1996); Tyteca (1997); Tyteca (1999); and Golany et al. (1994); Haeri et al. (1997); Forrester et al. (1998)].

Capital is the ability of the individual plant to produce electricity and is measured by the nameplate generating capacity of the plant. Nameplate generating capacity is the full-load capacity rating of a plant to continuously produce electricity. Its use as a proxy for capital is consistent with prior studies [Goto and Tsutsui (1998); Fare et al. (1996); Whiteman (1995)]. The cost of producing electricity consists of fuel and operating costs

(Freedman and Jaggi, 1994, p. 38).[1] **Fuel Costs** represent all of the costs associated with the purchase, handling, and storage of fuel inputs burned as part of the chain reaction to generate electricity. These costs are the largest and most variable and sensitive item on a utility's list of production expenses (Bossong, 1999, p. 22). In fact, the respondents of a survey on issues related to electric utility plant operating activity suggest that the environmental impact of the fuel supply, as well as its availability and deliverability are important factors to consider when evaluating any reduction in production expenses (Doughty and Rode, 1995, p. 26).

Operating Costs include the cost of labor and other expenses related to operating and maintaining a plant. Doughty and Rode (1995, p. 24) find that reducing operating expenses was ranked high among the major issues affecting the electric utility. Thus, an improving trend in operating costs usually indicates that there is a focus on streamlining operations and controlling costs. Finally, examining total production cost and its components is important because these categories are known to include many environmental costs [Joshi et al. (2001, pp. 172 – 175) and EPA (1995, p. 9)] and thus, can reflect whether costs are less for lower polluting DMUs than for higher polluting DMUs. If lower polluting DMUs have lower production costs, there is evidence to suggest that environmental costs decrease as environmental quality improves.

[1] Because of inflation, nominal prices from different years cannot be compared without making some adjustments. Thus, the Consumer Price Index (CPI) will be used to deflate 1995 to 1990 prices. This approach is consistent with other studies that examine the electric utility industry on a longitudinal basis (i.e., Freeman and Jaggi, 1994). CPI is a useful measure of inflation because it demonstrates the same general patterns as other indicators but with less volatility (U.S. Census Bureau, 2001, p. 450).

4.2.3 The Malmquist Productivity Index

One of the sophisticated extensions of DEA is the ability to analyze productivity over time through the use of the Malmquist Productivity Index (MPI). The MPI is a measure of productivity in a general production function framework. Fare et al. (1992, 1994) introduced the MPI within a DEA setting to evaluate the change in DMUs between two time periods. One of the most important contributions of a DEA based MPI is that it can be multiplicatively decomposed into two parts: one accounting for the changes in efficiency (i.e., the catching-up effect) and the other accounting for changes in the efficient frontier technology (i.e., the frontier shift). When evaluating a DEA based MPI and its components, amounts greater than one indicate progress, while numbers smaller than one show regress. Amounts equal to one represent no change between the two periods. Evaluating temporal changes using the DEA based MPI is particularly relevant to an investigation of the electric utility industry's response to the 1990 CAAA because it has been suggested that plants reacted to the regulation by improving efficiency and developing innovative technology (Hughes, 2000, p. 211).

Equation 1 illustrates the DEA based MPI and its components[2]. Denoted as $M_{j,1,2}$, the DEA based MPI provides a comparison of the productivity of DMU j between two time periods 1 and 2.

$$M_{j1,2} = \frac{E^2_{j2}}{E^1_{j1}} \cdot \frac{E^1_{j2}}{E^2_{j2}} = M_{cj1,2} \cdot M^{1,2}_{Fj}, \quad 1,2 \in \mathrm{T} \qquad [1]$$

[2] The majority of this discussion of the DEA based Malmquist Productivity Index can be found in Forsund and Kittlesen (1998, p. 210).

The catching-up effect, $M_{cj1,2}$, is related to the benefits a DMU gains through efficiency improvements and thus, captures the relative movement of the observed DMU to the frontier. It is expressed as the ratio of the efficiency of the DMU relative to period 1 and period 2 frontiers. The numerator is the efficiency of the DMU relative to the second period frontier and the denominator is the efficiency of the DMU relative to the first period frontier. Therefore, a higher (lower) contemporary efficiency score for the second period implies increased (decreased) efficiency over the two periods.

The frontier technology shift, $M_{Fj}^{1,2}$, is the change in the efficient frontier between the two time periods. It is expressed by the ratio of the efficiency scores for the second period observation relative to the two technologies. The numerator expresses the scaling of period 2 inputs in order to be on period 1 technology, while the denominator expresses the scaling of the same input vector in order to be on period 2 technology, with both cases subject to period 2 observed output. This serves as a measure of technology shift, and is greater than one if period 2 technology is more efficient relative to period 1 technology for the input-output mix of the period 2 observation.

CHAPTER 5

RESEARCH DESIGN

5.1 Sample Design and Data Collection

Data were collected for Phase One plants for the periods 1990 and 1995. Data were also collected for a control group made up of non-Phase-One plants for the same periods. Control plants were selected using the *Inventory of Power Plants in the United States for 1990*. The control plants were matched based on nameplate generating capacity within a North American Electric Reliability Council (NERC) region. There are nine NERC regions that encompass all the power in the United States, Canada, and Mexico. NERC regions were formed in 1968 by the electric utility industry to promote the reliability and adequacy of bulk power in the electric systems of North America. Electric reliability councils have operating utilities as members. The function of these councils is to develop standards for bulk power supply and service reliability (Ferry, 2000, p. 28). The NERC region is used as part of the matching criteria because it is assumed that plants located within the same region face a common set of production, operating, and regulatory characteristics. In addition, prior studies have used NERC regions as a basis for cost comparisons [Blacconiere et al. (1997); Knutson, 1995)]. Nameplate generating capacity is the capital investment within a plant most directly associated with electricity production. Its use as a matching criteria is consistent with existing studies making comparisons within the electric utility industry [Goto and Tsutsui (1998, p. 184); Whiteman, 1995, (1995, p.73)].

The input and output needs of DEA determined most of the data requirements of this study. *The Federal Energy Regulatory Commission (FERC) Form 1* reports were used to gather data related to the inputs and good output. Only major investor-owned electric utilities are required to submit a FERC Form 1[1]. Data incorporated in a FERC Form 1 include income and earnings, operating and maintenance expenses, and various production statistics. Plant level financial and operating data are located in the "Steam Generating Plant Statistics for Large Plants" section of the FERC Form 1. *The Energy Information Administration of the Department of Energy* was the source for SO_2 emissions. Specific tests of Hypothesis Two required measures of state regulatory climate and state environmentalism. The assessments of state regulatory climate were obtained from the *Value Line* investment service. Proxies for state environmentalism were modeled after those reflected in Meyer (1995) where the score of each state was based on a set of twenty environmental policy indicators. Finally, the relative efficiencies (i.e., DEA scores) for this study were produced using DEA-Solver-Pro 3.0.[2]

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[1] Investor owned utilities are those electric utilities owned by investors. In contrast, publicly owned utilities are those operated by the federal government, a state or local municipality, or an electric cooperative.
[2] There are several commercially available DEA software packages that combine inputs and outputs to produce DEA scores. DEA-Solver-Pro 3.0 is a windows based linear programming package developed by Saitech, Inc.

5.2 Tests of Hypotheses

5.2.1 Cross-Sectional Tests

The 1990 CAAA identified two groups of plants: those that have a relatively high level of pollution and those that have a relatively lower level of pollution. The high polluters are Phase One plants that must reduce pollution by specified levels by 1995. Low polluters are those plants not required to reduce pollution until Phase Two. Thus, for 1990, these two groups of plants were pooled and then the DEA model (Program B) was used to measure the relative efficiency of each DMU in the pooled group. Next, the difference in efficiency between the two groups was tested statistically. Since the theoretical distribution of the DEA efficiency score is unknown, the Wilcoxon-Mann-Whitney rank-sum test was used to determine whether the difference between the two groups is significant (Cooper, Seiford, and Tone, 2000, p. 200 - 202).

The rank-sum test is a nonparametric test based on the ranking of data. The test is conducted as follows. Let n_A be the number of Phase One plants and n_B the number of control plants. The DEA scores of the two groups are arranged in ascending order. These scores are then ranked from 1 to $n_A + n_B$. Tied observations receive an average of rankings. Next, the sum of the rankings for the Phase One firms is computed. Let S represent this sum. This statistic, S, follows a normal distribution with mean $\frac{n_A(n_A + n_B + 1)}{2}$ and variance $\frac{n_A n_B(n_A + n_B + 1)}{12}$. A standardized test statistic will be calculated and a one-tail test will be executed. The null hypothesis pertaining to the *1990 cross-sectional relative efficiency* assumes that the expected rank sum (efficiency) of the

Phase One plants is greater than the expected rank sum (efficiency) of the control plants. Rejection of the null hypothesis supports Hypothesis One.

The same type of cross sectional analysis was conducted for the 1995 period. In 1995 the pollution levels of Phase One plants should have been reduced. Further, because pollution is a form of technical inefficiency, a reduction in SO_2 output by the Phase One plants should result in an improvement in the efficiency of the Phase One plants. Non-Phase One plants are not affected by the 1990 CAAA and thus, when evaluated relative to Phase One Plants, should not display a significant change in technical efficiency. Therefore, the null hypothesis pertaining to the *1995 cross-sectional relative efficiency* assumes that the expected rank sum (efficiency) of the Non-Phase-One plants is greater than the expected rank sum (efficiency) of the Phase One plants. Rejection of the null hypothesis would support Hypothesis One.

5.2.2 Longitudinal Tests

5.2.2.1 Rank Sum Test

Hypothesis Two assumes that plants mandated to reduce pollution will be relatively more efficient after the mandate than before the mandate. Thus, Hypothesis Two could be labeled as an interventionist hypothesis because it relies on an intervening event to bring about a reduction in pollution. Therefore, Hypothesis Two provides a more direct examination of the Porter Hypothesis. Following an approach similar to the cross-sectional analysis, the 1990 and 1995 Phase One plants were pooled together and a DEA score was calculated for each DMU in the pooled group. Next, the difference in efficiency between the 1990 and 1995 Phase One plants was tested statistically using the rank-sum test. The null hypothesis pertaining to the *longitudinal relative efficiency of the Phase One plants* assumes that the expected rank sum (efficiency) of the 1990 Phase One plants is greater than the expected rank sum (efficiency) of the 1995 Phase One plants. Rejection of the null hypothesis supports Hypothesis Two.

The same analysis was performed on the pooled group of 1990 and 1995 control plants. The null hypothesis pertaining to the *longitudinal relative efficiency of the control plants* assumes that the expected rank sum (efficiency) of the 1995 control plants is greater than the expected rank sum (efficiency) of the 1990 control plants. Rejection of the null hypothesis provides evidence that the difference in relative efficiency between the 1990 and 1995 Phase One plants is attributable to the intervening regulatory event and not to other time varying factors. This provides additional support for Hypothesis Two and would provide evidence that the Act induced eco-efficient behavior.

5.2.2.2 Within-Plant-Type Regression Analysis

DEA scores provide a measure of efficiency based on how well units of inputs are used to produce units of outputs. However, the indexes generated by DEA may not by themselves provide information relative to the empirical determinants of plant level efficiency. This issue is particularly important when efficiency is being evaluated before and after an intervening event. One approach to identifying the determinants of efficiency on a longitudinal basis is to run DEA scores as a dependent variable in a regression estimation against a set of hypothesized determinants.

Therefore, in addition to the rank-sum test, a regression that explains differences among DEA scores may provide additional evidence concerning the validity of

Hypothesis Two. However, since DEA scores are bounded between zero and one, OLS may be biased and thus, may not be an appropriate estimation technique [Judge et al. (1987); Cooper, Seiford, and Tone (2000); Kennedy (1996)] To avoid this potential bias, a tobit censored regression model was used [Claggert et al. (1998); Olatubi and Dismukes (2000); Puig-Junoy (1998)]. In order to explain differences in efficiency on a longitudinal basis, three explanatory variables were chosen (predicted signs appear in parentheses):

EVENT (+): Dummy variable equal to one if 1995 and equal to zero if 1990.

CLIM (-): A variable that measures how favorably a state regulatory commission addresses rate increase requests. It assumes the following values: below average (-1), average (0), and above average (+1).[3]

STRICT (+): A variable that measures the stringency of state environmental policies. It assumes the following values: weak (-1), moderate (0), strong (+1).[4]

With the above variable definitions, the following tobit regression model was estimated:

$$DEA = \beta_0 + \beta_1 EVENT + \beta_2 CLIM + \beta_3 STRICT + e \qquad [2]$$

The regression analysis in Equation 2, referred to as **Model 1**, was conducted for both test and control plants. Hypothesis Two predicts that 1995 Phase One plants will be more efficient than 1990 Phase One plants. For the control plants there is no reason to expect

[3] This is the same approach used by Hughes (2000, p. 214) to assess the longitudinal impact of the state regulatory climates.

[4] The basis for these measures is Meyer (1995).

the efficiency to increase from 1990 to 1995. Thus, a significant positive β_1 for the test plants, coupled with an insignificant β_1 for the control group provides evidence supportive of Hypothesis Two.

The other two explanatory variables are control variables although both have some bearing on the validity of the Porter Hypothesis. The electric utility industry falls under the control of state regulatory commissions. Prior research has implied that there is an association between a utility's value and the favorableness of its regulatory climate because state regulatory commissions are responsible for determining a utility's rate base and allowable operating expenses [Loudder et al. (1996); D'Souza et al. (2000); Blacconiere et al. (1997)]. However, critics have argued that rate-setting procedures by state regulatory commissions may not provide an incentive to become efficient (Bossong, 1999, p. 9). In fact, many industry analysts argue that these procedures promote a wasteful application of resources, and provide utility managers with little motivation to cut costs or improve efficiency (Haeri et al., 1997, p. 26). The variable **CLIM** measures the propensity of state regulatory commissions to allow utilities to recover costs. As the value of **CLIM** increases, the propensity to allow cost recovery increases. As the ability to recover costs increases, the incentive for increasing productive efficiency decreases; thus, a negative sign for β_2 is expected. Therefore, a favorable regulatory climate works against eco-efficiency.

Environmental regulation varies across regions that impose greater or lesser penalties for pollution (King and Lenox, 2002, p. 295). State environmentalism is a measure of the level of environmental controls (polices, programs, statutes) adopted by a state to protect the environment. Ringquist and Feiock (1998) examine how state environmental activities affect state industrial growth. They conclude that strong state environmentalism can reduce pollution without adversely impacting economic growth (Ringquist and Feiock, 1998, p. 21). The variable **STRICT** is a measure of the stringency of state environmentalism. If the Porter Hypothesis is valid, then efficiency should increase as **STRICT** increases. Thus, a significant positive sign for β_3 is expected.

