PRODUCTION EFFICIENCIES OF U.S. ELECTRIC GENERATION PLANTS: EFFECTS OF DATA AGGREGATION AND GREENHOUSE GAS AND RENEWABLE ENERGY POLICY

by

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B.S., High Point University, 2007
M.A., Kansas State University, 2013

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

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Abstract

Over the last few decades there has been a shift in electricity production in the U.S. Renewable energy sources are becoming more widely used. In addition, electric generation plants that use coal inputs are more heavily regulated than a couple decades ago. This shift in electricity production was brought on by changes in federal policy – a desire for electricity produced in the U.S. which led to policies being adopted that encourage the use of renewable energy.

The change in production practices due to policies may have led to changes in the productivity of electric generation plants. Multiple studies have examined the most efficient electric generation plants using the data envelopment analysis (DEA) approach. This study builds on past research to answer three questions: 1) Does the level of aggregation of fuel input variables affect the plant efficiency scores and how does the efficiency of renewable energy input compare to nonrenewable energy inputs; 2) Are policies geared toward directly or indirectly reducing greenhouse gas emissions affecting the production efficiencies of greenhouse gas emitting electric generation plants; and 3) Do renewable energy policies and the use of intermittent energy sources (i.e. wind and solar) affect the productivity growth of electric generation plants.

All three analysis, presented in three essays, use U.S. plant level data obtained from the Energy Information Administration to answer these questions. The first two essays use DEA to determine the pure technical, overall technical, and scale efficiencies of electric generation plants. The third essay uses DEA within the Malmquist index to assess the change in productivity over time.

Results indicate that the level of aggregation does matter particularly for scale efficiency. This implies that valuable information is likely lost when fuel inputs are aggregated together. Policies directly focused on reducing greenhouse gas emissions may improve the production efficiencies of greenhouse gas emitting electric generation plants. However, renewable energy policies do not have an effect on productivity growth. Renewable energy inputs are found to be as efficient if not more efficient than traditional energy sources.

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Chapter 1 - Introduction

Over the last few decades there has been a shift in electricity production in the U.S. Renewable energy sources are becoming more widely used. In addition, electric generation plants that use coal inputs are more heavily regulated than a couple of decades ago. This shift in electricity production was brought on by changes in federal policy – a desire for electricity produced in the U.S. which led to policies being adopted that encourage the use of renewable energy.

The change in production practices due to policies may have led to changes in the productivity of electric generation plants. Multiple studies have examined the most efficient electric generation plants using the data envelopment analysis (DEA) approach. This study builds on past research to answer three questions: 1) Does the level of aggregation of fuel input variables affect the plant efficiency scores and how does the efficiency of renewable energy input compare to nonrenewable energy inputs; 2) Are policies geared toward directly or indirectly reducing greenhouse gas emissions affecting the production efficiencies of greenhouse gas emitting electric generation plants; and 3) Do renewable energy policies and the use of intermittent energy sources (i.e. wind and solar) affect the productivity growth of electric generation plants.

DEA is a nonparametric linear-programming approach used to determine the best practice of firms in an industry. The nonparametric aspect of the model ensures that no functional form is established for the production function or the error structure. In addition to determining the efficiency scores for each firm, DEA can also show where the inefficiencies occur. Most of these studies have either considered one type of fuel category i.e. coal, as one fuel input, or multiple fuel categories, i.e. thermal plants (coal, natural gas, and/or petroleum) as one fuel input in their production analysis. However, these studies have not tested if the level of aggregation of fuel inputs affect the results from the efficiency analysis.

The first of the three essays determines if the level of aggregation of fuel inputs affects the production efficiency scores of power plants in the U.S. DEA is used to determine the pure technical, overall technical, and scale efficiencies of power plants in the U.S. Three different levels of aggregation are used in the analysis. The first is disaggregate fuel inputs – every type of fuel (i.e. bituminous coal, distillate fuel oil, natural gas, wind) is an input. The second level of fuel input aggregation is at the category level (i.e. coal, petroleum, solid renewable fuels). Here each aggregate category is an input. The third level of aggregation is total aggregation, where all fuel inputs are aggregated into one input variable. An average of 4,750 U.S. electric generation plants are studied each year between 2003 and 2012.

Many DEA analyses are concerned with more than just which electric generation plant is the most efficient firm. They use their analysis to determine how policies affect the efficiencies of the firms in the analysis, or determine why some firms are efficient and other firms are not. The first group of studies typically determine if the policies have affected certain firms by comparing the efficiency scores of the firms that must be in compliance with the policy to firms that do not have to comply with the policy. If the mean efficiency scores are different, then the policy is said to affect the efficiency of the firms that must comply with the policy. To determine why some firms are efficient while other firms are not, the second stage uses the estimated efficiency scores from the DEA model as the dependent variable in a regression analysis. The independent variables typically include plant characteristics, regional characteristics, and policy variables.

The second study determines if policies designed to reduce greenhouse gas emissions of electric generation plants affect the production efficiencies. This study builds on the overall technical, pure technical, and scale efficiency models of electric generation plants by including undesirable outputs (greenhouse gas emissions) in the analysis.

The adoption of policies focused on clean energy production has led to changes in the fuel mix used to produce electricity. Sulfur dioxide pollution that led to acid rain was the main pollutant of concern for electric generation plants in the Clean Air Act of the 1970s. With new technology and a shift away from coal, sulfur dioxide is not as large of a concern as in the past. Many are concerned with greenhouse gas emissions. A percentage of greenhouse gases in the atmosphere can be attributed to the production of electricity. Coal, natural gas, petroleum, and some renewable fuel power plants produce greenhouse gas emissions as a by-product of producing electricity. The by-product is referred to as an undesirable output. To reduce greenhouse gas emissions a number of policies that directly or indirectly focus on reducing greenhouse gas emissions have been developed.

It is useful to know more than how efficient a firm is during a given year and instead determine how the efficiency of the industry is changing over time leading to productivity growth. The Malmquist index shows how the overall productivity of how a firm changes from one period to the next. Productivity growth occurs when there is an increase total factor productivity (TFP) which is represented by a shift up and to the left of the TFP curve. The TFP may change due to changes in technical efficiency (overall technical efficiency) or due to technological changes between one period and the next. An increase in technical efficiency occurs when the electric generation plant experiences improvements in management and technical experience. An increase in technology occurs when innovation occurs and the production frontier shifts out.

The third study uses the Malmquist index to determine if renewable energy policies and choice of fuel input affect the productivity growth of electric generation plants. Once a renewable energy policy has been passed it can take years of planning and construction to build a new electric generation plant or a significant amount of time and money to make drastic changes to the operation of an existing electric generation plant. Often the policies give electric generation plants several years to become compliant and/or incorporate a tiered system to help the electric generation plants achieve the final goal of policy. This implies that when a policy is passed, it may affect the productivity growth as it moves forward. Power plants affected by these policies need to incorporate the requirements of the policy in their long run production decisions.

Chapter 2 - Power Plant Production Efficiencies: A Comparison of Input Aggregation Levels Using DEA

2.1 Introduction

With the demand for energy in general and clean energy specifically on the rise, the mix of inputs for electricity production is becoming more varied. Since the early 2000s there has been a large increase in the amount of renewable energy that is used to produce electricity in the United States. In 2001, only five states were generating 5% or more of their electricity from non-hydroelectric renewable energy. By 2011, 20 states were producing 5% or more of their electricity from non-hydroelectric renewable energy (EIA 2012).

With the addition of more data on the production of electricity including renewable energy and better computing power, it is possible to conduct data envelopment analysis (DEA) using more than a single aggregate fuel input variable in an efficiency analysis. It is now possible to use categories of fuel inputs or disaggregated fuel use data. Based on a study by Lynes and Featherstone (2015), inputs within the same fuel category (i.e. coal, natural gas, etc.) could have statistically significant positive and negative impacts on the efficiency score of an electric generation plant. This implies that the efficiency score of the electric generation plant could be affected due to the level of aggregation of the energy input variable, since some types of fuel inputs have a positive effect while others have a negative effect. Using more aggregated input data as opposed to less could result in a flawed recommendation of what the plant should do to become more efficient. Using an input-oriented DEA model, a firm is efficient if their efficiency scores equals one. Using aggregate data this could result in more power plants receiving efficiencies of less than one.

Despite the increased access to data and higher computing power, currently the majority of research conducted on electric generation plants use a single fuel variable input when determining plants' efficiency scores. To the author's knowledge, no one has determined if the level of aggregation affects the efficiency score of electric generation plants. The purpose of this study is to determine if the aggregation level of fuel input variables affects the efficiency score of electric generation plants. DEA is used to determine the pure technical, overall technical, and scale efficiencies of power plants in the U.S. Three different levels of aggregation are used in the analysis. The first is disaggregate fuel inputs – every type of fuel (i.e. bituminous coal, petroleum, natural gas, wind) is an input measured is millions of British Thermal Units (MMBTU). The second level of fuel input aggregation is at the category level (i.e. coal, petroleum, solid renewable fuels). Here each aggregate category is an input. The third level of aggregation occurs when all fuel inputs are aggregated into one input variable. This paper provides a recommendation on commonly used methodology in the analysis of the efficiency of power plants.

2.2 Literature Review

DEA is a linear programming, non-parametric model that is commonly used to determine production, cost, and revenue efficiencies of firms. Farrell (1957) laid the groundwork for DEA analysis. However it is not until the late 1970s and early 1980s that production oriented DEA analysis was developed. Charnes, Cooper, and Rhodes (1978) developed overall technical efficiency analysis which is referred to as CCR and Banker, Charnes, and Cooper (1984) developed the pure technical efficiency analysis approach which is often referred to as BCC.

Since the 1980s, when DEA models were first developed, the use of DEA to determine the production efficiencies of power plants has remained common in the literature. Numerous studies have been conducted in the U.S. and abroad, with several studies comparing power plants in different countries. DEA studies of electricity production typically fall into one of two categories: generation and distribution. Numerous studies have considered the efficiencies of electricity distribution utilities (Forsund and Kittelsen 1998, Hialmarsson and Veiderpass 1992, Jamasb and Pollitt 2003, Pombo and Taborda 2006). However, this study focuses on efficiencies from the generation of electricity and is not concerned with the distribution of electricity. Most of the previous studies of electricity generation, have focused on conventional electricity production. Only a handful of studies have considered electric generation plants that use nuclear or renewable energy as inputs.

In addition, most studies focusing on conventional energy production have used an aggregate fuel input. Typically the data is aggregated to the highest level of aggregation – only one input variable for fuel consumption regardless of how many types of fuel are consumed in the production of electricity. However, there have been a few studies that have taken the approach of disaggregating the fuel inputs to a category level.

2.2.1 Aggregate Fuel Approach

Numerous studies using DEA make no distinction on the type of fuel that is used in the analysis. The first was Färe, Grosskopf, and Logan (1983). They included fuel (BTUs), labor, and capital (MW) as inputs and net generation (kWh) as the output. Using labor, fuel (BTUs) and capital as inputs and kilowatt hours (kWh) as the output, Färe, Grosskopf, and Logan (1985) compare privately and publicly held utilities to determine the utilities that are more efficient. Both production and cost efficiencies are calculated in this analysis. Golany, Roll, and Rybak (1994) determine the overall technical efficiency (CCR) of 87 electric generation plants in Israel operating in a closed market. Four outputs and three inputs are considered. The three inputs include installed capacity, fuel consumption (physical units consumed), and manpower. The four outputs considered are generated power (MWh), operational availability (time), deviation from operational parameters (reciprocal of deviations from optimal operational parameters), and SO_2 emissions, where SO_2 is taken into account using dummy variables that signify the electric generating plants' level of compliance.

Using fuel quantity consumed (tons of oil equivalent), installed power (kW), and labor inputs, Park and Lesourd (2000), determine the overall technical (CCR) and pure technical (BCC) efficiencies of 64 conventional thermal steam-electric power plants in South Korea. The output is electrical energy production (MWh). In another study, using a two-stage model, Raczka (2001) determines why 41 heat plants in Poland are technically (in)efficient. One output and three inputs are considered. The one output is heat production (terajoules) and the three inputs are labor, fuel (terajoules), and pollution.

Other studies aggregate multiple fuel categories together to create an aggregate fuel variable. Two outputs and four inputs are used to compare the efficiencies of Japanese and U.S. investor owned utilities (Goto and Tsutsui 1998). The two outputs are quantity of electricity sold to residential customers and quantity sold to non-residential customers. The four inputs used are nameplate generation capacity (MW), quantity of fuel (kilo calories), total number of employees, quantity of power purchase (GWh). Goto and Tsutsui (1998) sum the quantities of coal, petroleum, natural gas, and nuclear to create the quantity of fuel variable. In a study by Lam and Shiu (2001), three different fuels are used for power generation – coal, oil, and gas – and are aggregated to determine the total fuel (terajoules) use variable used to determine the technical efficiencies of thermal power generation plants in China. The one output is the electricity generated (GWh). Aggregating oil, coal, and natural gas (10^9 kcal), Sueyoshi and Goto (2001) use a slack-adjusted DEA model, to determine the efficiencies of 10 vertically-integrated and investor-owned Japanese power plants and compares these plants to 15 wholesale generation facilities. The one output is total generation (GWh). In addition to the aggregate fuel input the two other inputs are total capacity (MW) and number of employees.

Fallahi, Ebrahimi, and Ghaderi (2011) find the overall technical (CCR) and pure technical (BCC) efficiencies of 32 power electric generation management companies in Iran from 2005-2009. The one output modeled is net electricity produced (MWh) and the five inputs considered are labor – number of employees by company, capital – installed capacity (MW), fuel (10^6 calories), electricity (MWh), and average operational time (h). The fuel used is the sum of the heating values of the fossil fuels used by the producer. In addition, they used the Spearman Correlation Coefficient model to test which variables are most essential to include in the model. Six different models are considered. The first model used all inputs. The second model replaced labor with two sub categories of labor – expert labor and non-expert labor and found that there was little difference between the two results. When electricity used was dropped from the analysis the model had a 98% correlation with the original model. If average operational time was dropped, the model had a 96% correlation with the original model. If both were dropped, the correlation remained at 96% used. In the last model labor was also dropped leaving only installed capacity and fuel as inputs and the correlation was 91%.

2.2.2 Disaggregate Fuel Approach

Fewer studies have used a disaggregate fuel input approach than an aggregate approach. Färe, Grosskopf, and Tyteca (1996) disaggregated fuel inputs into categories. Quantities of coal (1000 short tons), oil (1000 Bdls), and natural gas (MMcf) are each separate fuel inputs. In addition, capital – installed generating capacity (MW), and labor are included as inputs. Four outputs are considered, one desirable output – net generation (kWh), and three undesirable outputs – SO_2 (tons), nitrous oxides (NO_X tons), and CO_2 (tons).

Liu, Lin, and Lewis (2010) consider four different types of generation units in their analysis – steam turbine, combined cycle, gas turbine, and diesel engines in Taiwan. Instead of disaggregating the fuel used by each power plant, if multiple types of fuel are used by a thermal power plant in Taiwan, then multiple decision making units (DMUs) are created for that particular plant. One analysis is conducted using all DMUs to determine the most efficient DMUs. Three inputs are used in the analysis – installed capacity (MW), electricity used (MWh), and heat value of total fuels used (10^9 calories). The one output is net electricity (MWh) produced.

Bi et al. (2014) partially separated out fuel inputs to determine the energy and environmental efficiencies of thermal plants in China. Four outputs and four inputs are considered. The four inputs included are installed capacity (10^4 kW), labor, coal (10^4 tons), and gas (10^8 cubic meters). Instead of including an additional variable in the analysis for other inputs, any non-coal or non-gas fossil fuel used to produce electricity (i.e. oil) was aggregated with coal. The four outputs include one good output – power generated (10^8 kWh), and three bad outputs – SO_2 (tons), NO_X (tons), and soot (tons).

One study finds the efficiencies of thermal and renewable power plants by analyzing two types of electric generation plants separately. Sarica and Or (2007) developed two different DEA models. The first model is for thermal power plants that used coal, natural gas, and oil. The second model is a renewable energy model that used hydro and wind. The thermal power plant model includes four outputs and two inputs. The four outputs are availability, thermal efficiency, environmental cost, and CO. The two inputs include fuel cost ($) and production (kWh). The renewable energy model includes one input and two outputs. The two outputs are production (kWh) and utilization. The one input is operating cost.

Lynes and Featherstone (2015) disaggregated the fuel inputs. In all, 33 different inputs are included for an average of 4,800 power plants in the U.S. from 2003 to 2012. Capital – measured as capacity (MW) and up to 32 different fuel types (BTUs) are used as inputs (some fuel types are not reported in every year). Net generation is the output (MWh).