5.2.2.3 Between-Plant-Type Regression Analysis

Model 1 provides a direct test of the longitudinal effects of the 1990 CAAA on technical efficiency on a within-plant-type basis. This analysis is useful because it provides information about the determinants of the efficiency of plants that have been impacted by a regulation in a similar fashion. A logical extension would be to examine the determinants of efficiency when both Phase One and Non-Phase One plants are considered. This analysis is important for several reasons. First, it produces relative measures of efficiency based on industry activity and thus, provides a benchmark of external performance. Second, when investigating the determinants of these industry measures, the variation in efficiency resulting from differences in plant type can be evaluated. This evaluation is useful because it provides insight relative to the effect of both the Act and plant-type on efficiency.

To capture these effects, two conditions must be satisfied. First, longitudinal industry efficiency measures must be calculated. Thus, all of the 1990 and 1995 Phase One and Non-Phase One plants were pooled and the DEA model (Program B) was used to measure the relative efficiency of each DMU in the pooled group. Second, a variable must be identified that captures the effects of between-plant-type efficiency variation.

Therefore, **TYPE** was added to **Model 1** and the following tobit regression, referred to as **Model 2**, was estimated:

$$DEA = \beta_0 + \beta_1 EVENT + \beta_2 CLIM + \beta_3 STRICT + \beta_4 TYPE + e \qquad [3]$$

TYPE is a dummy variable equal to one if the plant is a Phase One plant and zero if it is a Non-Phase One plant. A significant and positive sign for β_4 is expected. Thus, a significant and positive β_4 coupled with a significant and positive β_1 suggests that intervention improves efficiency, that the improvements in efficiency differ between plant-type, and that Phase One plants are relatively more efficient after the intervention. All of these results provide additional support for Hypothesis Two.

5.3 The Malmquist Productivity Index

The DEA based MPI decomposes the change in productivity between two time periods into an efficiency and a technology effect. Thus, a direct test of the index and its components can provide information about the time varying effects of the 1990 CAAA on productivity and the extent to which efficiency and technology play a part in the change. Therefore, in a procedure similar to the rank sum tests and regression analyses, the 1990 and 1995 Phase One plants were pooled and DEA was used to produce a MPI, an efficiency, and a technology index for each DMU in the pooled group. The Porter Hypothesis assumes that plants mandated to reduce pollution would be more efficient after the mandate than before. Thus, there should be progress in the productivity of Phase One Plants between 1990 and 1995. Non-Phase One plants were not required to reduce pollution and thus, can be used to determine if the changes in the productivity, efficiency and technology of the test group relate to the Act. Thus, in an approach similar to that conducted for the test group, the 1990 and 1995 control plants were pooled and DEA was used to produce MPI, efficiency, and technology indexes for each DMU in that group.

CHAPTER 6

EMPIRICAL RESULTS

6.1 Sampling Results

Phase One of the 1990 CAAA affected 164 plants. Table 1 illustrates the process used to select Phase One plants for this study. Twenty-five plants were eliminated because they did not file a FERC Form 1. Fifteen Phase One plants were excluded because their plant level data was not included in the FERC Form 1 submission. Of the Phase One plants submitting data, 26 had missing or incomplete operating or financial information. Thus, based on data availability, 98 Phase One plants were on hand for matching. Fourteen of these remaining plants were eliminated because a suitable Non-Phase One plant match could not be located. Therefore, based on data *and* matching availability, 84 of the original 164 Phase One plants were selected. Finally, after matching the selected Phase One plants with Non-Phase One counterparts the grand sample of the study consists of 168 plants (84 Phase One and 84 Non-Phase One). Table 2 provides a distribution of the grand sample by NERC region. As indicated, all but one of the nine NERC regions is represented in the study. Table 3 lists the states included in the study. Twenty-nine states are represented, with Phase One and Non-Phase One plants located in 20 and 23 states, respectively.

6.2 Descriptive Statistics

Table 4 provides a summary of plant level data and the descriptive statistics for Phase One and Non-Phase One plants for 1990 and 1995. Panels A and B of Table 4 reflect cross-sectional comparisons of Phase One and Non-Phase One plants at 1990 and 1995, respectively. Panels C and D provide a longitudinal comparison of plant types across 1990 and 1995. Statistical tests of the means of the data presented in the Panels are also included to provide a preliminary assessment of the effects of the 1990 CAAA on the plants.

Panel A of Table 4 indicates that there was not a significant difference between the nameplate capacities of the test and control plants in 1990. This provides evidence that efforts to match Phase One with Non-Phase One plants are appropriate. In 1990 the KWH (good output) of the test plants was slightly higher but not significantly different from that of the control plants. A comparison of SO_2 (bad output) production conveys a different story. In 1990, test firms produced over 5 million tons of SO_2 while control plants produced only 1.38 million. This difference is significant at the 0.0001 level. However, the variation in SO_2 does not appear to create a difference in production costs across plant type. Specifically, in 1990 there was not a significant difference in the production, fuel, or operating costs across the two groups. Thus, prior to the Act it appears that test plants were able to produce roughly the same level of good output and significantly more bad output without incurring a significant amount of additional cost. In fact, as noted in a comparison of the unit cost of good output production, the cost per kilo-watt hour for the test plants was significantly less than that of the control plants at the 0.005 level.

Panel B of Table 4 provides a comparison of Phase One and Non-Phase One plants in 1995. This period is important because it is the first year of Phase One. In 1995, there was no significant difference between nameplate capacities, which indicates that the matching criteria remained appropriate after intervention. During 1995, test and control plants produced the same level of good output. Moreover, no significant differences were reflected between the production, fuel, or operating costs of the two groups. At 2.8 million tons, test plant SO_2 is significantly higher than the 1.4 million posted by the control plants. This difference is statistically significant at the 0.002 level. However, the variance in SO_2 production between the test and control plants in 1995 is less than that of 1990. This reflects the effort made by Phase One plants to reduce pollution. Finally, even though test plants reduced pollution, they produced good output at a significantly lower unit level cost than control plants.

Panel C of Table 4 provides a longitudinal analysis of the Phase One plants. Between 1990 and 1995 there was no statistical difference in good output production. However, as mandated by the 1990 CAAA, Phase One plants did post a significant reduction in bad output. Specifically, test plant SO_2 emissions went from 5.1 million tons in 1990 to about 2.8 million in 1995. This difference is statistically significant at the 0.002 level. The constancy in good output and reduction in bad output were accompanied by cost reductions as total production cost went from an average of 83 to 54 million dollars. The difference between 1990 and 1995 production costs is significant at the 0.03 level. Production cost reductions were primarily driven by significant declines in fuel costs, which, on average, decreased by 19 million dollars between 1990 and 1995. The difference in fuel costs between 1990 and 1995 is significant at the 0.02 level. Finally, the reductions in fuel costs and pollution appeared to have a positive effect on the cost required to produce a kilo-watt of electricity (CKWH). This measure is important because it provides an indication of the per-unit cost of good output. As denoted, Phase One plants reduced CKWH from an average of 0.023 in 1990 to 0.019 in 1995. This difference is significant at the 0.003 level. Taken together, all of these results appear to counter the traditional pollution control model's assumption that reducing pollution will cause either an increase in cost or a reduction in good output.

Panel D of Table 4 provides a time-varying analysis of the Non-Phase One Plants. The control plants did not post a significant change in good output between 1990 and 1995 but did experience a significant decrease in production cost which was driven by fuel cost reductions. However, the economic gains posted by Non-Phase One plants were not accompanied by SO_2 reductions. In fact, although not significant, Non-Phase One plants actually increased SO_2 output from 1.37 to 1.39 million tons between 1990 and 1995.

6.2.1 Analysis of Production Costs

Table 4 indicates that total production costs fell between 1990 and 1995 and that fuel cost reductions account for the majority of the decrease. There has been some analysis conducted on the change in production costs between the pre-Phase One and the Phase One periods. Knutson (1995) notes that the average production and fuel costs of the electric utility industry fell and will continue to fall as the industry persists in its efforts to find new ways to cut costs (Knutson, 1995, p. 13). Swift (2001) conducted an analysis of the change in production costs relative to the 1990 CAAA and makes several observations. First, he argues that the changes in cost are directly attributable to the Act's focus on promoting innovative methods to reduce pollution. Further, he suggests the major drivers of lower costs in Phase One were innovation and increased efficiency. Finally, he suggests that the innovations implemented during this period take on one of two forms: 1) endogenous changes made directly to production processes; and 2) those created by parties outside of the electric utility industry in response to changes made by the plants. According to Swift (2001), these latter innovations reflect a "spillover effect" whereby the innovations of one industry spur innovations in another industry.

Innovations made during Phase One were significant. As estimated by Swift (2001), the Act promoted over $12 billion in innovative technologies designed to reduce pollution, improve fuel access and transportation, and eliminate waste (Swift, 2001, p. 334 – 338). In the electricity industry, fuel represents the single highest production cost and thus, any production changes aimed at reducing this cost would have a significant impact. A significant amount of innovations that impacted production costs were those created to reduce fuel costs through the use of fuel blending (U.S. Department of Energy, Energy Information Administration, 1997, p. 5). Fuel blending involves the use of more than one type of fuel to produce electricity. In general, power plants are designed for a particular type of fuel and under traditional technologies, switching or blending fuels carries a high cost and could potentially reduce productivity (U.S. Department of Energy, Energy Information Administration, 1994, p. 13 – 14). However, the 1990 CAAA lead to the experimentation and innovation of fuel blending techniques that removed these barriers and ultimately led to both the reduction of cost and pollution (Swift, 2001, p. 336).

As Table 4 indicates, fuel costs reductions account for the majority of the production cost improvements of both the Phase One and the Non-Phase One plants. One of the reasons for this may be the blending of various coal types within plants. Coal is a major source of fuel used by the electric utility industry. It is also a major fuel source for the plants included in this study.[1] The delivered price of coal generally includes the mine price, transportation costs, and shipping and loading fees. The cost of coal declined between 1990 and 1995 [Swift (2001); U.S. Department of Energy, Energy Information Administration (1994); U.S. Department of Energy, Energy Information Administration (1997)]. The decline in coal prices was directly attributable to fuel blending innovations because the use of cheaper and cleaner burning coal increased [U.S. Department of Energy, Energy Information Administration (1994, p.13); Swift (2001, p. 336 – 338)]. Moreover, the increase in the use of different types of coal created the opportunity for plants to renegotiate long-term fuel contracts and thus, introduce price competition [Swift (2001, p. 339); Hughes (2000, p. 213); U.S. Department of Energy, Energy Information Administration (1997, p. 23)].

The effects of fuel blending extended beyond the electric utility industry. For instance, when faced with increased competition, coal producers developed new mining technologies. As a result, coal mining productivity rose by almost 7 percent between 1990 and 1995 (U.S. Department of Energy, Energy Information Administration, 1997, p.23). A similar response occurred in the rail industry, which is the primary carrier of coal for the electric utility industry. Transportation costs are a significant portion of the

[1] The majority of the Phase One and a large portion of the Non-Phase One plants in this study listed some type of coal as their primary fuel source. Thus, it is appropriate to assume that both groups were affected by the changes in technology related to the use of coal as a fuel source.

average delivered cost of coal, accounting for over 31 percent of the average delivered price of contract coal (U.S. Department of Energy, Energy Information Administration, 1997, p. 23). However, transportation costs related to coal purchases fell tremendously between the pre-Phase One and Phase One periods. Reasons suggested for this fall include the innovations made to improve rail car capacity and rail system infrastructures (Swift, 2001, p. 338).

Thus, based on a preliminary investigation of the plant level data, it appears that the 1990 CAAA induced the electric utility industry and those associated with the industry to react. These reactions included both direct and indirect innovations that contributed to reductions in pollution and production costs, but did not negatively affect good output. Thus, it appears that both control and test plants benefited as the descriptive statistics indicate both groups significantly reduced costs. These results run counter to the traditional pollution control model and thus, provide some tentative support for the Porter Hypothesis and eco-efficiency.

6.3 Efficiency Measure Distributions

The DEA scores produced using Program B are presented in Tables 5, 6, 7, and 8. Tables 5 and 6 present the results when Phase One and Non-Phase One plants were pooled in 1990 and 1995 respectively. Table 7 presents the results when 1990 and 1995 Phase One plants were pooled. Table 8 reflects the results when 1990 and 1995 Non-Phase One plants were pooled. DEA scores are relative measures of performance that indicate how efficiently a plant uses the three inputs of nameplate capacity, fuel, and other operating inputs to produce the good output, kilo-watts hours of electricity. Thus, they are measures of efficiency. These efficiency measures are bounded between zero and one, where one represents maximum efficiency. Therefore, at any point in time, plants assigned a score of one are deemed the most efficient relative to others in the reference set and thus, are placed on the efficiency frontier. All other plants are deemed inefficient and fall within the interior. Finally, an increase in the score of an individual plant or a group of plants across time suggests that an improvement in efficiency has been made.

The descriptive statistics and the distribution of the efficiency measures by deciles are presented in Table 9. Panel A of Table 9 provides a cross-sectional distribution of the efficiency scores of the pooled 1990 Phase One and Non-Phase One plants. In 1990, there were 16 plants on the efficiency frontier; nine related to Phase One and seven to Non-Phase One. Further, it appears that the Phase One plants dominate the high-end deciles, while Non-Phase One plants dominate the low-end deciles. This pattern is reflected in the averages as well. Specifically, the 1990 plants were moderately efficient and averaged an overall efficiency of 0.68. The average efficiency of the Phase One plants was 0.71, implying that these plants were a driving force in the efficiency of the overall group efficiency in 1990. The Non-Phase One plants posted an average efficiency of only 0.65, which was below both overall and Phase One efficiencies.

Panel B of Table 9 provides a cross-sectional analysis of the 1995 efficiency scores. After intervention, all three average efficiencies improved as overall efficiency averaged 0.69, while Phase One and Non-Phase One plants posted mean efficiencies of 0.72 and 0.67 respectively. In addition, of the 17 plants placed on the efficiency frontier 8 are Phase One. As with 1990, Phase One plant efficiency is higher than both the overall average and Non-Phase One efficiency, suggesting that the 1995 Phase One plants dominate the high-end deciles.

Panel C of Table 9 reflects the distribution of Phase One plant efficiency between 1990 and 1995. The results reveal an overall pool mean efficiency of 0.71, meaning that the inputs of the combined Phase One plants were 29 percent higher than they should have been. There also appears to be a difference in efficiency over time. Specifically, the 1990 Phase One plants posted an average efficiency of 0.68. However, at 0.73 the 1995 Phase One plants post a higher efficiency relative to both the overall and the 1990 plant average efficiencies. In terms of the deciles, the 1995 plants appear to moderately dominate the high-end distributions, and 9 of the 17 most efficient plants in the pool relate to 1995. This is an important observation because during this same time period, Phase One plants were required to and did successfully reduce pollution. Traditional pollution control theories suggest that any reduction in pollution would have caused either an increase in costs or a reduction in good output, either of which would have caused a reduction in efficiency. This outcome did not emerge and thus, there is some tentative support for the Porter Hypothesis and eco-efficiency.

Results of the Non-Phase One plant efficiency distributions are presented in Panel D of Table 9. Nineteen plants are on the best practices frontier. The overall pool efficiency for the Non-Phase One plants was 0.65. Comparatively, the average of the 1990 and 1995 Non-Phase One plants were 0.62 and 0.67 respectively. This suggests that relative to their 1990 counterparts, the 1995 Non-Phase One plants posted improvements.

6.4 Tests of the Malmquist Productivity Index

The descriptive statistics of Table 4 and the efficiency measure distributions of Table 9 indicate the possibility that Phase One plants were able to create value at a lower cost through productivity improvements. An additional evaluation of the effect of the 1990 CAAA on productivity over time is the Malmquist Productivity Index (MPI). The MPI measures the change in the productivity of a DMU between two time periods. One of the most important contributions of the MPI is that it can be multiplicatively decomposed into two parts: 1) an index that accounts for changes in technical efficiency (i.e., the catching-up effect); and 2) an index that accounts for shifts in the efficient frontier due to technological innovation (i.e., the frontier shift). When evaluating the MPI and its components, amounts greater than one indicate progress, while numbers smaller than one show regress. Amounts equal to one represent no change between the two periods.

There are several benefits of using the MPI to analyze changes in Phase One and Non-Phase One plants between 1990 and 1995. First, it has been suggested that improving technical efficiency and creating innovations can reduce pollution, lower production costs and hence, improve performance within the electric utility industry. The overall MPI provides a direct approach to evaluating these claims. Second, the component indexes quantify the extent efficiency and innovations impact the overall change. Finally, a comparison of the MPI, catch-up, and frontier shift indexes of the Phase One and Non-Phase One plants can highlight whether significant differences in productivity exist across plant type and moreover, how efficiency and innovation contribute to such a variance.

Table 10 presents the MPI, efficiency, and technology indexes for the Phase One plants and Table 11 presents the same information relative to the Non-Phase One plants. As denoted in Table 10, the maximum and minimum MPI value for Phase One plants was 1.998117 and 0.436665 respectively. Comparatively, the maximum and minimum MPI value for the Non-Phase One plants were 2.063284 and 0.28739 respectively. Further, it appears that the majority of the plants in both groups posted overall MPI improvements between 1990 and 1995. However, a comparison of all three indexes in both Tables 10 and 11 suggests that the improvements in the MPI of the two groups were achieved differently.

Table 12 provides summarized MPI, efficiency and technology data related to both Phase One and Non-Phase One plants. As denoted in Panel A of Table 12, over 75 percent of the Phase One plants improve productivity between 1990 and 1995. A mean MPI of 1.139 reflects this progress. A one-sample t-test indicates that this progress is significantly different from 1 at the 0.0001 level. Panel A of Table 12 also shows that the majority of the Phase One plants took advantage of *both* efficiency and innovation to improve productivity. Specifically, at 1.003 the catch-up index indicates that most of the Phase One plants maintained or slightly increased efficiency between the pre-Phase One and the Phase One periods in spite of reducing pollution from 5.1 to 2.8 tons. In addition, over 96 percent of Phase One plants posted improvements related to frontier shifts. Thus, at 1.141, the frontier shift index of Phase One plants supports the claims that this group used innovations to move to a higher efficiency frontier to improve productivity.

Panel B of Table 12 indicates that over 74 percent of the Non-Phase One plants improved productivity between 1990 and 1995 and that the overall MPI for the group was

1.204. A one-sample t-test indicates that this progress is significantly different from 1 at the 0.0001 level. However, relatively few Non-Phase One plants improved because of enhanced efficiency. Specifically, less than 40 percent of the Non-Phase One plants had an individual efficiency index greater than unity. Thus, the mean catch-up index of Non-Phase One plants was 0.968, which reflects a regress in efficiency between 1990 and 1995. Comparatively, the frontier shift index for Non-Phase One plants was 1.256. It appears that the Non-Phase One plants may have benefited from the Act as well, and that this benefit is due to changes in innovation that spilled over to that group.

6.4.1 Analysis of the Productivity Results

The results in Table 12 suggest that both Phase One and Non-Phase One plants improved productivity between 1990 and 1995. However, while the productivity gains posted by the groups are similar, the reasons for, approaches to, and implications of these changes vary across plant type. The productivity gains posted by the Phase One plants are easily explained. The 1990 CAAA required Phase One plants to reduce pollution but did not mandate any specific method to reduce the pollution. Therefore, Phase One plants were free to develop and promote innovations that would reduce pollution in an efficient and cost effective manner. Based on the component indexes posted by the Phase One plants, it is obvious the group took advantage of this latitude by creating innovative approaches to reduce pollution reduction while at the same time *at least* maintain efficiency. These results are consistent with those presented in Panel C of Table 4, which shows that between 1990 and 1995 Phase One plants maintained good output and reduced production costs while simultaneously reducing pollution. Together, these results suggest that the productivity of Phase One plants between the pre-Phase One and the Phase One periods was positively affected by efficiency *and* innovation.

The ability of Phase One plants to maintain or post improvements in efficiency between the pre-Phase One and the Phase One periods is particularly significant given these plants were required to reduce pollution. Traditional pollution control theory suggests that reducing pollution would require either an increase in costs or a reduction in good output, and that either of these reactions would cause a reduction in technical efficiency. There is no indication that this outcome occurred. In fact, in relation to their counterparts, Phase One plants performed *no worse* than Non-Phase One plants after intervention even though Phase One plants were required and did reduce their pollution.

Comparatively, Non-Phase One plants were not required to reduce pollution until Phase Two. In fact, Non-Phase One plants actually increased pollution between the pre-Phase One and Phase One periods. However, as Panel B of Table 12 indicates, Non-Phase One plants significantly improved overall productivity between the pre-Phase One and the Phase One periods. Moreover, the component indexes of MPI indicate Non-Phase One plants experienced a regress in efficiency and relied exclusively on frontier shifts to improve productivity. Thus, one possible and compelling explanation is that the improvement of Non-Phase One plants is the result of that group's capitalization of the technological innovations either directly created or spurred by Phase One plants.

The ability of Non-Phase One plants to take advantage of industry innovations is referred to as a second mover advantage. A second mover advantage is the ability of a firm to benefit from the experiences of others who were either required to implement a technology or strategy early or chose to do so. Day and Montgomery (1983) advocate that the presence of a second mover advantage in a technologically driven market occurs when followers end up with the same or lower costs than pioneers because they have the opportunity to learn from the pioneers' mistakes (Day and Montgomery, 1983, p. 48). Theoretical work suggests that this phenomenon is not uncommon. For instance, Lederer and Rhee (1995) show that early adopters have a competitive advantage only when competitors are slow to adopt technology. Further, they contend that when all firms are able to quickly respond to technological innovations and adopt them soon after they are introduced, returns on such investments are normal or have a zero net present value (Lederer and Rhee, 1995, p. 361 – 362). Mohr (2002) provides a specific discussion of second mover advantage in relation to the Porter Hypothesis and environmental regulation. His theoretical model assumes that the introduction of a new technology created in response to an environmental regulation allows for the possibility that all firms can jointly increase long-term productivity. Thus, he suggests that firms can gain a second mover advantage if they wait for others to bear the short-term costs of adopting a technology (Mohr, 2002, p. 162 – 163).

6.5 Test of Hypotheses

The descriptive evidence presented thus far suggests that Phase One plants responded to the 1990 CAAA by reducing pollution. In addition, it appears that this group improved efficiency and adopted innovative technologies to improve productivity. Therefore, Phase One of the 1990 CAAA offers an attractive opportunity for a *direct* test of the validity of the Porter Hypothesis and its influence on the promotion of eco-efficient behavior. In order to determine this influence, a two-stage approach is adopted. In the first stage the plant level DEA efficiency measures computed via Program B are used to determine whether traditional, pure eco-efficient, or regulation induced eco-efficient behavior is present prior to and after the intervention of the Act. This will provide some indication of how plants operated prior to intervention and whether intervention had an impact on subsequent behavior. In the second stage, regression Models 1 and 2 are used to empirically determine if the variation in the calculated efficiencies significantly relate to the intervention of the 1990 CAAA.

6.5.1 Hypothesis One

6.5.1.1 Results of Rank Sum Tests

Hypothesis One addresses the impact of pollution on plant efficiency. This is done by pooling Phase One and Non-Phase One plants in both 1990 and 1995 to create DEA scores and then using rank sum tests to determine how the presence of pollution and efforts to reduce it affect efficiency. This test investigates whether the traditional or pure eco-efficient approach to pollution control exists prior to the Act and thus, provides a benchmark for those activities occurring after intervention. The null hypothesis pertaining to 1990 cross sectional efficiency assumes that Phase One plants are more efficient than Non-Phase One plants. Rejection of the null supports Hypothesis One.

Subsequent to intervention, the Porter Hypothesis assumes that Phase One plants have been induced to adopt eco-efficient behavior. Therefore, Phase One plants should be more efficient than the Non-Phase One plants after intervention. However, if the traditional approach holds, then Phase One plants will become less efficient because they are required to reduce pollution. The Porter Hypothesis would project an opposite outcome because it assumes that firms will be free to develop innovative ways to reduce pollution while reducing costs. Thus, the null hypothesis pertaining to 1995 cross sectional efficiency assumes that Non-Phase One plants are more efficient than Phase One plants. Therefore, rejection of the null will provide evidence that the Act stimulates eco-efficient behavior and will offer support for Hypothesis One.

Table 13 reports the results of the 1990 and 1995 cross sectional analyses. In 1990, the rank sum test reveals that at the 0.02 level of significance, the efficiency of Phase One plants is higher than that of the Non-Phase One plants. These results fail to reject the null hypothesis related to 1990 cross sectional efficiency and thus, do not provide support for Hypothesis One. These results can be interpreted as support that the traditional view of pollution control was in place in 1990. Therefore, these results can be used as a benchmark for analyzing the impact of intervention in 1995.

In 1995, the rank sum test indicates that the efficiency of the Phase One plants is greater than the Non-Phase One plants at a 0.05 level of significance. Thus, these results reject the null hypothesis related to 1995 cross sectional relative efficiency and thus, provide support for Hypothesis One. While the tests suggest that Phase One plants were more efficient than their Non-Phase One counterparts in 1990 and 1995, the 1995 outcome is especially important. Specifically, while cross sectional tests for both 1990 and 1995 indicate Phase One plants are more efficient, the 1995 results emerge even after an intervening event required Phase One plants to reduce pollution. Thus, in 1995 Phase One plants maintained the dominance of Non-Phase One that they established in 1990 plants even though the were required to and did reduce pollution. In addition, as evidenced in Panel B of Table 4, the Phase One plants had a significantly lower CKWH than Non-Phase One plants, which also suggests that Phase One plants improved efficiency relative to the Non-Phase One plants after intervention. Thus, when all of these results are evaluated, there is evidence to suggest that the Act did promote eco-efficient behavior to the extent that plants affected did find ways to reduce pollution while at the same time reduced costs and at least maintained good output.

6.5.2 Hypothesis Two

6.5.2.1 Results of Rank Sum Tests

Hypothesis Two addresses how the 1990 CAAA impacted plant efficiency over time. Plants were pooled by plant type and DEA scores were calculated for each plant type and used in the rank sum test to evaluate changes within the pool. The null hypothesis pertaining to Phase One plants assumes that they are more efficient in 1990 than in 1995. Rejection of the null supports Hypothesis Two. The null hypothesis pertaining to Non-Phase One plants assumes that they are more efficient in 1995 than in 1990. Rejection of the null supports Hypothesis Two.

Table 14 reports the results of the Phase One and the Non-Phase One longitudinal rank sum tests. Tests reveal that at the 0.06 level of significance, the efficiency of the 1995 Phase One plants is greater than the efficiency of the 1990 Phase One plants. Therefore, even after intervention the Phase One plants were able to improve their efficiency. This suggests that this group of plants was able to develop and implement techniques to reduce pollution and production costs while simultaneously at least maintaining the production of good output. Thus, the results reject the null hypothesis relative to the longitudinal efficiency of Phase One plants and provide support for Hypothesis Two.

The rank sum test of the Non-Phase One plants indicates that at the 0.11 level of significance, there is no difference between the efficiency of the 1990 and 1995 Non-Phase One plants. This appears to indicate that the efficiency of the Non-Phase One plants remained relatively the same between 1990 and 1995. These results reject the null hypothesis that Non-Phase One plants improved efficiency between the pre-Phase One and the Phase One periods. This provides support for Hypothesis Two.

Therefore, the results of the longitudinal rank sum tests provide solid evidence in support of Hypothesis Two along several dimensions. First, the results of the test of Phase One plants show that the group improved efficiency between 1990 and 1995 in spite of the fact that Phase One plants reduced SO_2 by more than 50 percent. Moreover, it appears that these gains were made through the use of both improvements in efficiency and the use of innovation. Finally, Phase One plant results are corroborated the Non-Phase One plant results. Specifically, the longitudinal tests of the Non-Phase One plants indicate that their efficiency did not materially differ between 1990 and 1995. Thus, all of these results combine to suggest that plants can use efficiency and innovation to reduce pollution and production costs, while simultaneously maintaining good output. Therefore, there is direct evidence to support the Porter Hypothesis and eco-efficiency.

6.5.2.2 Results of Regression Analysis

Hypothesis Two is an interventionist hypothesis that assumes that the Act actually encouraged Phase One plants to become efficient. As denoted in Chapter 5, Model 1 is used to estimate the relationship between efficiency and the Act. This is accomplished by regressing the efficiency scores of the pooled 1990 and 1995 Phase One plants on a proxy of intervention (EVENT) and two control variables (CLIM and STRICT). A similar regression is conducted for Non-Phase One plants. Positive and significant results for intervention for Phase One plants provide support for Hypothesis Two. Insignificant results for intervention for Non-Phase One plants also provide support for Hypothesis Two.