2.2.3 No Fuel Approach

A few studies on the efficiencies of power plants have not included a fuel variable. Whiteman and Bell (1994) disaggregated the capacity input that is typically used in a DEA analysis for electric generation plants. Instead of including only one input variable for capacity they used a thermal capacity input variable and a non-thermal capacity input variable (both in MW). However the quantity and type of fuel used is not included in their analysis. In addition to using thermal and non-thermal capacity as inputs, employment is used. The two outputs considered are electricity generated (MWh) and sales per customer (GWh). This study is also one of a few studies where renewable and non-renewable sources are considered in the same analysis.

In the U.S., Cook et al. (1998), Cook and Green (2005), and Cook and Zhu (2007) consider how creating a hierarchy between units and utility plants affect the efficiencies at eight thermal plants. The inputs used were total maintenance expenditure, total occupied hours and the outputs used were capacity operating hours, outages, and forced deratings.

Barros and Peypoch (2008) did not include a variable related to fuel in their DEA analysis. Instead, a dummy variable for gas, and a dummy variable for fuel oil is included in their second stage regression analysis. For their DEA analysis two outputs and three inputs are included. The two outputs include energy production and capacity utilization. The three inputs consist of labor, physical assets, and the operational cost.

This study contributes to the literature by providing a recommendation on commonly used methodology in the analysis of the efficiency of power plants – what level of aggregation should be used for fuel inputs. Since a majority of the literature uses highly aggregated fuel data, this study determines if and by how much the analysis is affected by using aggregate data.

2.3 Methods

DEA is a nonparametric linear-programming approach used to determine the best practice of firms in an industry. The nonparametric aspect of the model ensures that no functional form needs to be established for the production function and no distribution is assumed for the error structure. In addition to determining the efficiency scores for each firm, the DEA can also show where the inefficiencies occur. Three different input-oriented efficiency models are used in this study – overall technical efficiency, pure technical efficiency, and scale efficiency. By considering all three types of production efficiencies, a firm is able to determine how best to adjust their production practices to become more efficient. All three efficiency scores range from zero to one, where one implies the firm is efficient. For every type of efficiency, at least one DMU must have an efficiency score of one, however no DMU has to have an efficiency score of zero. Input-oriented DEA is used in this analysis. If a firm has an overall technical or pure technical efficiency score of less than one, this implies that the firm could become more efficient by using less inputs to reach the same level of output. If the scale efficiency is less than one, this implies that the firm is operating at an inappropriate scale.

Charnes, Cooper, and Rhodes (1978) first introduced how to estimate overall technical efficiency (CCR) of a firm under constant returns to scale. The model determines how far a producer is from producing at the level of constant returns to scale. The model is as follows:

2.1 $$\min_{\theta_i, z_i} \theta_i$$

Subject to:

$$\sum_{k=1}^{K} z_k x_{mk} \leq \theta_i x_{mi} \text{ for } m = 1, \dots, M$$

$$\sum_{k=1}^{K} y_k z_k \geq y_i$$

$$(z_1, \dots, z_K) \geq 0$$

where z is an intensity (or weight) of each electric generation plant k, x_{mk} are the inputs, y_k is the output of each electric generation plant k, and m is the number of inputs. M varies based on the aggregation level used in various sections of this study. θ_i is the measure of overall technical efficiency (CCR). If θ_i is equal to one then the power plant is efficient.

The pure technical efficiency (BCC) which measures how far a producer is from the production function, allowing for variable returns to scale, was first introduce by Banker, Charnes, and Cooper (1984). Using the pure technical efficiency analysis researchers are able to determine how to reduce inputs to make firms more efficient. The model is as follows:

2.2 $$\min_{\lambda_i, z_i} \lambda_i$$

Subject to:

$$\sum_{k=1}^{K} z_k x_{mk} \leq \lambda_i x_{mi} \text{ for } m = 1, \dots, M$$

$$\sum_{k=1}^{K} y_k z_k \geq y_i$$

$$\sum_{k=1}^{K} z_k = 1$$

$$(z_1, \ldots, z_K) \geq 0$$

where the same definition exists as in the overall technical efficiency model – z is an intensity (or weight) vector, x_{mk} are the inputs, y_k is the output. The number of electric plants is K. There are M different inputs, which vary depending on the level of aggregation used in the study. λ_i is the measure of pure technical efficiency (BCC). If λ_i is equal to one then the power plant is efficient.

The scale efficiency can be derived using the efficiency scores of the overall technical and pure technical efficiency scores. If the scale efficiency score equals one this implies that the firm is operating at constant returns to scale. If the scale efficiency score equals the overall technical efficiency (CCR) score and is not equal to one then increasing returns to scale exists. If the scale efficiency does not equal one or the overall technical efficiency score then decreasing returns to scale exists. The scale efficiency is:

2.3 $$\gamma_i = \frac{\theta_i}{\lambda_i}$$

where γ_i is the scale efficiency, θ_i is the overall technical efficiency, and λ_i is the pure technical efficiency for power plant i.

Figure 2-1 shows the input-oriented DEA graph. The overall technical efficiency is represented by the constant returns to scale line. The pure technical efficiency is represented by the variable returns to scale line. The scale efficiency is represented by the area between the constant returns to scale and variable returns to scale lines. Firms A, B, and C have a pure technical efficiency of one while only firm B has an overall efficiency of one. Figure 2-2 shows how inefficient Firm D is from a technical efficiency and scale efficiency perspective. Since the area of the scale efficiency is larger, it would be more beneficial for the firm to improve its scale efficiency instead of its technical efficiency. Figure 2-3 shows how inefficient Firm E is from a technical efficiency and scale efficiency perspective. Unlike Firm D, Firm E has more to gain from a production efficiency perspective by improving its technical efficiency than its scale efficiency.

Following Fallahi, Ebrahimi, and Ghaderi (2011) to determine the correlation between different models, the Spearman Correlation Coefficient (SCC) is used. This study determines the correlation between the efficiency scores of the two aggregated fuel group levels and the disaggregate fuel group level of inputs by using the rankings of the electric generation plants at each level of aggregation. This is used to help determine if the level of aggregation affects the ranking and therefore the efficiency scores of a plant. The SCC ranges from -1 to 1. If the correlation coefficient equals ‘1’ (-1) this implies that there is a perfect positive (negative) correlation between the rank of the two efficiency scores being analyzed. If the correlation coefficient equals ‘0’ this implies that there is no correlation between the rank of the two efficiency scores being analyzed. It is expected that the correlation coefficient will be positive implying that the direction of association between the disaggregate efficiency scores and the aggregate efficiency scores are the same. The SCC model is:

2.4 $$\rho = \frac{\sum_i (R_i - \bar{R})(S_i - \bar{S})}{\sqrt{\sum_i (R_i - \bar{R})^2 \sum_i (S_i - \bar{S})^2}}$$

where R_i and S_i are the ranks of the efficiency scores for power plant i for two levels of aggregation and $\bar{R}$ and $\bar{S}$ are the mean efficiency scores. The Spearman Correlation Coefficient is determined for the overall technical (CCR), pure technical (BCC), and scale efficiencies.

For the purpose of this study, all of the results are presented at the aggregate fuel group level. This implies that the average efficiency score is reported for every firm that uses a particular category of fuel (e.g. coal). Approximately 20% of electric generating plants use more than one category of fuel (i.e. coal and natural gas). When this happens, their efficiency score is included in both averages. Typically DEA studies report the efficiency scores by DMU, however since an average of 4,750 DMU are included in this analysis considering the average efficiency scores by aggregate fuel type is believed to be more meaningful. In addition, the SCC is determined at the aggregate fuel group level. The aggregate fuel group is used for a number of reasons. The first is that if the SCC was conducted at the disaggregate fuel group level there may not be enough degrees of freedom to calculate standard errors for some inputs. This would make interpretation on the correlation coefficient impossible. The second reason is that if the analysis was conducted at the total aggregate fuel level, the differences in the correlations based on type of fuel would be lost. The analysis would result in one correlation coefficient for all the electric generation plants.

The cumulative distribution function (CDF) is used to compare the distribution of efficiency scores for each fuel category by level of aggregation. All years of efficiency scores for each fuel category by aggregation level are combined to create the CDF. The area under the curve will be smaller for the relatively efficient fuel categories and much large for the relatively inefficient fuel categories.