As presented in Chapter 5, Model 2 is designed to measure the effect of intervention on efficiency when Phase One and Phase Two plants are evaluated together. Simultaneously regressing Phase One and Non-Phase One plant efficiencies on the intervention and conditioning variables, as well as the additional variable TYPE accomplishes this task. TYPE is included to account for any variation in efficiency related to plant type. Positive and significant results for the intervention *and* the type variable provide strong support for Hypothesis Two.

Tables 15–17 show the coefficient matrices for the Phase One, Non-Phase One, and the combined groups. The data were examined for evidence of multicollinearity as its presence makes it difficult to obtain accurate estimates of the individual effects of the explanatory variables. All of the correlation coefficients between the explanatory variables are below 20 percent. Based on these results, multicollinearity is not considered a problem. The highest correlations in all Tables are between STRICT and CLIM. This type of relationship is expected given that both variables measure the restrictions imposed on a plant by the state in which it is located. No statistical relationship between STRICT and EVENT is posted in Tables 15, 16, or 17. Additionally, no relationship between TYPE and EVENT is posted in Table 17.

The evidence from Model 1 for Phase One plants is summarized in Panel A of Table 18. First, EVENT is positive and significant at the 0.06 level. This infers that intervention had a positive effect on the efficiency of Phase One plants. As expected, CLIM has a negative impact on efficiency. However, the impact is not significant at the 0.45 level. STRICT is significant at the 0.004 level but has a negative impact, which is contrary to that expected. Together, these results suggest that plants affected by the 1990 CAAA responded by simultaneously reducing pollution and production costs while at least maintaining good output. This provides direct support for the Porter Hypothesis and eco-efficiency. Moreover, the efficiency of Phase One plants does not appear to be materially affected by how favorably state regulators approve requests for increased expenditures. However, contrary to expectations, the stringency of the environmental climate of the state in which a plant operates has a significant negative impact on efficiency. This may infer that states do not allow flexibility in pollution control and thus, may establish laws and regulations that add additional costs beyond those incurred to satisfy federal mandates.

Panel B of Table 18 presents the regression results of the Non-Phase One plants. For this group, intervention is positive and significant at the 0.08 level. These results run counter to those expected. There are several possible reasons for this outcome. First, there is a clear indication that Non-Phase One plants made use of the second mover advantage to create improvements between 1990 and 1995. Specifically, the frontier shift index analysis in Panel B of Table 12 indicates that Non-Phase One plant productivity improved between the pre-Phase One and the Phase One period because of shifts in the efficiency frontier created by innovations. However, because the frontier shift was so large, the Non-Phase One plants were able to post overall improvements in productivity between the two time periods. Thus, one can conclude that while intervention had a significant and positive impact on Non-Phase One plants, the progress is more a function of improvements that arose because of the actions taken by Phase One plants in reaction to the Act and not those initiated by the Non-Phase One plants themselves. With respect to the control variables, CLIM is the right sign but is not significant at the 0.17 level of significance. STRICT is negative and significant at the 0.02 level. Thus, the previous discussion of the results related to CLIM and STRICT remain applicable.

Model 2 results are presented in Panel C of Table 18. For the combined model, intervention is positive and significant at the 0.03 level. TYPE is positive and significant and the 0.0073 level. These results provide some additional insights about the relationship between efficiency and intervention. First, the results for intervention suggest continued support for the Porter Hypothesis. More importantly, when these results are combined with the favorable outcome of TYPE, there is evidence to infer that the efficiency improvements of the electric utility industry between the pre-Phase One and the Phase One periods were significantly related to Phase One plants. This provides strong and direct evidence for eco-efficiency and the Porter Hypothesis. As before, CLIM is the right sign but is not significant at the 0.26 level. Finally, STRICT is significant at the 0.0002 level but doesn't have the hypothesized sign.

In summary, the regression results provide support for the Porter Hypothesis as Phase One and Non-Phase One plants were positively affected by the Act. This indicates that environmental regulations can be used to improve efficiency while at the same time reduce pollution. However, while both types were positively affected, Phase One plants were impacted the most.

CHAPTER 7

CONCLUSIONS

The purpose of this study is to evaluate the Porter Hypothesis by investigating how endogenous changes made by utilities in response to Phase One of the 1990 CAAA affect productive efficiency. If the Porter Hypothesis is valid, then utilities subject to the 1990 CAAA should engage in process improvement and process innovation, thus exhibiting an increase in productive efficiency relative to performance prior to the Act. Thus, the study had two objectives. First, it sought to find evidence to support the premise that pollution is a form of technical inefficiency. Second, it sought to determine whether a properly designed environmental regulation enacted to reduce pollution actually spurred improvements in efficiency.

Tests conducted reveal that pollution is a form of technical inefficiency. Cross sectional rank sum tests indicate that prior to intervention, Phase One plants were more efficient even though they had higher levels of pollution. This outcome suggests that prior to the Act, Phase One plants may have actually used excessive pollution as a way to maintain efficiency relative to their Non-Phase One counterparts by passing the cost of their pollution to others. However, after intervention Phase One plants reduced pollution significantly and were more efficient than Non-Phase One plants who increased pollution. Longitudinal rank sum tests provide evidence to suggest that regulation can induce efficiency. Specifically, Phase One plants post an improvement between 1990 and

1995 even though they significantly reduced pollution during the same time. This outcome suggests that eliminating pollution does improve efficiency. This observation is corroborated by the results of Non-Phase One plant tests during the same period. Non-Phase One plants were not required to reduce pollution. Tests reveal that these plants did not materially change pollution levels between 1990 and 1995 and that no statistical difference in efficiency existed between this time period.

Regression results reveal that the Act was a determinant in the variation in efficiency between 1990 and 1995. Thus, there is evidence to support the claim that a properly designed regulation can induce changes that have a positive impact. However, both Phase One and Non-Phase One plants were significantly and positively affected by intervention. Additional analyses indicate that Phase One productivity was affected by both efficiency and innovation while Non-Phase One plants relied exclusively on innovations to post progress. Non-Phase One improvements indicate the presence a second mover advantage. Specifically, the innovations created by the Phase One plants may have indirectly produced benefits for the Non-Phase One because they were able to capitalize on these innovations. However, an analysis of the combined group indicates that the Act and the Phase One plant type significantly and positively affect the variation in efficiency between 1990 and 1995. All of these results provide direct support for the Porter Hypothesis and eco-efficiency.

The implications of adopting innovation techniques have also been used as a possible explanation of why the market for pollution permits did not evolve as anticipated. One of the cornerstones of the Act was the emergence of pollution permits that could be traded. It was felt that these permits would contribute to cost reductions by allowing a firm to either bank allowances or to trade them on the open market (Swift, 2001, p. 341). However, one of the issues that surrounds these permits is their valuation. Indeed, as noted by Sansing and Strauss (1998), establishing a value for these permits is important when addressing how environmental policies can be combined with other regulatory tools mandated by the government.

The results of investigating the cost of compliance before and after intervention can be used to explain how the value of these permits is achieved. For instance, it was anticipated that with the technology available prior to intervention, compliance costs would be high and, therefore, these costs would drive the price of permits to settle at around $1,500/ton (Hughes, 2000, p. 213). However, by 1992 compliance cost projections had been reduced from the initial estimate of $151 billion to just around $836 million (U.S. Department of Energy, Energy Information Administration, 1997, p. 12). At the same time, permits were trading at around $265/ton (Hughes, 2000, p. 213). Hughes (2000) suggests that the cost of pollution permits were less than that projected during Phase One because of lower compliance costs (Hughes, 2000, p. 213). Hughes goes on to imply that the installation of innovative technologies allowed firms to over-comply with emission reduction requirements, which freed thousands of allowances for the market and drove permit prices down. An analysis by the Energy Information Administration goes further and suggests that because of the flexibility provided by the Act and the cost reductions created by its flexibility, permit prices became much lower (U.S. Department of Energy, Energy Information Administration, 1997, p. 46).

The findings of this study are important because they can provide management with information that can be used to develop value-adding strategies on how to handle pollution and regulations. They are especially important because they demonstrate these implications at the plant level where it is expected that any changes made in reaction to a regulation will initially surface. However, a noted criticism of pollution control studies is that they may not recognize the economic consequences of the interaction between the various governmental policies controlling firm activities (Freedman and Jaggi, 1994). For instance, a regulatory tool that the government uses to implement public policy is taxation. Sansing and Strauss (1998) suggest that tax policies should be evaluated in conjunction with pollution control regulations. Using a stylized model, they theoretically investigate how compliance with SO_2 emission standards could be affected by tax policy. Their findings indicate that tax policies could undermine the efficiency of pollution control regulations. Therefore, a logical extension of this study would be to empirically investigate whether tax policies inhibit the ability of the 1990 CAAA to induce eco-efficient behavior.

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APPENDIXES

APPENDIX A

TABLES

TABLE 1
Sample of Phase One Plants with Available FERC Form 1 Data[a]

Total Phase One Plants[b]	164
Plants Not Required to File a FERC Form 1[c]	(25)
Initial Set of Plants with FERC Form 1 Data	139
Data Not Located in the FERC Form 1[d]	(15)
Data in FERC Form 1 was Unusable[e]	(26)
Unable to Match[f]	(14)
Final Phase One Plants Used[g]	84

[a] The data for the study are obtained from the Federal Energy Regulatory Commission Form 1 (FERC Form 1). Only major investor-owned electric utilities are required to submit a FERC Form 1. FERC Form 1 submissions are required annually. Data presented in a FERC Form 1 include income and earnings, operating and maintenance expenses, and various production statistics. Plant level financial and operating data are located in the "Steam Generating Plant Statistics for Large Plants" section of the FERC Form 1.

[b] Includes all of the electric utility plants affected by Phase One of Title IV of the 1990 CAAA. These plants are referred to as Phase One plants. Starting in 1995, the SO_2 emissions of Phase One plants were evaluated by the Environmental Protection Agency (EPA) to ensure that they are in compliance with the 1990 CAAA.

[c] Includes those plants that are publicly-owned and thus, are not required to submit a FERC Form 1. Publicly-owned utilities are operated by (1) the federal government; (2) a state or local municipality; or (3) an electric cooperative.

[d] Includes those Phase One plants whose "Steam Generating Plant Statistics For Large Plants" data were not included with the FERC Form 1 filed with the Commission.

[e] Includes those Phase One plants whose "Steam Generating Plant Statistics For Large Plants" data filed in the FERC FORM 1 were incomplete.

[f] Includes those Phase One plants that could not be matched with a control plant based on the criteria established.

[g] Reflects the total number of Phase One Plants: (1) whose data is complete; (2) can be successfully with Non-Phase One plants. Thus, the grand total of the plants included in the study is 168 (i.e., 84 Phase One and 84 Non-Phase One).

TABLE 2
Total Sample Distribution by NERC Region[a]

NERC Region	No. of Total Sample Plants	No. of Phase One Plants	No. of Non-Phase One Plants
ECAR [b]	52	26	26
SERC [c]	28	14	14
MAIN [d]	26	13	13
NPCC [e]	20	10	10
SPP [f]	20	10	10
MACC [g]	16	8	8
WSCC [h]	4	2	2
MAPP [I]	2	1	1
Total Plants	168	84	84

[a] The North American Electric Reliability Council (NERC) region was used to match Phase One with Non-Phase One plants. This table provides a distribution of the total sample (Phase One and Non-Phase One) by NERC region. The Council was formed in 1968 by the electric utility industry to promote the reliability and adequacy of bulk power supply in the electric systems of North America. There are nine regional reliability councils that encompass all the power of the United States, Canada, and Mexico. With the exception of the Electric Reliability Council of Texas (ERCOT), all NERC regions are represented in this study.
[b] East Central Area Reliability Coordination Agreement
[c] Southeastern Electric Reliability Council
[d] Mid-America Interconnected Council
[e] Northeast Power Coordinating Council
[f] Southwest Power Pool
[g] Mid-Atlantic Area Council
[h] Western Systems Coordinating Council
[i] Mid-Continent Area Power Pool

TABLE 3
Total Sample Distribution by State[a]

State	No. of Total Sample Plants	No. of Phase One Plants	No. of Non-Phase One Plants
Illinois [d]	17	8	9
Indiana [b]	16	11	5
New York [e]	15	7	8
Pennsylvania [g,b]	13	7	6
Florida [c]	12	3	9
Georgia [c]	10	8	2
Ohio [b]	10	8	2
Missouri [f,d]	9	9	0
Kentucky [b]	8	3	5
Wisconsin [d]	8	5	3
Michigan [b,d]	8	0	8
Virginia [c,b,]	6	1	5
West Virginia [b]	5	2	3
Oklahoma [f]	5	0	5
Maryland [g]	4	2	2
Louisiana [f]	3	0	3
New Hampshire [e]	3	2	1
California [h]	2	0	2
Kansas [f]	2	1	1
Mississippi [c]	2	2	0
Wyoming [h]	2	2	0
Arkansas [f]	1	0	1
Connecticut [e]	1	0	1
Delaware [g]	1	0	1
Iowa [i]	1	0	1
Massachusetts [e]	1	1	0
Minnesota [I]	1	1	0
New Jersey [g]	1	1	0
South Carolina [c]	1	0	1
Total Plants	168	84	84
Total States	29	20	23

[a] The North American Electric Reliability Council (NERC) regions were used to match Phase One with Non-Phase One plants. This table provides a distribution of the states included in this study and the NERC region(s) in which they reside. Twenty-nine states in eight regions are represented in this study. The regions associated with the states are:

[b] East Central Area Reliability Coordination Agreement
[d] Mid-America Interconnected Council
[f] Southwest Power Pool
[h] Western Systems Coordinating Council
[c] Southeastern Electric Reliability Council
[e] Northeast Power Coordinating Council
[g] Mid-Atlantic Area Council
[i] Mid-Continent Area Power Pool

TABLE 4
Summary and Descriptive Statistics for Phase One and Non-Phase One Plants[a]

Panel A: Cross Sectional Analysis – 1990 Comparisons (n = 84)

Part I: Total Unit Comparisons

Variable	1990 Phase One Plants	1990 Non-Phase One Plants	Net Diff	% Diff
NPC	72407	73064	657	0.91
KWH	332428	264437	(67991)	(20.45)
PC	6995	6837	(158)	(2.26)
FC	5467	5370	(97)	(1.78)
OC	1527	1467	(60)	(3.96)
CKWH	1.98	3.31	1.33	67.17
POLL	5153797	1378377	(3775420)	(72.26)

Part II: Mean Unit Comparisons

	1990 Phase One Plants (n = 84)				*1990 Non-Phase One Plants (n = 84)*					
Variable	Mean	Std. Dev	Min.	Max.	Mean	Std. Dev	Min.	Max.	T Statistic	Prob > |T|
NPC	861.98	607.60	98	2600	869.81	613.93	83.50	2932	0.08	0.9339
KWH	3957	3307	214	14559	3148	3084	13	16088	-1.64	0.1029
PC	83	63	10	270	81	70	2	366	-0.18	0.8567
FC	65	54	5	243	63	56	1	251	-0.13	0.8931
OC	18	11	2	61	17	20	1	164	-0.28	0.7776
CKWH	0.023	0.008	0.011	0.071	0.039	0.050	0.014	0.416	2.84***	0.0056
POLL	61354	68062	3259	365308	16409	29040	0	205662	-5.57**	0.0001

TABLE 4 (continued)

Panel B: Cross Sectional Analysis –1995 Comparisons (n = 84)

Part I: Total Unit Comparisons

Variable	1995 Phase One Plants	1995 Non-Phase One Plants	Net Diff	% Diff
NPC	71816	72557	741	1.03
KWH	317387	266246	(51141)	(16.11)
PC	5331	5008	(323)	(6.06)
FC	3907	3835	(72)	(1.84)
OC	1424	1172	(252)	(17.70)
CKWH	1.66	2.21	0.55	33.13
POLL	2810175	1397005	(1413170)	(50.29)

Part II: Mean Unit Comparisons

	1995 Phase One Plants (n = 84)				*1995 Non-Phase One Plants (n = 84)*					
Variable	**Mean**	**Std. Dev**	**Min.**	**Max.**	**Mean**	**Std. Dev**	**Min.**	**Max.**	**T Statistic**	**Prob > |T|**
NPC	854.96	614.16	98	2600	863.77	614.14	108	2932	0.09	0.9260
KWH	3778	3573	112	14806	3169	2984	46	17772	-1.20	0.2324
PC	63	54	4	286	59	48	3	303	-0.48	0.6305
FC	46	42	1	199	45	36	1	162	-0.14	0.8892
OC	16	14	2	87	13	16	1	140	-1.27	0.2076
CKWH	0.019	0.007	0.009	0.045	0.026	0.022	0.008	0.183	2.46****	0.0157
POLL	33454	40824	6	252365	16631	27285	0	186399	-3.14**	0.0020

TABLE 4 (continued)

Panel C: Longitudinal Analysis - Phase One Plants (n = 84)

Part I: Total Unit Comparisons

Variable	1990 Phase One Plants	1995 Phase One Plants	Net Diff	% Diff
NPC	72407	71816	(591)	(0.82)
KWH	332428	317387	(15041)	(4.52)
PC	6995	5331	(1664)	(23.79)
FC	5467	3907	(1560)	(28.53)
OC	1527	1424	(103)	(6.75)
CKWH	1.98	1.66	(0.32)	(16.16)
POLL	5153797	2810175	(2343622)	(45.47)

Part II: Mean Unit Comparisons

	1990 Phase One Plants (n = 84)				*1995 Phase One Plants (n = 84)*					
Variable	**Mean**	**Std. Dev**	**Min.**	**Max.**	**Mean**	**Std. Dev**	**Min.**	**Max.**	**T Statistic**	**Prob > |T|**
NPC	861.98	607.60	98	2600	854.96	614.16	98	2600	0.07	0.9407
KWH	3957	3307	214	14559	3778	3573	112	14806	0.34	0.7365
PC	83	63	10	270	63	54	4	286	2.16****	0.0322
FC	65	54	5	243	46	42	1	199	2.45****	0.0154
OC	18	11	2	61	16	14	2	87	0.61	0.5397
CKWH	0.023	0.008	0.011	0.071	0.019	0.007	0.009	0.045	3.07*	0.0025
POLL	61354	68062	3259	365308	33454	40824	6	252365	3.22*	0.0016

TABLE 4 (continued)

Panel D: Longitudinal Analysis - Non-Phase One Plants (n = 84)

Part I: Total Unit Comparisons

Variable	1990 Non-Phase One Plants	1995 Non-Phase One Plants	Net Diff	% Diff
NPC	73064	72557	(507)	(0.69)
KWH	264437	266246	1809	0.68
PC	6837	5008	(1829)	(26.75)
FC	5370	3835	(1535)	(28.58)
OC	1467	1172	(295)	(20.11)
CKWH	3.31	2.21	(1.10)	(33.23)
POLL	1378377	1397005	18628	1.35

Part II: Mean Unit Comparisons

	1990 Non-Phase One Plants (n = 84)				*1995 Non-Phase One Plants (n = 84)*					
Variable	**Mean**	**Std. Dev**	**Min.**	**Max.**	**Mean**	**Std. Dev**	**Min.**	**Max.**	**T Statistic**	**Prob > |T|**
NPC	869.81	613.93	83.50	2932	863.77	614.14	108	2932	0.06	0.9493
KWH	3148	3084	13	16088	3169	2984	46	17772	-0.05	0.9634
PC	81	70	2	366	59	48	3	303	2.33****	0.0211
FC	63	56	1	251	45	36	1	162	2.48****	0.0142
OC	17	20	1	164	13	16	1	140	1.24	0.2174
CKWH	0.039	0.050	0.014	0.416	0.026	0.022	0.008	0.183	2.17***	0.0322
POLL	16409	29040	0	205662	16631	27285	0	186399	-0.05	0.9594

TABLE 4 (continued)

[a] This table reports selected summary level plant data an descriptive and statistics for the sample plants on: (1) a cross-sectional (between) plant type basis; and (2) a longitudinal (within) plant type basis. Part One of this Table provides a comparison of the unit level activity of plants. Part Two reflects the mean of those activities as a well as the results of tests of the difference in the means. All statistics (i.e., maximum, minimum) are based on single year means. All p-values relate to a two-sided test where * $p < 0.005$, ** $p < 0.005$, *** $p < 0.01$, and **** $p < 0.05$. The variable definitions:

NPC = The nameplate generating capacity is the full-load capacity rating of a plant to continuously produce electricity. Table amounts are presented as millions of watts capacity.

KWH = The kilowatt per hour of electricity generated. A watthour (Wh) is an electrical energy unit of measure equal to 1 watt of power supplied to an electric circuit steadily for an hour. Thus, KWH represents one thousand watthours. Table amounts are presented as millions of KWH.

PC = The total production costs incurred to produce electricity as defined by the accounting requirements of the Operation and Maintenance Expense Accounts of the FERC Uniform System of Accounts. Production costs are generally decomposed into two components: (1) fuel costs; and (2) all other operating costs. Because of inflation, nominal prices from different years cannot be compared without making some adjustments. Thus, the Consumer Price Index is used to deflate 1995 to 1990 prices. Table amounts are presented in millions of dollars.

FC = The costs associated with the purchase, handling, and storage of the fuel burned to produce electricity. These costs are the largest and most variable item on a utility's list of production expenses. Because of inflation, nominal prices from different years cannot be compared without making some adjustments. Thus, the Consumer Price Index is used to deflate 1995 to 1990 prices. Table amounts are presented in millions of dollars.

OC = The operating costs incurred to produce electricity. These costs include labor and other expenses related to operating and maintaining a plant. Because of inflation, nominal prices from different years cannot be compared without making some adjustments. Thus, the Consumer Price Index is used to deflate 1995 to 1990 prices. Table amounts are presented in millions of dollars.

CKWH = The cost per kilowatt hour.

POLL = The amount of SO_2 pollution (i.e., bad output) created when good output (KWH) is produced. Table amounts are presented in tons.

TABLE 5

1990 Cross Sectional DEA Scores – Phase One and Non-Phase One Plants (n = 168)[a]

Plant	DEA Score	Plant	DEA Score	Plant	DEA Score	Plant	DEA Score
NPO-03	1	PO-60	0.818604	NPO-69	0.673732	NPO-58	0.549753
NPO-14	1	NPO-07	0.815684	PO-47	0.670449	NPO-43	0.547782
NPO-18	1	NPO-37	0.810494	PO-30	0.669502	NPO-31	0.544256
NPO-40	1	PO-76	0.805899	PO-32	0.667319	PO-78	0.53478
NPO-55	1	PO-08	0.801139	PO-63	0.662074	NPO-85	0.531145
NPO-61	1	NPO-63	0.800779	NPO-32	0.661927	PO-59	0.529372
NPO-68	1	NPO-48	0.796831	NPO-62	0.660411	NPO-59	0.526684
PO-03	1	NPO-02	0.796067	PO-24	0.657238	NPO-24	0.525934
PO-23	1	NPO-26	0.791251	PO-21	0.653897	PO-14	0.522985
PO-36	1	PO-68	0.791014	PO-52	0.650439	PO-20	0.519636
PO-40	1	NPO-42	0.784866	NPO-45	0.647357	PO-18	0.506282
PO-42	1	PO-80	0.784271	PO-73	0.644146	PO-02	0.505418
PO-64	1	NPO-67	0.782949	NPO-34	0.642362	NPO-72	0.504343
PO-67	1	NPO-65	0.777706	PO-26	0.641667	NPO-16	0.502
PO-85	1	NPO-46	0.776658	PO-37	0.639261	NPO-28	0.501682
PO-86	1	NPO-33	0.767665	NPO-60	0.637656	PO-53	0.495975
NPO-36	0.996157	PO-54	0.763582	NPO-04	0.637109	NPO-27	0.490782
NPO-64	0.996121	PO-34	0.75932	PO-72	0.634463	NPO-86	0.489902
NPO-35	0.987356	PO-41	0.759079	NPO-77	0.634381	NPO-41	0.471176
PO-28	0.986298	NPO-22	0.758498	PO-58	0.629334	PO-15	0.466945
NPO-29	0.973607	PO-16	0.758082	PO-31	0.629268	PO-50	0.464643
NPO-57	0.95976	PO-01	0.753439	PO-65	0.62774	NPO-74	0.459459
PO-33	0.938478	PO-43	0.752125	NPO-56	0.627191	NPO-38	0.448724
PO-57	0.929296	PO-38	0.747275	NPO-15	0.62511	NPO-01	0.436509
NPO-82	0.929204	PO-75	0.74716	PO-29	0.619449	NPO-50	0.424441
NPO-71	0.928452	NPO-39	0.746991	PO-09	0.615248	NPO-49	0.422489
PO-69	0.927042	NPO-81	0.743243	PO-79	0.613832	NPO-84	0.417248
PO-82	0.893329	PO-70	0.742026	NPO-08	0.604963	NPO-10	0.41195
NPO-79	0.873181	NPO-51	0.739161	NPO-44	0.602591	PO-77	0.409375
NPO-66	0.862678	PO-51	0.723095	PO-48	0.602329	PO-44	0.37846
PO-35	0.859353	PO-62	0.713047	NPO-53	0.596306	NPO-75	0.340647
PO-84	0.858185	PO-61	0.708191	PO-27	0.595802	NPO-13	0.337114
PO-22	0.855152	PO-46	0.704263	PO-39	0.594147	NPO-78	0.32577

Plant	DEA Score	Plant	DEA Score	Plant	DEA Score	Plant	DEA Score
NPO-30	0.853549	PO-45	0.696177	PO-06	0.5939	NPO-76	0.321759
PO-81	0.843922	NPO-11	0.691469	NPO-47	0.592767	NPO-80	0.301022
PO-07	0.836654	PO-49	0.686765	NPO-25	0.590121	NPO-73	0.299072
PO-10	0.833021	NPO-06	0.684554	NPO-21	0.581247	NPO-54	0.298552
PO-66	0.831735	PO-25	0.684345	PO-17	0.57927	PO-71	0.270512
NPO-23	0.827953	PO-13	0.682835	NPO-05	0.578879	NPO-17	0.266033
PO-74	0.827032	PO-11	0.678745	PO-04	0.57717	NPO-19	0.261278
PO-56	0.820378	NPO-09	0.675936	PO-05	0.57	NPO-20	0.253509
PO-55	0.820117	NPO-52	0.674825	PO-19	0.569431	NPO-70	0.251576

[a] This table reports the cross sectional DEA scores for the Phase One (PO) and Non-Phase One (NPO) plants for 1990. DEA Score are bound between zero and one. Thus, the maximum DEA score is equal to one. The table contents are presented in descending DEA score order.

TABLE 6
1995 Cross Sectional DEA Scores – Phase One and Non-Phase One Plants (n = 168)[a]

Plant	DEA Score	Plant	DEA Score	Plant	DEA Score	Plant	DEA Score
NPO-03	1	PO-80	0.858943	PO-61	0.682714	PO-52	0.554835
NPO-09	1	NPO-06	0.855769	NPO-72	0.682026	PO-15	0.554751
NPO-14	1	PO-76	0.851435	PO-39	0.681129	NPO-25	0.551612
NPO-36	1	PO-32	0.844618	NPO-24	0.679456	PO-18	0.53578
NPO-40	1	PO-68	0.84456	NPO-11	0.674921	NPO-51	0.530669
NPO-44	1	NPO-82	0.842386	PO-21	0.670514	PO-65	0.529192
NPO-48	1	PO-74	0.839055	PO-24	0.669727	PO-11	0.51306
NPO-68	1	PO-13	0.835351	PO-19	0.665646	PO-77	0.51077
NPO-79	1	PO-07	0.830078	PO-34	0.66486	NPO-59	0.507303
PO-03	1	NPO-47	0.828009	NPO-39	0.660469	NPO-84	0.502163
PO-23	1	NPO-29	0.826392	PO-48	0.655854	NPO-38	0.501184
PO-36	1	NPO-04	0.824089	NPO-15	0.653331	PO-09	0.498944
PO-40	1	NPO-37	0.821632	PO-26	0.644037	NPO-08	0.49583
PO-62	1	PO-51	0.821614	NPO-27	0.642416	NPO-17	0.494113
PO-67	1	NPO-32	0.817739	NPO-45	0.636635	PO-58	0.488903
PO-85	1	PO-55	0.81164	NPO-31	0.619017	NPO-76	0.48578
PO-86	1	PO-75	0.799	NPO-05	0.618031	NPO-01	0.484085
PO-42	0.996585	NPO-56	0.792475	NPO-23	0.617347	NPO-50	0.478647
PO-82	0.978624	PO-47	0.791343	PO-27	0.615034	NPO-19	0.477499
NPO-64	0.968032	PO-64	0.789061	PO-54	0.614105	NPO-86	0.476382
PO-84	0.965586	PO-16	0.786828	PO-31	0.609289	PO-17	0.475661
NPO-22	0.963979	PO-41	0.777572	NPO-16	0.603477	NPO-61	0.475005
NPO-55	0.961199	PO-25	0.777154	PO-37	0.602777	PO-44	0.474031
NPO-41	0.955612	PO-38	0.77453	PO-49	0.588184	NPO-75	0.456943
PO-63	0.935258	NPO-71	0.770314	NPO-46	0.588066	NPO-43	0.456903
NPO-33	0.928305	NPO-57	0.768475	NPO-52	0.58659	PO-14	0.44682
PO-28	0.925	PO-66	0.766237	PO-04	0.581731	PO-05	0.434646
NPO-63	0.921177	PO-46	0.764405	NPO-28	0.581182	PO-02	0.421866
NPO-67	0.918065	PO-72	0.740615	PO-20	0.580388	NPO-10	0.410681
NPO-35	0.902269	PO-10	0.731218	PO-73	0.576975	NPO-49	0.409936
NPO-30	0.902139	NPO-69	0.729316	NPO-02	0.576863	PO-59	0.408826
PO-33	0.890751	NPO-65	0.725424	NPO-26	0.575856	NPO-70	0.399836
PO-01	0.890652	PO-69	0.717864	NPO-62	0.574293	NPO-13	0.399139