2.4 Data

Plant level data is used to determine the overall technical (CCR), pure technical (BCC), and scale efficiencies for conventional and renewable utility plants from 2003 to 2012 in the U.S (EIA 2015). The inputs used in the analysis are fuel and capital. There are up to 32 different types of fuel included in the analysis depending on the level of analysis and year (Table 2-2). The fuel sources are measured by total fuel consumption MMBTU (million British Thermal Units) annually. Due to the nature of the DEA, the fuel types do not need to be in the same units for analysis, however, since multiple fuel types are aggregated together for part of the analysis, BTUs is used.

Disaggregate Fuel Group

The first level of aggregation is the *Disaggregate Fuel Group*. Here all different fuel inputs are considered separately. Depending on the year, up to 33 different inputs are included in this analysis: capital and up to 32 different types of fuel measured in MMBTUs.

Aggregate Fuel Group

The second level of aggregation is the *Aggregate Fuel Group* which consists of all inputs aggregated together within a specific groups of fuels: *coal, petroleum, natural gas and other gases, nuclear, solid renewable fuels, liquid renewable fuels, gaseous renewable fuels, other renewable energy sources,* and *other energy sources* (MMBTUs) as defined by the Energy Information Administration (EIA) Form 923. In this analysis there are 10 inputs used – one for each fuel group and capital.

Total Aggregate Fuel Group

The last level of aggregation is the *Total Aggregate Fuel Group* case, fuel consumption is aggregated across all fuel types. For this analysis, there are only two inputs for every DMU in every year: total aggregated fuel (MMBTUs) and capital.

For all three analyses, capital is represented by net capacity in megawatts (MW) at a power plant. The output is net generation in megawatt hours (MWh) (Table 2-2). There are, on average, 4,750 plants per year considered in the analysis. The analysis is conducted using cross-sectional data for ten years. The number of power plants in each year varies depending on the number of plants included in the survey for a given year and completeness of the data for each plant during a given year.

When deciding the variables to include in the DEA, it is important to consider three factors: 1) availability of data; 2) the body of literature; and 3) professional opinion of relevant individuals. A key variable that is missing from this analysis is labor. However, due to a lack of availability of a labor variable for the entire data set, it was not included in the analysis. Despite not including labor in the analysis, the results may not be significantly affected. A study conducted by Fallahi, Ebrahimi, and Ghaderi (2011) found the most important inputs are the installed capacity and fuel that described 91% of the full model. In addition, Welch and Barnum (2009) did not include labor for a number of reasons. First their study, like this study, was not focused on labor decisions, instead it was focused on fuel choice decisions. Second, labor makes up a very small portion of the input resources. Lastly, fuel and labor are not substitutes for one another in the electric generation industry, instead they are complements so only one complementary variable needs to be included. According to the EIA for the duration of this study, expenditures related to labor make up approximately 10% or less of total expenditures for the utility (EIA 2015). It is important to make sure there are enough degrees of freedom to estimate the DEA model. In general, there are enough degrees of freedom if the number of DMUs is greater than or equal to three times the number of inputs plus the number of outputs (C. P. Barros 2008). Given that the minimum number of observations for any year is 3,800, degrees of freedom is not an issue for even the disaggregate analysis (3,800 > 3(33+1)).

2.5 Results

The overall technical (CCR), pure technical (BCC), and scale efficiencies are determined on a yearly basis, for each level of aggregation. The three levels of aggregation included in the analysis are disaggregate, aggregate, and total aggregate fuel groups where the disaggregate fuel group includes each individual fuel input variable; the aggregate fuel group aggregates all the fuel inputs to nine categories of input variables; and the total aggregate fuel group aggregates all fuel types into one fuel input variable. The mean and standard deviations of the efficiency scores by year are reported at the aggregate fuel group level for all three aggregation levels in Table 2-3 - Table 2-12. Even though the analysis is conducted using three levels of aggregation, to compare the results, the Spearman Correlation Coefficient is determined at the aggregate fuel group level for each level of aggregation. The correlation coefficient compares the aggregate fuel group level and the total aggregate fuel group level to the disaggregate fuel group level of inputs.

In general, the disaggregate fuel group mean efficiency scores are higher and result in more efficient plants than either the aggregate or total aggregate fuel groups for the pure technical and overall technical efficiencies. In addition, the SCC are typically higher for both levels of aggregation in the pure technical and overall technical efficiencies than the scale efficiencies.

2.5.1 All Fuels

The mean efficiency scores and SCC for all electric generation plants are presented by year in Table 2-3. The range of SCC for the pure technical, overall technical, and scale efficiencies scores is higher between the disaggregate and aggregate fuel groups than between the disaggregate and total aggregate fuel groups. The range of SCC for the pure technical efficiency is 0.818 in 2011 to 0.969 in 2004 between the disaggregate aggregate fuel groups and

0.737 in 2012 to 0.865 in 2004 between the disaggregate and total aggregate fuel groups. The range of SCC for the overall technical efficiency is 0.824 in 2011 and 0.739 in 2012 to 0.988 and 0.900 in 2004 between the disaggregate and aggregate fuel groups and between the disaggregate and total aggregate fuel groups, respectively. The SCC for the scale efficiency scores is 0.686 and 0.183 in 2012 to 0.958 in 2003 and 0.595 in 2007 between the disaggregate and aggregate fuel groups and between the disaggregate and total aggregate fuel groups, respectively.

The mean pure technical efficiency ranges from 0.352 at the total aggregate fuel group level in 2007 to 0.733 at the disaggregate level in 2012. The mean pure technical and overall technical efficiency scores are highest at the disaggregate fuel group level and lowest at the total aggregate fuel group level. The mean overall technical efficiencies range from 0.249 at the total aggregate fuel group level in 2007 to 0.703 at the disaggregate fuel group level in 2012. The range of the mean scale efficiencies is 0.714 at the total aggregate fuel group level in 2007 to 0.928 at the disaggregate fuel group level in 2012.

The distribution of efficiency scores can be seen in Figure 2-4, Figure 2-5, and Figure 2-6 for 2012. The CDF reveals that the disaggregate fuel group results in more efficient firms for all three types of efficiencies, than either the aggregate or total aggregate fuel groups for all fuel inputs. Approximately 27% of the disaggregate fuel group has a pure technical efficiency score of approximately 1 or more, while approximately 8% of the aggregate fuel group and approximately 4% of the total aggregate fuel group have a pure technical efficiency score of approximately 1 (Figure 2-4). Similar results can be seen in Figure 2-5 for the overall technical efficiency scores. Approximately 22% of the disaggregate fuel group have an overall technical efficiency score of approximately 1, approximately 3% of the aggregate fuel group have an overall technical efficiency of approximately 1 or more while less than 1% of the total aggregate fuel group have an overall technical efficiency of approximately 1. There are more electric generating plants that are scale efficient (Figure 2-6) than are technically efficient (Figure 2-4 and Figure 2-5). Approximately 45% of the disaggregate fuel group, approximately 30% of the aggregate fuel group, and approximately 11% of the total aggregate fuel group have a scale efficiency of approximately 1.

The remaining results are reported at the category level. This implies that if an electric power plant uses a particular category of input, the efficiency score of that plant is included in the results for that category. A majority of the electric generation plants use only on category of inputs, however when a plant uses more than one category of inputs, the efficiency score for the plant is used in the results for both fuel categories.

2.5.2 Coal

The results for *coal* are presented in Table 2-4. The SCC between disaggregate and aggregate fuel group levels range between 0.895 in 2008 to 0.968 in 2004 and range between 0.839 in 2003 to 0.972 in 2004 between the disaggregate and total aggregate levels for the pure technical efficiency (columns 3-4 in Table 2-4). This implies that for the pure technical efficiency, the relationship between the disaggregate and aggregate fuel groups is similar to the relationship between the disaggregate and total aggregate fuel groups based on the range of the SCC. This is a result of the electric generation plants having similar rankings regardless of which level of aggregation is used. However, there are large differences between the efficiency scores. The disaggregate fuel group has the highest mean pure technical efficiency scores ranging from 0.141 in 2007 and 2009 to 0.171 in 2003. The mean pure technical efficiency scores in the aggregate fuel group range from 0.107 in 2007 to 0.136 in 2005 and 2012. The total aggregate fuel group has the lowest mean pure technical efficiency scores ranging from 0.050 in 2007 to 0.096 in 2012.

The same can be seen when considering the overall technical efficiency (columns 6-7 in Table 2-4). The SCC for the overall technical efficiency ranges between 0.893 in 2008 to 0.992 in 2004 for the SCC between disaggregate and aggregate fuel group levels and ranges between 0.901 in 2008 to 0.993 in 2004 between the disaggregate and total aggregate levels. These results imply that the rankings are similar regardless of which level of aggregation is used, however the actual efficiency scores vary depending on which level of aggregation is used. The lowest mean overall technical efficiency score is 0.097 in 2009 for the disaggregate fuel group, 0.074 in 2008 for the aggregate fuel group, and 0.026 in 2007 for the total aggregate fuel group. The highest mean overall technical efficiency score for all three levels of aggregation is in 2012 – 0.124, 0.105, and 0.078 for the disaggregate fuel group, aggregate fuel group and total aggregate fuel group, respectively.

The correlation between the disaggregate fuel group and the other two fuel groups is not as strong for the scale efficiency (columns 9 and 10 in Table 2-4). The SCC range for disaggregate and aggregate fuel group levels is 0.810 in 2012 to 0.883 in 2010. The range between disaggregate and total aggregate levels is 0.540 in 2011 to 0.825 in 2006. Unlike with the overall technical and pure technical efficiencies for seven of ten years the mean scale efficiencies are highest at the total aggregate level (columns 8-10 in Table 2-4). The mean scale efficiency scores are more similar to each other across aggregate fuel groups, however the rankings are not as similar as seen with the overall technical and pure technical fuel groups. The ranges for the mean scale efficiencies are 0.588 in 2003 to 0.721 in 2012 for the disaggregate fuel group, 0.531 in 2004 to 0.883 in 2010 for the mean aggregate fuel group, and 0.563 in 2007 and 2008 to 0.828 in 2011 for the total aggregate fuel group.

Based on the SCC, when determining the pure technical or overall technical efficiencies, the researcher would not lose much information if ranking is most important by conducting the analysis using any level of aggregation since correlations are high every year. However, for the scale efficiencies the correlation is not as strong which likely results from higher efficiency scores at the total aggregate fuel level. Due to the higher efficiency scores at the total aggregate fuel group level, too little emphasis may be placed on encouraging firms to improve their scale efficiency.

The distribution of efficiency scores can be seen in Figure 2-7, Figure 2-8, and Figure 2-9 for 2012. The CDF reveals that the disaggregate fuel group results in more efficient firms for all three types of efficiencies, than either the aggregate or total aggregate fuel groups for coal inputs. Approximately 13% of the disaggregate fuel group has a pure technical efficiency score of 0.5 or more, while approximately 10% of the aggregate fuel group and approximately 5% of the total aggregate fuel group have a pure technical efficiency score of 0.5 or greater (Figure 2-7). Similar results can be seen in Figure 2-5 for the overall technical efficiency scores. Approximately 10% of the disaggregate fuel group have an overall technical efficiency score of 0.5 or more, approximately 7% of the aggregate fuel group have an overall technical efficiency of 0.5 or more while only approximately 3% of the total aggregate fuel group have an overall technical efficiency of 0.5 or more. There are more electric generating plants that are scale efficient (Figure 2-9) than are technically efficient (Figure 2-7 and Figure 2-8). Approximately 78% of the disaggregate fuel group have a scale efficiency of 0.5 or more, approximately 74% of the aggregate fuel group have a scale efficiency of 0.5 or more, and approximately 75% of the total aggregate fuel group have a scale efficiency of 0.5 or more.

2.5.3 Natural Gas

The SCC between disaggregate and aggregate fuel group levels for *natural gas* are greater than 0.900 for all years for all three efficiencies, with the exception of the scale efficiency in 2012 which is 0.899 (Table 2-5). The correlation between the disaggregate and aggregate fuel groups implies that the efficiency scores between the two groups are similar and the researcher would not lose much information by using the aggregate fuel group instead of the disaggregate fuel group. The SCC between the disaggregate and total aggregate fuel group levels is also greater than 0.900 for the pure technical and overall technical efficiencies. However, the range for SCC for the scale efficiency is 0.244 in 2011 to 0.861 in 2010. This implies that any of the fuel aggregation levels could be used if the researcher is mostly concerned with the rankings for the pure technical and overall technical efficiencies. However, with lower SCC scores for the scale efficiency, it may be better to use the disaggregate or aggregate fuel groups instead of the total aggregate fuel group. If not, then potential valuable information about the scale efficiency of firms may be lost.

The mean pure technical and overall technical efficiencies are higher for *natural gas* than for *coal*. The mean pure technical efficiency ranges from 0.269 at the total aggregate fuel group level in 2007 to 0.525 at the disaggregate level in 2012 (columns 2-4 in Table 2-5). The mean pure technical and overall technical efficiency scores are highest at the disaggregate fuel group level and lowest at the total aggregate fuel group level. The mean overall technical efficiencies range from 0.186 at the total aggregate fuel group level in 2005 to 0.489 at the disaggregate fuel group level in 2012 (columns 5-7 in Table 2-5). The range of the mean scale efficiencies is

0.653 at the total aggregate fuel group level in 2003 to 0.897 at the disaggregate fuel group level in 2012 (columns 8-10 in Table 2-5). The scale efficiency is highest for four of ten years at the total aggregate fuel group level.

The CDFs reveal that the distribution of the efficiency scores of the disaggregate and aggregate fuel groups are similar to one another, for all three efficiencies, while the distribution of the total aggregate fuel group results in lower efficiency scores for the pure technical and overall technical efficiencies (Figure 2-10 - Figure 2-12). Approximately 37% of the disaggregate fuel group and 35% of the aggregate fuel group have a pure technical efficiency of 0.5 or more while only approximately 47% of the total aggregate fuel group have a pure technical efficiency of 0.5 or more (Figure 2-10). Approximately 53% of the disaggregate and 50% of the aggregate fuel groups have an overall technical efficiency score of 0.5 or more while only approximately 35% of total aggregate fuel groups have an overall technical efficiency score of 0.5 or more (Figure 2-11). The distribution of the scale efficiency scores for the disaggregate and aggregate fuel groups are almost the same (Figure 2-12). However, the distribution of the scale efficiencies for the total aggregate fuel group is closer than for the distribution of the pure technical or overall technical efficiency scores. At least 92% of the power plants have a scale efficiency of 0.5 or more for all three aggregation groups.

2.5.4 Petroleum

The mean efficiencies and SCC for *petroleum* (Table 2-6) are similar to those of *natural gas*. All of the SCC are above 0.900 between the disaggregate fuel group level and the aggregate fuel group for the pure technical and overall technical efficiencies in all years (columns 3 and 6 Table 2-6). The lowest SCC for the scale efficiency is 0.871 in 2004 (column 9 Table 2-6). The lowest SCC for the pure technical and overall technical efficiency between the disaggregate and total aggregate fuel group levels are in 2003. The SCCs are 0.754 and 0.738 for the pure technical and overall technical efficiency, respectively (columns 4 and 7 Table 2-6). The highest SCC for the pure technical efficiency is 0.916 in 2012 (column 4 Table 2-6). While the highest SCC for the overall technical efficiency is 0.949 in 2005 and 2010 (column 7 Table 2-6). The range of SCC for the scale efficiency is from 0.345 in 2003 to 0.782 in 2010 (column 10 Table 2-6). The correlation between the disaggregate and aggregate fuel groups implies that the efficiency scores between the two groups are similar and the researcher would not lose much information by using the aggregate fuel group instead of the disaggregate fuel group. However, since the SCC is much lower between the disaggregate and total aggregate fuel groups, this implies that the efficiency scores are very different from each other and some valuable information about the efficiency of firms may be lost.

The mean pure technical efficiency is lowest at the total aggregate fuel group level at 0.199 in 2003 and highest at the disaggregate level at 0.429 in 2012 (columns 2-4 Table 2-6). The mean overall technical efficiency is also lowest at the total aggregate fuel group level, with the lowest being 0.096 in 2003 and 2007. The highest mean efficiency is 0.380 in 2012 at the disaggregate fuel group level (columns 5-7 Table 2-6). The lowest mean scale efficiency is 0.543 at the total aggregate fuel group level in 2007. The highest is 0.844 at the disaggregate and aggregate fuel group levels in 2012 (columns 8-10 Table 2-6).