Plant	DEA Score	Plant	DEA Score	Plant	DEA Score	Plant	DEA Score
PO-56	0.889142	PO-08	0.710853	PO-06	0.570838	NPO-20	0.395407
NPO-66	0.886351	PO-70	0.706248	PO-50	0.570338	NPO-80	0.386417
NPO-81	0.884722	NPO-07	0.699961	NPO-74	0.56865	PO-60	0.379199
PO-35	0.880678	PO-78	0.697904	PO-30	0.567065	NPO-85	0.373464
PO-81	0.873955	NPO-34	0.69646	NPO-73	0.563147	NPO-60	0.361058
NPO-18	0.866459	PO-29	0.695448	NPO-42	0.563057	NPO-58	0.347957
PO-43	0.865356	NPO-77	0.695117	PO-53	0.562295	NPO-54	0.340432
PO-57	0.863871	PO-79	0.690798	NPO-53	0.558212	NPO-78	0.311013
PO-22	0.860805	PO-45	0.686503	NPO-21	0.558123	PO-71	0.260754

[a] This table reports the cross sectional DEA scores for the Phase One (PO) and Non-Phase One (NPO) plants for 1995. DEA Score are bound between zero and one. Thus, the maximum DEA score is equal to one. The table contents are presented in descending DEA score order.

TABLE 7
Longitudinal DEA Scores – 1990 verses 1995 Phase One Plants (n = 168)[a]

Plant	DEA Score	Plant	DEA Score	Plant	DEA Score	Plant	DEA Score
PO-90-03	1	PO-95-57	0.847602	PO-90-46	0.694786	PO-95-50	0.571578
PO-90-23	1	PO-95-38	0.847393	PO-95-79	0.691942	PO-95-30	0.568694
PO-90-36	1	PO-90-07	0.846024	PO-95-78	0.691466	PO-95-52	0.568277
PO-90-40	1	PO-95-68	0.842412	PO-95-45	0.690374	PO-90-27	0.565939
PO-90-64	1	PO-95-74	0.840649	PO-90-43	0.68685	PO-90-05	0.565888
PO-90-67	1	PO-95-07	0.830346	PO-90-34	0.682341	PO-95-53	0.562625
PO-90-85	1	PO-90-55	0.824362	PO-95-39	0.680476	PO-90-45	0.561074
PO-90-86	1	PO-95-76	0.822153	PO-90-62	0.676693	PO-90-48	0.553975
PO-95-03	1	PO-90-56	0.820378	PO-90-11	0.675949	PO-90-72	0.552748
PO-95-22	1	PO-95-55	0.815454	PO-95-61	0.674805	PO-95-18	0.552302
PO-95-23	1	PO-90-28	0.813736	PO-95-15	0.672931	PO-90-26	0.544035
PO-95-36	1	PO-90-10	0.813243	PO-90-30	0.667766	PO-90-29	0.538474
PO-95-40	1	PO-90-08	0.805036	PO-95-19	0.667234	PO-90-19	0.538203
PO-95-42	1	PO-95-47	0.801323	PO-90-49	0.665408	PO-95-58	0.533104
PO-95-67	1	PO-90-74	0.798001	PO-90-52	0.661986	PO-90-59	0.531114
PO-95-85	1	PO-95-10	0.797705	PO-90-25	0.660328	PO-95-65	0.530977
PO-95-86	1	PO-95-51	0.797178	PO-90-47	0.65836	PO-90-79	0.529364
PO-95-82	0.992346	PO-90-80	0.790284	PO-95-26	0.658021	PO-90-39	0.522278
PO-95-32	0.989188	PO-95-16	0.786187	PO-95-48	0.657469	PO-90-17	0.520931
PO-95-28	0.985557	PO-95-75	0.778845	PO-95-21	0.653927	PO-95-11	0.514633
PO-95-62	0.968837	PO-95-41	0.778317	PO-95-27	0.650623	PO-95-77	0.508429
PO-90-42	0.957537	PO-95-25	0.778198	PO-90-63	0.646324	PO-95-09	0.507964
PO-95-84	0.944998	PO-90-81	0.776951	PO-95-54	0.638349	PO-90-78	0.507184
PO-95-63	0.936454	PO-90-54	0.772234	PO-90-41	0.627113	PO-90-31	0.495772
PO-90-57	0.932274	PO-95-64	0.766673	PO-90-58	0.626787	PO-95-17	0.476279
PO-90-60	0.916651	PO-95-66	0.763697	PO-90-65	0.619353	PO-95-44	0.474461
PO-90-76	0.916474	PO-90-16	0.760554	PO-90-13	0.61698	PO-90-53	0.471207
PO-95-13	0.910999	PO-90-01	0.753439	PO-95-31	0.610389	PO-90-02	0.459596
PO-90-33	0.900944	PO-90-75	0.74822	PO-90-73	0.603993	PO-90-20	0.457253
PO-90-69	0.899241	PO-90-38	0.746254	PO-95-37	0.599462	PO-90-14	0.457081
PO-95-81	0.895599	PO-90-70	0.744482	PO-90-09	0.595786	PO-95-14	0.449691
PO-95-43	0.893933	PO-95-24	0.743051	PO-90-24	0.595095	PO-90-15	0.447032
PO-95-33	0.89289	PO-95-72	0.740858	PO-90-37	0.594378	PO-95-05	0.435538

Plant	DEA Score	Plant	DEA Score	Plant	DEA Score	Plant	DEA Score
PO-90-82	0.890799	PO-90-68	0.73552	PO-95-06	0.591146	PO-95-60	0.434892
PO-95-56	0.877364	PO-90-66	0.734127	PO-90-04	0.590433	PO-90-18	0.427388
PO-95-35	0.862073	PO-90-51	0.730054	PO-95-49	0.589789	PO-95-02	0.422163
PO-95-01	0.861044	PO-95-69	0.713499	PO-90-06	0.589371	PO-90-50	0.403092
PO-90-35	0.860203	PO-95-08	0.711493	PO-95-20	0.586446	PO-95-59	0.400919
PO-90-84	0.858185	PO-90-61	0.710719	PO-95-04	0.582095	PO-90-77	0.396718
PO-90-22	0.85496	PO-95-70	0.709325	PO-90-32	0.578906	PO-90-44	0.308048
PO-95-46	0.851927	PO-95-34	0.70541	PO-95-73	0.578622	PO-95-71	0.282237
PO-95-80	0.851405	PO-95-29	0.70041	PO-90-21	0.577659	PO-90-71	0.217221

[a] This table reports the longitudinal DEA scores for the Phase One (PO) plants for 1990 (90) and 1995 (95). DEA Score are bound between zero and one. Thus, the maximum DEA score is equal to one. The table contents are presented in descending DEA score order.

TABLE 8
Longitudinal DEA Scores – 1990 verses 1995 Non-Phase One Plants (n = 168)[a]

Plant	DEA Score	Plant	DEA Score	Plant	DEA Score	Plant	DEA Score
NPO-90-03	1	NPO-95-63	0.817877	NPO-95-73	0.621425	NPO-95-86	0.485507
NPO-90-14	1	NPO-90-07	0.815684	NPO-95-31	0.619904	NPO-95-01	0.482929
NPO-90-18	1	NPO-90-67	0.808578	NPO-90-60	0.613134	NPO-90-31	0.481393
NPO-90-36	1	NPO-95-32	0.802944	NPO-90-62	0.612462	NPO-90-47	0.478827
NPO-90-55	1	NPO-95-47	0.801759	NPO-95-53	0.610385	NPO-95-19	0.478797
NPO-90-57	1	NPO-90-33	0.799885	NPO-90-53	0.606677	NPO-90-28	0.474799
NPO-90-61	1	NPO-90-35	0.798371	NPO-95-52	0.603224	NPO-95-50	0.47399
NPO-90-64	1	NPO-90-26	0.796099	NPO-90-08	0.60132	NPO-90-74	0.461196
NPO-90-71	1	NPO-90-23	0.793395	NPO-95-16	0.593213	NPO-95-43	0.45667
NPO-95-03	1	NPO-95-57	0.79303	NPO-95-74	0.590962	NPO-90-41	0.439953
NPO-95-09	1	NPO-90-02	0.792117	NPO-90-05	0.58795	NPO-90-72	0.435299
NPO-95-14	1	NPO-90-63	0.780334	NPO-90-15	0.586547	NPO-90-38	0.430722
NPO-95-36	1	NPO-90-81	0.779295	NPO-90-58	0.58488	NPO-95-61	0.429669
NPO-95-40	1	NPO-90-51	0.769466	NPO-95-72	0.58452	NPO-95-80	0.426029
NPO-95-44	1	NPO-95-69	0.756382	NPO-95-28	0.582869	NPO-95-20	0.424458
NPO-95-48	1	NPO-95-56	0.750842	NPO-95-02	0.580914	NPO-95-70	0.421302
NPO-95-64	1	NPO-90-39	0.749281	NPO-95-46	0.57783	NPO-95-10	0.410311
NPO-95-68	1	NPO-95-77	0.736165	NPO-95-62	0.577421	NPO-95-49	0.409876
NPO-95-79	1	NPO-90-48	0.732059	NPO-90-46	0.57409	NPO-95-75	0.408333
NPO-95-55	0.978601	NPO-95-65	0.725424	NPO-90-21	0.573861	NPO-95-13	0.399139
NPO-95-22	0.974982	NPO-95-24	0.708234	NPO-95-45	0.572175	NPO-90-01	0.398364
NPO-95-30	0.97409	NPO-95-07	0.699961	NPO-95-21	0.570856	NPO-90-49	0.388992
NPO-95-41	0.955612	NPO-95-34	0.698974	NPO-95-42	0.562957	NPO-95-60	0.387214
NPO-90-29	0.952614	NPO-90-52	0.691894	NPO-90-86	0.561461	NPO-95-85	0.3695
NPO-95-66	0.944353	NPO-90-42	0.687702	NPO-95-25	0.555546	NPO-90-43	0.368499
NPO-95-35	0.943887	NPO-90-09	0.685517	NPO-90-59	0.554071	NPO-90-10	0.364937
NPO-95-81	0.934572	NPO-90-06	0.6788	NPO-95-59	0.553735	NPO-90-78	0.353896
NPO-95-33	0.93451	NPO-90-22	0.678359	NPO-90-85	0.543717	NPO-95-58	0.347799
NPO-90-30	0.920958	NPO-95-11	0.67699	NPO-90-34	0.542737	NPO-90-75	0.345569
NPO-90-40	0.913563	NPO-90-11	0.671582	NPO-90-25	0.542425	NPO-90-50	0.344838
NPO-90-68	0.90139	NPO-90-32	0.671071	NPO-90-24	0.535818	NPO-90-84	0.333145
NPO-90-66	0.884359	NPO-90-65	0.669813	NPO-95-51	0.535589	NPO-95-78	0.328273
NPO-90-82	0.876576	NPO-95-15	0.667969	NPO-90-45	0.535413	NPO-90-13	0.317786

Plant	DEA Score	Plant	DEA Score	Plant	DEA Score	Plant	DEA Score
NPO-95-67	0.870239	NPO-90-04	0.662318	NPO-95-18	0.534987	NPO-95-54	0.317355
NPO-95-06	0.867829	NPO-90-69	0.660522	NPO-90-44	0.521817	NPO-90-73	0.316924
NPO-95-82	0.862085	NPO-95-27	0.651571	NPO-95-76	0.519045	NPO-90-76	0.314434
NPO-95-37	0.850187	NPO-90-56	0.647462	NPO-95-08	0.515932	NPO-90-54	0.287376
NPO-95-71	0.846727	NPO-95-39	0.639781	NPO-90-16	0.505758	NPO-90-80	0.286691
NPO-90-79	0.841932	NPO-90-77	0.638829	NPO-95-38	0.503007	NPO-90-20	0.251223
NPO-95-29	0.832277	NPO-95-26	0.632357	NPO-95-17	0.500121	NPO-90-19	0.249323
NPO-95-04	0.831824	NPO-95-05	0.63078	NPO-90-27	0.49323	NPO-90-17	0.247433
NPO-90-37	0.830956	NPO-95-23	0.62308	NPO-95-84	0.492595	NPO-90-70	0.234609

[a] This table reports the longitudinal DEA scores for the Non-Phase One (NPO) plants for 1990 (90) and 1995 (95). DEA Score are bound between zero and one. Thus, the maximum DEA score is equal to one. The table contents are presented in descending DEA score order.