The CDFs reveal that the distribution of efficiency scores are similar between the disaggregate and aggregate fuel group levels for all three efficiencies (Figure 2-13 – Figure 2-15). However, the distribution of the total aggregate fuel group efficiency scores results in noticeably lower efficiency scores for all three efficiencies. Approximately 42% of the disaggregate fuel group and 40% of the aggregate fuel group have a pure technical efficiency of

0.5 or more while only approximately 25% of the total aggregate fuel group have a pure technical efficiency of 0.5 or more (Figure 2-13). Approximately 33% of the disaggregate and 31% of the aggregate fuel groups have an overall technical efficiency score of 0.5 or more while only approximately 15% of total aggregate fuel groups have an overall technical efficiency score of 0.5 or more (Figure 2-14). The distribution of the scale efficiency scores for the disaggregate and aggregate fuel groups are almost the same (Figure 2-15). At least 85% of the power plants have a scale efficiency of 0.5 or more for all three aggregation levels.

2.5.5 Nuclear

Nuclear power plants have the highest mean efficiencies of all inputs (Table 2-7). The input is the same for the disaggregate and aggregate fuel groups. However the SCC is not 1.000 for all three efficiencies for all years. The SCC is 1.000 for the overall technical efficiency for all 10 years, however it only equals 1.000 for four years for the pure technical efficiency and 1.000 for seven years for the scale efficiency. The lowest SCC for the pure technical efficiency is 0.920 in 2007 and 0.845 for the scale efficiency in 2003 (columns 3, 6, and 9 Table 2-7). The SCC is much lower between the disaggregate and total aggregate fuel group levels. The lowest SCC for the pure technical efficiency is 0.439 and 0.246 for the overall technical efficiency, both in 2012 (columns 4 and 7 Table 2-7). However, two years were not statistically significant for the overall technical efficiency. The lowest SCC for the scale efficiency is -0.282 in 2009 (column 10 Table 2-7). It would imply that there is a weak negative relationship between the disaggregate and total aggregate fuel group scale efficiencies. In addition eight years of SCC are not statistically significant, implying there is not relationship between the rankings. The highest SCC for scale efficiency is 0.224 in 2012 (column 10 Table 2-7).

The lowest mean pure technical efficiency is 0.892 in 2012 at the total aggregate fuel group level. All other years and levels of aggregation, the mean efficiency is greater than 0.900 (columns 2-4 Table 2-7). The lowest mean overall technical efficiency is 0.435 at the total aggregate level in 2007. All of the mean overall technical efficiencies at the disaggregate and aggregate fuel group levels are greater than 0.900 (columns 5-7 Table 2-7). The lowest mean scale efficiency is 0.470 in 2007 at the total aggregate fuel group level. The highest mean scale efficiency is 0.999 at the disaggregate fuel group level in 2012 (columns 8-10 Table 2-7).

Since the input variable is the same for the disaggregate and aggregate fuel groups, *nuclear* is a good example of how the efficiency scores are affected by the level of aggregation. If, the level of aggregation had no effect on the efficiency scores, the SCC would be 1.000 for every year for all three efficiencies. However, it is not. This implies that by aggregating some of the inputs other inputs are also affected. The minimum SCC was lower than what is seen for any other nonrenewable energy input between the disaggregate and total aggregate fuel groups and often not statistically significant, this implies that the ranking of efficiency scores are very different from each other.

The CDF functions show how drastically different the distribution of total aggregate fuel group is from the disaggregate and aggregate fuel groups for the pure technical and overall technical efficiencies (Figure 2-16 - Figure 2-17). Approximately 93% of the disaggregate and aggregate fuel groups have a pure technical and overall technical efficiency score of approximately 1 while only 9% of the total aggregate fuel group has a pure technical efficiency of 1 and less than 1% of the total aggregate fuel group has an overall technical efficiency of 1. However the distribution of efficiency scores appear very similar for the scale efficiencies (Figure 2-18). Approximately 96% of all nuclear electric generation plants have a scale efficiency of approximately 1, for the disaggregate and aggregate fuel levels while only approximately 12% of the total aggregate fuel group has a scale efficiency of 1.

There are four renewable energy aggregate fuel groups. The first three are *solid, liquid,* and *gaseous renewable fuels*. The last is other renewable sources that consists of *geothermal, hydroelectric, solar,* and *wind* energy. The mean efficiency scores are similar between the *solid* and *liquid renewable fuels*. Like *nuclear*, *other renewable sources* has high mean efficiency scores.

2.5.6 Solid Renewable Fuels

The *solid renewable fuels* efficiencies and SCC are in Table 2-8. The range of SCC for pure technical efficiency for both the aggregate fuel group and total aggregate fuel group is 0.840 in 2011 and 0.770 in 2008 to 0.969 in 2003 and 0.891 in 2004, respectively (columns 3 and 4 Table 2-8). The highest SCC for the overall technical efficiency between the disaggregate and aggregate fuel group levels is 0.992 in 2003 and the lowest is 0.865 in 2008 (column 6 Table 2-8). The range in the SCC is similar between the disaggregate and total aggregate fuel group levels. The range is between 0.835 in 2008 to 0.971 in 2004 for the overall technical efficiency (column 7 Table 2-8). The SCC for scale efficiency ranges from 0.717 in 2008 to 0.943 in 2005 between disaggregate and aggregate fuel group levels (column 9 Table 2-8). The range of SCC between the disaggregate and total aggregate fuel group levels is lower. The range is from 0.115 in 2011 to 0.665 in 2005 (column 10 Table 2-8). This implies that there is a potential for loss of information if either the aggregate or total aggregate fuel groups are used for all of the efficiencies. This is especially true if the total aggregate fuel group is used to calculate the scale efficiencies.

The mean pure technical efficiency range from 0.206 in 2007 at the total aggregate fuel group level to 0.589 in 2011 at the disaggregate level (columns 2- 4 Table 2-8). The mean overall technical efficiency range from 0.142 at the total aggregate fuel group level in 2007 to 0.524 at the disaggregate fuel group level in 2008 (columns 5- 7 Table 2-8). The mean scale efficiency range from 0.712 in 2007 to 0.903 in 2011, both at the total aggregate fuel group level (columns 8-10 Table 2-8).

The CDFs reveal how different the distribution of efficiency scores are depending on the level of aggregation used for the pure technical and overall technical efficiency scores Figure 2-19 - Figure 2-20). Approximately 15% of the disaggregate fuel group, 8% of the aggregate fuel group and 1% of the total aggregate fuel group have a pure technical efficiency score of 1 (Figure 2-19). Approximately 6% of the disaggregate fuel group, 4% of the aggregate fuel group and none of the total aggregate fuel group have an overall technical efficiency score of 1 (Figure 2-20). Approximately 20% of the disaggregate fuel group and the aggregate fuel group and 23% of the total aggregate fuel group have a scale efficiency score of 1 (Figure 2-21).

2.5.7 Liquid Renewable Fuels

The *liquid renewable fuels* efficiencies and SCC are in Table 2-9. The SCC between the disaggregate and aggregate fuel group levels is above 0.960 for the pure technical and overall technical efficiencies (columns 3 and 6 Table 2-9). The range of SCC for scale efficiencies is larger ranging from 0.734 in 2006 to 0.970 in 2005 (column 9 Table 2-9). The minimum SCC for the pure technical efficiency and overall technical efficiency is 0.746 and 0.891 in 2007, respectively between the disaggregate and total aggregate fuel groups. The maximum SCC for the pure technical efficiency is 0.956 in 2009 and the maximum SCC for the overall technical efficiency is 0.982 in 2006 (columns 4 and 7 Table 2-9). The range of SCC for scale efficiency is

0.299 in 2011 to 0.801 in 2009 (column 10 Table 2-9). The correlation between the disaggregate and aggregate fuel groups implies that the efficiency scores between the two groups are similar and the researcher would not lose much information by using the aggregate fuel group instead of the disaggregate fuel group when analyzing the pure technical and overall technical efficiency scores. However, since the SCC is lower between the disaggregate and total aggregate fuel groups, this implies that the ranking of the electric generating plants and their efficiency scores are very different from each other implying some valuable information about the efficiency of firms may be lost.

The mean efficiencies for the *liquid renewable fuels* are slightly lower than that of *solid renewable fuels* (Table 2-9). The lowest mean pure technical efficiency is 0.086 at the total aggregate fuel group level in 2007. The highest mean pure technical efficiency is 0.394 at the disaggregate fuel group level in 2011 (columns 2-4 Table 2-9). The range of mean overall technical efficiency scores is from 0.047 in 2007 at the total aggregate group level to 0.346 in 2011 and 2012 at the disaggregate fuel group level (columns 5-7 Table 2-9). The mean scale efficiencies are higher than the pure technical and overall technical efficiencies. The range of scale efficiencies is 0.610 in 2009 to 0.887 in 2011 both at the total aggregate fuel group level (columns 8-10 Table 2-9).