TABLE 9
Frequencies and Summary Statistics of DEA Scores[a]

Panel A: Cross Sectional Analysis – 1990 Comparisons

Efficiency Score Ranges	Total Sample Plant Distribution	1990 Phase One Plant Distribution	1990 Non-Phase One Plant Distribution
1.00	16	9	7
0.90 – 0.99	11	4	7
0.80 – 0.89	21	14	7
0.70 – 0.79	27	15	12
0.60 – 0.69	39	23	16
0.50 – 0.59	27	13	14
0.40 – 0.49	14	4	10
0.30 – 0.39	6	1	5
0.20 – 0.29	7	1	6
N	168	84	84
Mean	0.68	0.71	0.65
Standard Deviation	0.19	0.16	0.21
Minimum	0.25	0.27	0.25
Maximum	1.00	1.00	1.00

Panel B: Cross Sectional Analysis – 1995 Comparisons

Efficiency Score Ranges	Total Sample Plant Distribution	1995 Phase One Plant Distribution	1995 Non-Phase One Distribution
1.00	17	8	9
0.90 – 0.99	14	5	9
0.80 – 0.89	27	17	10
0.70 – 0.79	19	14	5
0.60 – 0.69	30	16	14
0.50 – 0.59	30	14	16
0.40 – 0.49	20	8	12
0.30 – 0.39	10	1	9
0.20 – 0.29	1	1	0
N	168	84	84
Mean	0.69	0.72	0.67
Standard Deviation	0.19	0.17	0.20
Minimum	0.26	0.26	0.31
Maximum	1.00	1.00	1.00

TABLE 9 (continued)

Panel C: Longitudinal Analysis – Phase One Plant Comparisons

Efficiency Score Range	Total Sample Plant Distribution	1990 Phase One Plant Distribution	1995 Phase One Plant Distribution
1.00	17	8	9
0.90 – 0.99	12	5	7
0.80 – 0.89	27	11	16
0.70 – 0.79	28	13	15
0.60 – 0.69	29	16	13
0.50 – 0.59	36	20	16
0.40 – 0.49	15	8	7
0.30 – 0.39	2	2	0
0.20 – 0.29	2	1	1
N	168	84	84
Mean	0.71	0.68	0.73
Standard Deviation	0.17	0.17	0.17
Minimum	0.21	0.21	0.28
Maximum	1.00	1.00	1.00

Panel D: Longitudinal Analysis – Non-Phase One Plant Comparisons

Efficiency Score Range	Total Sample Plant Distribution	1990 Non-Phase One Plant Distribution	1995 Non-Phase One Plant Distribution
1.00	19	9	10
0.90 – 0.99	12	4	8
0.80 – 0.89	16	6	10
0.70 – 0.79	16	10	6
0.60 – 0.69	29	16	13
0.50 – 0.59	32	14	18
0.40 – 0.49	21	8	13
0.30 – 0.39	17	11	6
0.20 – 0.29	6	6	0
N	168	84	84
Mean	0.65	0.62	0.67
Standard Deviation	0.21	0.22	0.20
Minimum	0.23	0.23	0.31
Maximum	1.00	1.00	1.00

[a] This table reports the distribution and summary statistics for the Data Envelopment Analysis (DEA) scores for the sample plants. These scores are presented on: 1) a cross-sectional (between) plant type basis; and (2) a longitudinal (within) plant type basis. DEA Score are bound between zero and one. Thus, the maximum DEA score is equal to one.

TABLE 10
Phase One Malmquist Productivity Indexes and Their Decomposition (n = 84)[a]

Phase One Plant	Malmquist Index	Catch-Up Effect	Frontier Shift Effect	Phase One Plant	Malmquist Index	Catch-Up Effect	Frontier Shift Effect
PO-63	1.998117	1.397013	1.430279	PO-75	1.136542	1.024099	1.109797
PO-32	1.616576	1.243594	1.299922	PO-44	1.124605	0.986996	1.139421
PO-62	1.505976	1.473497	1.022042	PO-42	1.113746	1.013495	1.098916
PO-79	1.445558	1.276012	1.132871	PO-66	1.107385	0.953676	1.161176
PO-47	1.423572	1.226178	1.160983	PO-74	1.104692	0.981924	1.125028
PO-39	1.42022	1.262098	1.125285	PO-41	1.089629	0.896191	1.215845
PO-15	1.418822	1.306154	1.086259	PO-35	1.070595	0.950357	1.126519
PO-13	1.409057	1.181927	1.192169	PO-54	1.061961	0.955792	1.11108
PO-78	1.395606	1.277009	1.092871	PO-37	1.060144	0.965891	1.097582
PO-03	1.382821	1.092194	1.266095	PO-48	1.058525	0.93377	1.133604
PO-04	1.379774	0.833426	1.655545	PO-07	1.05494	1.017934	1.036354
PO-16	1.377662	1.053978	1.307107	PO-21	1.051145	0.931054	1.128985
PO-72	1.376413	1.254269	1.097382	PO-23	1.045968	1.0302	1.015306
PO-50	1.363251	1.196162	1.139688	PO-33	1.045826	0.895855	1.167406
PO-68	1.354211	1.211266	1.118013	PO-31	1.037579	0.918383	1.129789
PO-43	1.346866	1.203011	1.119578	PO-10	1.035126	0.97747	1.058985
PO-22	1.343228	1.269317	1.058229	PO-40	1.02417	0.989342	1.035204
PO-67	1.335717	0.902984	1.479225	PO-14	1.018136	0.900458	1.130687
PO-56	1.331017	1.224483	1.087004	PO-86	1.012789	0.908944	1.114248
PO-28	1.324398	1.18353	1.119023	PO-73	1.006443	0.914197	1.100904
PO-46	1.32328	1.089861	1.214174	PO-08	1.002688	0.907547	1.104833
PO-29	1.320122	1.189415	1.109892	PO-61	1.002602	0.908054	1.104122
PO-18	1.314101	1.168765	1.12435	PO-58	0.995564	0.918532	1.083864
PO-53	1.306385	1.192233	1.095747	PO-34	0.991227	0.895306	1.107138
PO-06	1.299056	0.967457	1.342754	PO-85	0.983426	1	0.983426
PO-19	1.283132	1.157182	1.108842	PO-36	0.979024	1.00654	0.972663
PO-38	1.270512	1.147961	1.106755	PO-02	0.957662	0.848727	1.128352
PO-45	1.25299	1.115636	1.123117	PO-30	0.941902	0.843636	1.11648
PO-84	1.243848	1.193314	1.042347	PO-65	0.901965	0.825003	1.093287
PO-81	1.23852	1.043282	1.187138	PO-52	0.891352	0.840497	1.060506
PO-24	1.237252	1.123451	1.101295	PO-59	0.875128	0.818509	1.069174
PO-25	1.232183	1.125066	1.095209	PO-57	0.862962	0.880374	0.980221
PO-82	1.220944	1.033579	1.181278	PO-09	0.861276	0.751769	1.145665
PO-26	1.217964	1.024547	1.188783	PO-49	0.847167	0.759266	1.115771
PO-27	1.200678	1.093905	1.097608	PO-77	0.825891	0.44019	1.876215
PO-55	1.192743	1.068649	1.116122	PO-69	0.810425	0.748889	1.08217
PO-01	1.186853	1.143324	1.038073	PO-11	0.796832	0.712408	1.118506
PO-80	1.185825	1.061001	1.117647	PO-17	0.772639	0.678417	1.138885
PO-20	1.173592	1.056906	1.110404	PO-05	0.70079	0.629175	1.113823
PO-51	1.172639	1.05967	1.106608	PO-76	0.686713	0.562188	1.221499
PO-71	1.155257	1.036206	1.114892	PO-64	0.584539	0.573632	1.019013
PO-70	1.151613	1.079233	1.067066	PO-60	0.436665	0.351266	1.24312

[a] This table reports the changes in productivity between 1990 and 1995 of the Phase One (PO) plants based on the DEA based Malmquist Productivity Index and its two components: 1) a change in efficiency (i.e., the catching-up effect); and 2) a change in the efficient frontier technology (i.e., the frontier shift). The contents of the table are presented in descending order based on the Malmquist Productivity Index.

TABLE 11
Non-Phase One Malmquist Productivity Indexes and Their Decomposition (n = 84)[a]

NonPhase One Plant	Malmquist Index	Catch-Up Effect	Frontier Shift Effect	NonPhase One Plant	Malmquist Index	Catch-Up Effect	Frontier Shift Effect
NPO-41	2.063284	1.572062	1.31247	NPO-67	1.161851	1.179535	0.985008
NPO-48	2.016323	1.555578	1.296189	NPO-77	1.15918	0.90161	1.285678
NPO-73	2.000387	1.697561	1.178389	NPO-40	1.153652	0.980625	1.176446
NPO-44	1.963719	1.76569	1.112154	NPO-35	1.153047	0.784923	1.468994
NPO-17	1.950501	1.441912	1.352718	NPO-11	1.13288	0.927001	1.222092
NPO-70	1.913443	1.404753	1.36212	NPO-37	1.131427	0.796644	1.420243
NPO-19	1.844568	1.407434	1.310589	NPO-68	1.129475	1	1.129475
NPO-09	1.686747	1.489293	1.132582	NPO-49	1.127231	0.853429	1.320826
NPO-20	1.661315	1.36455	1.217482	NPO-05	1.124905	0.877438	1.282033
NPO-22	1.595645	1.138201	1.4019	NPO-25	1.123872	0.856833	1.311658
NPO-31	1.554914	0.939801	1.654514	NPO-21	1.117578	0.84453	1.323314
NPO-76	1.538324	1.183198	1.300141	NPO-45	1.109204	0.886673	1.250972
NPO-32	1.517989	1.07558	1.411321	NPO-66	1.098873	0.839836	1.308437
NPO-34	1.494573	0.909319	1.643617	NPO-59	1.062353	0.847312	1.253792
NPO-50	1.475607	1.024366	1.440507	NPO-53	1.053648	0.815625	1.291829
NPO-84	1.45875	0.99635	1.464094	NPO-52	1.041706	0.823868	1.26441
NPO-28	1.427488	0.979776	1.456952	NPO-86	1.040371	0.867403	1.19941
NPO-24	1.421372	1.059799	1.341171	NPO-82	1.011944	0.68492	1.477462
NPO-79	1.413045	0.941714	1.500503	NPO-46	1.001644	0.767677	1.304772
NPO-47	1.405492	1.142625	1.230056	NPO-36	1.000982	0.967359	1.034758
NPO-80	1.39348	1.115579	1.249109	NPO-42	0.987307	0.763013	1.293959
NPO-81	1.372535	1.074846	1.276959	NPO-62	0.980745	0.6821	1.437832
NPO-33	1.356233	1.04177	1.301855	NPO-29	0.947233	0.687483	1.377828
NPO-13	1.321809	1.024825	1.28979	NPO-14	0.937392	0.724113	1.294537
NPO-06	1.313419	1.080084	1.216034	NPO-08	0.932758	0.741643	1.257691
NPO-74	1.311593	1.004893	1.305207	NPO-78	0.91857	0.875053	1.049731
NPO-27	1.310911	1.031444	1.270947	NPO-39	0.910295	0.78067	1.166043
NPO-72	1.310171	1.122442	1.16725	NPO-02	0.907073	0.70243	1.291337
NPO-30	1.28885	1.191865	1.081372	NPO-51	0.897986	0.728918	1.231944
NPO-54	1.269169	0.971438	1.306485	NPO-58	0.890643	0.657273	1.355058
NPO-69	1.256924	0.905378	1.388287	NPO-55	0.883394	0.748959	1.179496
NPO-75	1.251773	1.177079	1.063457	NPO-23	0.872291	0.60229	1.44829
NPO-38	1.24747	0.90477	1.378771	NPO-71	0.848611	0.788229	1.076604
NPO-63	1.24719	1.621574	0.769123	NPO-85	0.781253	0.560065	1.394934
NPO-04	1.238263	1.181292	1.048227	NPO-26	0.779356	0.617113	1.262908
NPO-56	1.219179	1.045906	1.165668	NPO-64	0.778263	0.767299	1.014289
NPO-43	1.217343	0.89483	1.360418	NPO-60	0.775971	0.607589	1.277132
NPO-16	1.21726	1.171421	1.039131	NPO-07	0.746724	1.179015	0.633345
NPO-01	1.192647	0.921046	1.294884	NPO-57	0.700566	0.62339	1.1238
NPO-10	1.188633	0.899754	1.321065	NPO-03	0.693506	0.676931	1.024487
NPO-15	1.182521	0.880583	1.342884	NPO-18	0.501524	1.003206	0.499921
NPO-65	1.178252	0.731962	1.609717	NPO-61	0.28739	0.245154	1.172283

[a] This table reports the changes in productivity between 1990 and 1995 of the Non-Phase One (NPO) plants based on the DEA based Malmquist Productivity Index and its two components: 1) a change in efficiency (i.e., the catching-up effect); and 2) a change in the efficient frontier technology (i.e., the frontier shift). The contents of the table are presented in descending order based on the Malmquist Productivity Index.

TABLE 12
Malmquist Productivity Indices and Their Decomposition[a]

Model: $$M_{j1,2} = \frac{E_{j2}^{2}}{E_{j1}^{1}} \cdot \frac{E_{j2}^{1}}{E_{j2}^{2}} = M_{cj1,2} \cdot M_{Fj}^{1,2}, \quad 1,2 \in T$$

	Panel A: Phase One MPI Analysis			*Panel B: Non-Phase One MPI Analysis*		
	Phase One Plants			**Non Phase One Plants**		
Plant Type Statistics	**Malmquist Index**	**Catch-Up Effect**	**Frontier Shift Effect**	**Malmquist Index**	**Catch-Up Effect**	**Frontier Shift Effect**
Mean	1.139	1.003	1.141	1.204	0.968	1.256
Plants with index < 1	20	39	3	22	51	4
Plants with index = 1	0	1	0	0	1	0
Plants with index > 1	64	44	81	62	32	80
N	84	84	84	84	84	84
Prob > |T|	5.31 * (0.0001)	0.15 (0.8784)	10.00* (0.0001)	5.47 * (0.0001)	-1.06 (0.2944)	12.77* (0.0001)

[a] This table reports the changes in productivity between 1990 and 1995 of the Phase One and the Non-Phase One plants using a DEA based Malmquist productivity index. This index, denotes as $M_{j,1,2}$, provides a comparison of the productivity of DMU j between two time periods 1 and 2. One of the most important contributions of a DEA based MPI is that it can be multiplicatively decomposed into two parts: one accounting for the changes in efficiency (i.e., the catching-up effect) and the other accounting for changes in the efficient frontier technology (i.e., the frontier shift). When evaluating a DEA based MPI and its components, amounts greater than one indicate progress, while numbers smaller than one show regress. Amounts equal to one represent no change between the two periods. Amounts in parenthesis contain the p-values for a one-sample test and * $p < 0.0001$

TABLE 13
Cross Sectional Analyses of Productive Efficiency[a]

H_{11}:	**1990 Phase One Plant verses 1990 Non-Phase One Plant Efficiency [b]**	
	Z-score	2.14*
	Prob < Z	(0.02)
H_{12}:	**1995 Phase One Plant verses 1995 Non-Phase One Plant Efficiency [c]**	
	Z-score	-1.63*
	Prob < Z	(0.05)

[a] This table provides the results of Hypothesis One testing. The amount in parenthesis contains the p-value for a one-sided Wilcoxon rank sum test where * $p < 0.05$.

[b] Hypothesis One pertains to cross-sectional relative efficiency. The 1990 null hypothesis assumes that the expected rank sum of the Phase One plants is greater than the expected rank sum of the Non-Phase One plants. Rejection of the null will provide support for Hypothesis One. Tests reveal that the expected rank sum of 1990 Phase One is significantly greater than that of the 1990 Non-Phase One plants. These results do not support Hypothesis One and provides evidence that the traditional approach to pollution control was in place prior to intervention.

[c] Hypothesis One pertains to cross-sectional relative efficiency. The 1995 null hypothesis assumes that the expected rank sum of the Non-Phase One plants is greater than that of the 1995 Phase One plants. Rejection of the null will provide support for Hypothesis One. Tests reveal that the expected rank sum of the 1995 Phase One plant is significantly higher than that of the 1995 Non-Non-Phase One plants. These results provide some support for Hypothesis One and indicate that the Act did induce eco-efficient behavior.

TABLE 14
Longitudinal Analyses of Productive Efficiency[a]

H_{21}:	**1990 Phase One Plant verses 1995 Phase One Plant Efficiency [b]**	
	Z-score	-1.56 **
	Prob < Z	(0.06)
H_{22}:	**1990 Non-Phase One Plant verses 1995 Non-Phase One Plant Efficiency [c]**	
	Z-score	-1.22
	Prob < Z	(0.11)

[a] This table provides the results of Hypothesis Two testing. The amount in parenthesis contains the p-value for a one-sided Wilcoxon rank sum test where ** $p < 0.10$.

[b] Hypothesis Two pertains to longitudinal relative efficiency. The null hypothesis for Phase One plants assumes that the expected rank sum of the 1990 Phase One plants will be greater than those of 1995. Rejection of the null will provide support for Hypothesis Two. Tests reveal that the expected rank sum of the 1995 Phase One plant is significantly greater than that of the 1990 Phase One plants. These results support Hypothesis Two.

[c] Hypothesis Two pertains to longitudinal relative efficiency. The null hypothesis for Non Phase One plants assumes that the expected rank sum of the 1995 Non-Phase One plants will be greater than those of 1990. Rejection of the null will provide support for Hypothesis Two. Tests reveal that the 1995 Non-Phase One efficiency is not statistically greater than that of the 1990 Non-Phase One plants. These results support Hypothesis Two.

Table 15
Correlation Coefficients for Longitudinal Analysis of Phase One Plants[a]
(n = 168)

	STRICT	CLIM	EVENT	DEA
STRICT	1.0000	0.1488 (0.0542) *	0.0000 (1.00)	-0.2022 (0.0086)**
CLIM		1.0000	0.0251 (0.7467)	-0.0476 (0.5394)
EVENT			1.0000	0.1233 (0.1112)
DEA				1.0000

[a] This table is the correlation matrix for the regression model of the longitudinal analysis of the Phase One plants. The amounts in parenthesis contain the p-value for a two-tailed test and * $p < 0.10$, ** $p < 0.01$. The variable definitions are:

STRICT = Measures the stringency of state environmentalism.
CLIM = Measures how favorably a state regulatory commission addresses rate increase requests.
EVENT = Dummy variable equal to one if 1995 and zero if 1990.
DEA = The data envelopment (efficiency) scores of the electric utility plants. These scores lie between zero and one.

Table 16
Correlation Coefficients for Longitudinal Analysis of Non-Phase One Plants[a]
(n = 168)

	STRICT	CLIM	EVENT	DEA
STRICT	1.0000	0.1643 (0.0332) *	0.0000 (1.0000)	-0.1710 (0.0267) *
CLIM		1.0000	0.0183 (0.8139)	-0.1033 (0.1824)
EVENT			1.0000	0.1095 (0.1573)
DEA				1.0000

[a] This table is the correlation matrix for the regression model of the longitudinal analysis of the Non-Phase One plants. The amounts in parenthesis contain the p-value for a two-tailed test and * $p < 0.05$. The variable definitions are:

STRICT = Measures the stringency of state environmentalism.
CLIM = Measures how favorably a state regulatory commission addresses rate increase requests.
EVENT = Dummy variable equal to one if 1995 and zero if 1990.
DEA = The data envelopment (efficiency) scores of the electric utility plants. These scores lie between zero and one.

Table 17
Correlation Coefficients for Longitudinal Analysis of All Plants[a]
(n = 336)

	TYPE	STRICT	CLIM	EVENT	DEA
TYPE	1.0000	-0.0819 (0.1339)	0.0833 (0.1273)	0.0000 (1.0000)	0.1486 (0.0063) *
STRICT		1.0000	0.1506 (0.0057) *	0.0000 (1.0000)	-0.2073 (0.0001) **
CLIM			1.0000	0.0208 (0.7035)	-0.05809 (0.2884)
EVENT				1.0000	0.1019 (0.0618) ***
DEA					1.0000

[a] This table is the correlation matrix for the regression model of the longitudinal analysis of all of the plants in the study. This would include both Phase One and Non-Phase One plants. The amounts in parenthesis contain the p-value for a two-tailed test and * $p < 0.01$**$p < 0.0001$, and $p < 0.10$. The variable definitions are:

TYPE = Dummy variable equal to one if Phase One Plant and zero if a Non-Phase One plant.
STRICT = Measures the stringency of state environmentalism.
CLIM = Measures how favorably a state regulatory commission addresses rate increase requests.
EVENT = Dummy variable equal to one if 1995 and zero if 1990.
DEA = The data envelopment (efficiency) scores of the electric utility plants. These scores lie between zero and one.

TABLE 18
Longitudinal Tests of the Effect of the 1990 CAAA on Efficiency[a]

Model One: $DEA = \beta_0 + \beta_1 EVENT + \beta_2 CLIM + \beta_3 STRICT + e$

Panel A: 1990 verses 1995 Phase One Plants (n = 168)

	β_0	β_1	β_2	β_3
		(+)	(-)	(+)
Coefficient Estimate	0.7135	0.0461	-0.003	-0.0635
t-value	32.34	1.55	-0.10	-2.68
p-value	0.0001	0.06 *	0.45	0.004 ***

Panel B: 1990 verses 1995 Non-Phase One Plants (N = 168)

	β_0	β_1	β_2	β_3
		(+)	(-)	(+)
Coefficient Estimate	0.6538	0.0503	-0.0272	-0.046
t-value	23.68	1.38	-0.96	-1.99
p-value	0.0001	0.08 *	0.17	0.02 **

Model Two: $DEA = \beta_0 + \beta_1 EVENT + \beta_2 CLIM + \beta_3 STRICT + \beta_4 TYPE + e$

Panel C: 1990/1995 Phase One verses 1990/1995 Non-Phase One Plants (n = 336)

	β_0	β_1	β_2	β_3	β_4
		(+)	(-)	(+)	(+)
Coefficient Estimate	0.6394	0.0412	-0.0126	-0.0559	0.0550
t-value	31.07	1.84	-0.63	-3.56	2.44
p-value	0.0001	0.03 **	0.26	0.0002*****	0.0073 ****

[a] This table provides the regression results related to Hypothesis Two. Model One represents plant-type specific regression tests for both the pooled 1990/1995 Phase One and the pooled 1990/1995 Non-Phase One plants. Model Two represents a regression test pooling of all plants (Phase One and Non-Phase One) for both years and * $p < 0.10$, ** $p < 0.05$, *** $p < 0.005$, **** $p < 0.01$, and ***** $p < 0.0005$. The variable definitions are:

EVENT = Dummy variable equal to one if 1995 and equal to zero if 1990.
CLIM = Measures how favorably a state regulatory commission addresses rate increases.
STRICT = Measures the stringency of state environmental policies
TYPE = Dummy variable equal to one if Phase One Plant and zero if a Non-Phase One plant.

APPENDIX B

FIGURE 1
Traditional Output Production Trade-offs

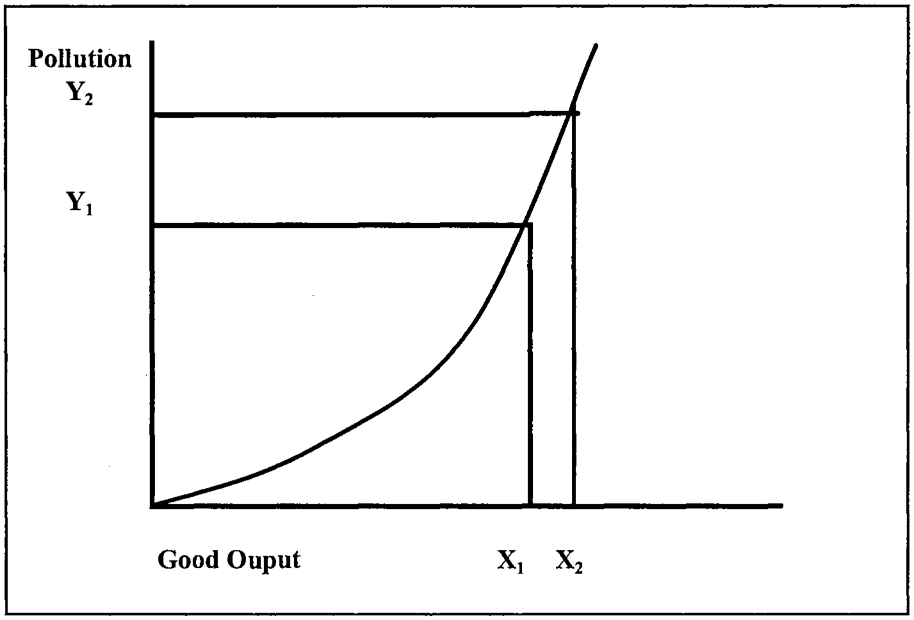


FIGURE 2
Eco-Efficient Reactions to Environmental Regulation

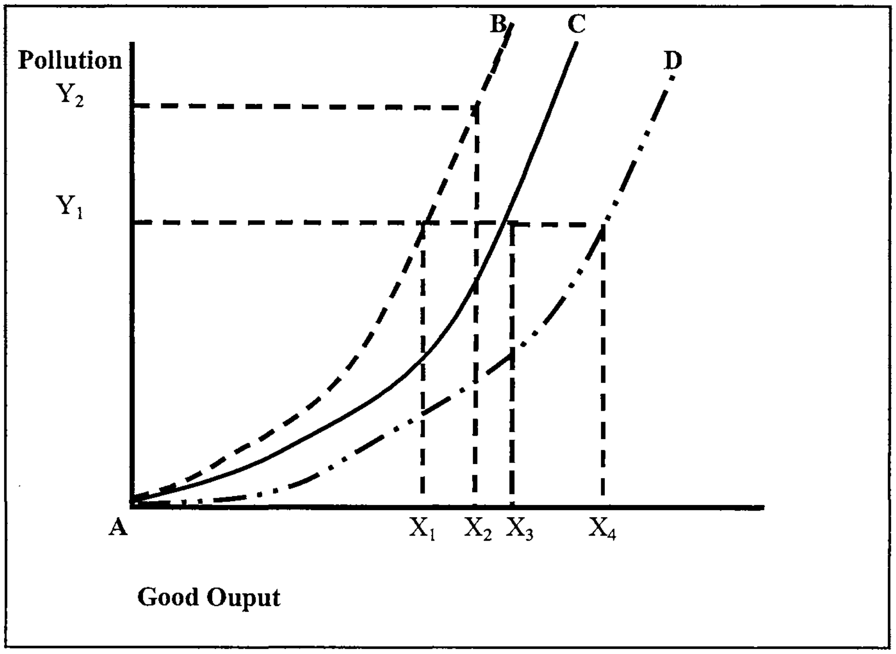
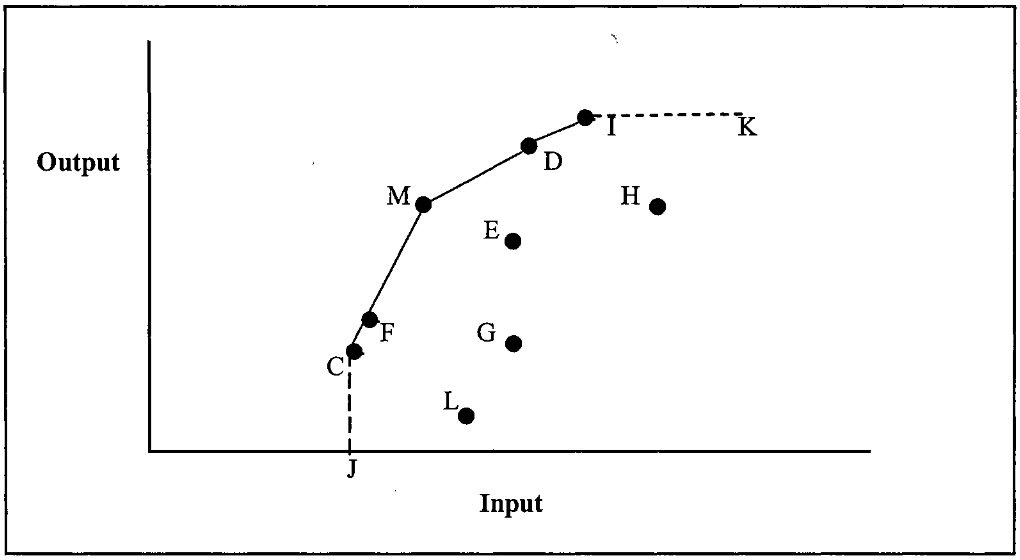


FIGURE 3
DEA Efficiency Frontier Estimation



VITAE

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Education:

Sam Houston State University, Huntsville, Texas, 1978 – 1981
Bachelor of Business Administration
Major: Accounting

Sam Houston State University, Huntsville, Texas, 1978 – 1981
Master of Business Administration
Major: Accounting

Oklahoma State University, Stillwater, Oklahoma 1997 – 2003
Completed the requirements for the Doctorate of Philosophy degree with a major in Business Administration at Oklahoma State University in May 2003

Experience:

Oklahoma State University, Stillwater, Oklahoma 1997 – 2003.
Employed as a graduate teaching associate. Taught Cost Accounting, Financial Accounting, Management Accounting

Royce D. Burnett, CPA, Houston, Texas 1993 – 1997.
Maintained accounting practice focused on business valuation

BP/Amoco, Houston, Texas 1988 – 1993
Held several positions within this multinational firm including Manager of Strategic Planning and Budgeting, Manager of General Accounting, Policy Analyst, and System Analyst

EDS/General Motors, Dallas, Texas, 1984 – 1986
Strategic Analyst

Price Waterhouse/Coopers, Houston, Texas 1983 - 1984
Audit Staff

Ernst and Young, Houston, Texas, 1981 – 1983
Audit Staff

Professional Certifications:

Certified Public Accountant (CPA)
Certified Management Accountant (CMA)

Professional Affiliations:

American Institute of Certified Public Accountants
American Accounting Association
Institute of Management Accountants
Texas Society of Certified Public Accountants