The CDFs reveals that the distribution of efficiency scores for the disaggregate and aggregate fuel groups are similar to each other for all three efficiencies (Figure 2-22 - Figure 2-24). However, the total aggregate fuel group only has efficiencies that are similar to the other two fuel groups for the scale efficiency (Figure 2-24). Approximately 7% of the disaggregate fuel group, 5% of the aggregate fuel group and 4% of the total aggregate fuel group have a pure technical efficiency score of approximately 1 (Figure 2-22). Approximately 2% of the disaggregate fuel group, 1% of the aggregate fuel group and none of the total aggregate fuel group have an overall technical efficiency score of 1 (Figure 2-23). Approximately 25% of the all the fuel groups have a scale efficiency score of 1 (Figure 2-24).

2.5.8 Gaseous Renewable Fuels

The *gaseous renewable fuels* efficiencies and SCC are in Table 2-10. All SCC for pure technical, overall technical, and scale efficiencies between the disaggregate and the aggregate fuel group levels are above 0.860 (columns 3, 6, and 9 Table 2-10). However, the minimum SCC between the disaggregate and total aggregate fuel group levels is approximately 0.674 in 2007 for the pure technical efficiency, 0.807 in 2007 for the overall technical efficiency and 0.215 in 2011 for the scale efficiency (columns 4, 7, and 10 Table 2-10). The highest SCC between the disaggregate and total aggregate fuel groups for the pure technical efficiencies is 0.942 in 2004, for the overall technical efficiency is 0.973 in 2012, and for the scale efficiency is 0.821 in 2003 (columns 4, 7, and 10 Table 2-10). The correlation between the disaggregate and aggregate fuel groups implies that the efficiency scores between the two groups are similar and the researcher would not lose much information by using the aggregate fuel group instead of the disaggregate fuel group. However, since the SCC is much lower between the disaggregate and total aggregate fuel groups, this implies that the efficiency scores are very different from each other and some valuable information about the efficiency of firms may be lost.

Gaseous renewable fuels have higher mean efficiencies than either *solid* or *liquid renewable fuels* (Table 2-10). The range of the mean pure technical efficiencies is 0.399 at the total aggregate fuel group level in 2007 to 0.750 at the disaggregate fuel group level in 2009 (columns 2-4 Table 2-10). The range of mean overall technical efficiencies is 0.308 at the total aggregate fuel group level in 2007 to 0.699 at the disaggregate fuel group level in 2009 (columns

5-7 Table 2-10). The mean scale efficiencies range from 0.789 in 2007 to 0.936 in 2011 at the total aggregate fuel group level (columns 8-10 Table 2-10).

The CDFs reveal that the distribution of all three levels of aggregation have similar scale efficiency scores (Figure 2-27). Approximately 90% of all electric generation plants have a scale efficiency of 0.6 or more for all levels of aggregation. However the distribution of pure technical and overall technical efficiency scores are noticeably lower for the total aggregate fuel group level than the disaggregate and aggregate fuel group levels (Figure 2-25 - Figure 2-26). Approximately 11% of the disaggregate fuel group, 8% of the aggregate fuel group and 1% of the total aggregate fuel group have a pure technical efficiency score of 1 (Figure 2-25). Approximately 4% of the disaggregate fuel group, 3% of the aggregate fuel group and less than 1% of the total aggregate fuel group have an overall technical efficiency score of 1 (Figure 2-26).

2.5.9 Other Renewable Sources

Other renewable sources has the highest efficiency of the four renewable energy input aggregate fuel groups (Table 2-11). However, the SCC are lower than for the other renewable fuel sources which implies that more information is lost when these inputs are aggregated than when the other types of renewable energy sources are aggregated. This is likely because the fuel inputs in this category are less similar than fuel inputs in any other category.

The lowest SCC levels between the disaggregate and aggregate fuel group levels are 0.206, 0.093, in 2011 and 0.212 in 2012 for the pure technical, overall technical, and scale efficiencies, respectively (columns 3, 6, and 9 Table 2-11). The highest SCC for the pure technical efficiency is 0.949 in 2004 (column 3 Table 2-11). The highest SCC for the overall technical efficiency and scale efficiencies 0.997 and 0.975 in 2005, respectively (columns 6 and 9 Table 2-11). The lowest SCC between the disaggregate and total aggregate fuel groups for the pure technical, overall technical, and scale efficiencies is 0.177 in 2005, 0.090 in 2011, and -2.83 in 2003, respectively (columns 4, 7, and 10 Table 2-11). There were two additional years that had a negative and statistically significant correlation between the disaggregate and total aggregate fuel groups. Even though the correlation is weak, it implies that the rankings between the two groups are opposing each other for three of the years. The highest SCC is 0.574, 0.620 in 2003, and 0.516 in 2008 for the pure technical, overall technical, and scale efficiencies, respectively (columns 4, 7, and 10 Table 2-11). The SCC are the lowest between the disaggregate and aggregate fuel groups for *other renewable sources* compared to all other types of aggregate fuel groups. This implies that caution should be taken before aggregating geothermal, hydroelectric, solar, and wind power even to the aggregate fuel level.

The range of mean pure technical efficiencies is 0.481 in 2007 at the total aggregate fuel group level to 0.980 at the disaggregate level in 2005 (columns 2-4 Table 2-11). The range for the mean overall technical efficiency is 0.385 in 2007 at the total aggregate fuel level to 0.978 at the disaggregate and aggregate fuel group levels in 2005 (columns 5-7 Table 2-11). The mean scale efficiencies range from 0.833 at the total aggregate fuel group level in 2007 to 0.993 in 2005 at the disaggregate and aggregate fuel group levels (columns 8-10 Table 2-11).

The level of aggregation plays a large role in how efficient firms are in the *Other Renewable Sources* category as seen in the distribution of efficiency scores in the CDFs in Figure 2-28 - Figure 2-30. For all three levels of aggregation, there are very few electric generation plants (less than 5%) that have a pure technical and overall technical efficiency score of less than 0.5, and scale efficiency score of less than 0.6. However, the total aggregate fuel group and aggregate fuel group only has 5% of firms with a pure technical efficiency of approximately 1, the disaggregate fuel group has 45% of firms with an efficiency of approximately 1 (Figure 2-28). Similar results are also found for the distribution of overall technical efficiency scores (Figure 2-29). The distribution of all three levels of aggregation for the scale efficiency scores show that nearly 80% of the disaggregate fuel group, 55% of the aggregate fuel group, and 5% of the total aggregate fuel group have a scale efficiency score of approximately 1 (Figure 2-30).

2.5.10 Other Energy Sources

The input *other energy sources* is the same for the disaggregate and aggregate fuel group levels (Table 2-12). Despite the input variable being the same for these aggregation levels, the SCC is never 1.000. The lowest SCC for the pure technical is 0.872 in 2006, which is the only year it is below 0.900 and for the overall technical efficiencies is 0.964 in 2003 (columns 3 and 6 Table 2-12). The SCC range between the disaggregate and aggregate fuel group levels for the mean scale efficiencies is 0.857 in 2003 to 0.997 in 2006 (column 9 Table 2-12). The minimum SCC between the disaggregate and total aggregate fuel groups is lower. The minimum SCC is 0.723 in 2007, 0.893 in 2003, and 0.491 in 2005 for the pure technical, overall technical, and scale efficiencies, respectively (columns 4, 7, and 10 Table 2-12). The maximum SCC is 0.964 in 2003, 0.983 in 2011, and 0.916 in 2010 for the pure technical, overall technical, and scale efficiencies, respectively (columns 4, 7, and 10 Table 2-12). The correlation between the disaggregate and aggregate fuel groups implies that the efficiency scores between the two groups are similar and the researcher would not lose much information by using the aggregate fuel group instead of the disaggregate fuel group. However, since the SCC is much lower between the disaggregate and total aggregate fuel groups, this implies that the efficiency scores are very different from each other and some valuable information about the efficiency of firms may be lost.

The mean efficiency scores vary drastically depending on the level of aggregation. The range for the mean pure technical efficiency is 0.147 at the total aggregate fuel group level in 2003 to 0.575 at the disaggregate level in 2006 (columns 2-4 Table 2-12). The range for the mean overall technical efficiency score is 0.098 at the total aggregate fuel group level in 2007 to 0.514 at the disaggregate level in 2005 (columns 5-7 Table 2-12). The range of the mean scale efficiency is 0.473 at the disaggregate fuel group level in 2003 to 0.828 in the aggregate fuel group level in 2005 (columns 8-10 Table 2-12).

The CDFs of the distribution of efficiency scores reveal that the disaggregate and aggregate fuel groups have similar efficiency scores for all three efficiencies (Figure 2-31 - Figure 2-33). However, the total aggregate fuel group results in noticeably different pure technical and overall technical efficiency scores. Approximately 30% of the disaggregate fuel group and aggregate fuel groups and none of the total aggregate fuel group have a pure technical efficiency score of 1 (Figure 2-31) and overall technical efficiency score of 1 (Figure 2-32). The distribution of the scale efficiency scores are similar for all three levels of aggregation for the lowest 50% of firms Approximately 42% of the disaggregate fuel group, 35% of the aggregate fuel group, and 1% of the total aggregate fuel group level have a scale efficiency of approximately 1 (Figure 2-33).

A ranking of the fuel inputs categories for each efficiency and level of aggregation is given in Table 2-13. In order to determine the ranking, the mean efficiency scores for all years were taken for each fuel category. Overall, N*uclear* is the most efficient fuel input for all efficiencies and aggregation levels except for the total aggregate fuel level for the scale efficiency where it is the third most efficient fuel input. *Other Renewable Sources* is the second most efficient fuel category for all levels of aggregation and all three efficiencies. *Gaseous*

Renewable Fuels is the third most efficient fuel input for all efficiencies and aggregations levels except for the total aggregate fuel level for the scale efficiency where it is the most efficient fuel input. *Solid Renewable Fuels* is the fourth most efficient fuel category at the disaggregate and aggregate fuel group level for the pure technical and overall technical efficiencies and for all aggregation levels for the scale efficiencies. *Other Energy Sources* is the fifth most efficient fuel input at the disaggregate and aggregate fuel group levels for the pure technical and overall technical efficiencies while *Natural Gas and Other Gases* is the sixth most efficient fuel input for the same efficiencies and levels of aggregation. *Petroleum* is the seventh most efficient fuel input category for all levels of aggregation and all efficiencies. *Liquid Renewable Fuels* is the eighth most efficient fuel input category for all levels of aggregation for the pure technical and overall technical efficiencies. The least efficient fuel category is *Coal* for all levels of aggregation and efficiencies except for the total aggregate fuel level of the scale efficiency.

2.6 Summary and Discussion

An input-oriented production DEA analysis was conducted to see if the level of aggregation of the input variables affect the pure technical, overall technical, and scale efficiencies. An average of 4,750 conventional and/or renewable power plants in the U.S. from 2003 – 2012 were analyzed. In general, the results show that power plants that use nuclear and other renewable energy sources have the highest mean pure technical, overall technical, and scale efficiencies of all the aggregate fuel groups. Whereas plants that use coal and other energy sources have the lowest mean efficiency scores.

Based on the Spearman Correlation Coefficient results the pure technical and overall technical efficiency scores achieved by the disaggregate and aggregate fuel groups are similar to each other. Across all years and aggregate fuel groups, most of the SCC scores are greater than

90%. Since scale efficiency is derived from both the pure technical and overall technical efficiencies, the deviation between the disaggregate and aggregate fuel groups are likely going to be magnified making the SCC for the scale efficiency lower than that of the pure technical and overall technical efficiencies. Despite the correlation being lower for the scale efficiency, most of the correlation coefficients are still above 80%. If the researchers main objective is to determine the overall technical or pure technical efficiencies of a plant, using the aggregate fuel group data will not likely bias the results very much. The efficiency scores will likely be lower, but the ranking of the power plants will be similar regardless whether the disaggregate or aggregate group level aggregation is used.

Again, the SCC scores between the disaggregate and total aggregate fuel groups levels are lower than the scores between the disaggregate and aggregate fuel levels. This implies that information about the efficiencies of different types of plants is lost in the aggregation of all the fuel inputs. The SCC for the disaggregate and total aggregation level is higher for the pure technical and overall technical efficiencies. The difference depends on the category of fuel examined, however the largest difference ranged from a SCC of 0.917 and 0.956 for the pure technical and overall technical efficiency scores to 0.244 for the scale efficiency scores. This implies that the efficiency score is biased down if the total aggregation fuel group level is used. The SCC for the scale efficiencies are likely lower due to two reasons. First the pure technical and overall technical efficiencies derive the scale efficiency which means that any deviation in the SCC for the pure technical and overall technical efficiencies will be magnified in the SCC for the scale efficiency. The second reason is that the mean scale efficiency was often higher for the total aggregate level than for the other two levels. This implies that under the total aggregation level, firms appear to be closer to achieving a scale efficiency equal to one than in the other two aggregation levels. This could be a problem if the plant is trying to determine what the best way to improve their efficiency is.

The other renewable energy sources aggregation level resulted in a lower SCC between the disaggregate and aggregate fuel groups than any other aggregation fuel group. This is likely due to the very different types of inputs that are considered in the group – geothermal, hydroelectric, solar, and wind. Even though in most cases the aggregate fuel group could be used in place of the disaggregate fuel group without losing a lot of information, for this aggregate fuel group, the disaggregate fuel group should be used whenever possible.

From the results, it is clear that using a total aggregate fuel input may make it difficult for researchers to suggest how a firm can improve their production practices to become efficient from a production standpoint. In addition, it may artificially penalize some power plants by suggesting they are inefficient even though for the type of plant and type of fuel the plant is using, they are running efficiently. This implies that if a researcher is considering thermal power plants that use different types of coal, oil, and/or natural gas as inputs and that all these inputs are aggregated together, the plants that use coal are likely to be less efficient. To fix the inefficiency the power plant that uses coal may be inclined to decrease their use of coal to become more efficient. However, if the inputs are disaggregated it might be clear the coal unit is operating efficiently, given it is a coal unit. In addition, by also considering nuclear and using multiple categories of renewable energy, it is easier to see what the most efficient fuel inputs are – nuclear and other renewable energy sources. Solid, liquid, and gas renewable fuel sources have efficiencies on par with coal, natural gas, and petroleum.

There are two limiting factors to these findings. The first is that researchers are often limited by degrees of freedom. If a particular study focuses on a small number of power plants, the researcher may not have the ability to completely disaggregate the fuel inputs. However, if they have the ability to disaggregate the inputs to the aggregate fuel group level, their results will likely be more accurate. The second limitation is data availability. Even though it is becoming easier to access information on power plants, disaggregate information may not always be available and the researcher will have to work with the data they have. However, if the analysis includes multiple aggregate fuel groups, the researcher should present the results with caution.

Table 2-1 – Literature Review of Production Efficiency Studies of Electric Generation Plants

Study	Model	Output	Inputs
		Aggregate Fuel Approach	
Färe, Grosskopf, and Logan (1983)	- BCC - Congestion - Scale	- Net generation (kWh)	- Labor - Fuel (BTUs) - Capital (MW)
Färe, Grosskopf, and Logan (1985)	- BCC - Congestion - Scale	- Net generation (kWh)	- Labor - Fuel (BTUs) - Capital (MW)
Golany, Roll, and Rybak (1994)	- CCR	- Total generated power (GWh)	- Installed capacity - Fuel consumption - Manpower
Park and Lesourd (2000)	- CCR - BCC	- Net electricity (MWh)	- Quantity of fuel consumed - Installed power (kW) - Total manpower
Raczka (2001)	- Technical - Scale	- Heat production (terajoules)	- Labor - Fuel (terajoules) - Pollution
Goto and Tsutsui (1998)	- Technical - Scale - Allocative	- Quantity sold to residential customers (GWh) - Quantity sold to non-residential customers (GWh)	- Nameplate capacity (MW) - Quantity of fuel used (kilo calories) - Total number of employees - Quantity of power purchased (GWh)
Lam and Shiu (2001)	- Technical	- Electricity generated (GWh)	- Generating capacity (MW) - Total fuel used (terajoules) - Labor
Sueyoshi and Goto (2001)	- Technical - Scale	- Total generation (GWh)	- Total fossil fuel generation capacity (MW) - Total fuel consumption (kcal) - Number of employees

Table 2-1 – Literature Review of Production Efficiency Studies of Electric Generation Plants

Study	Model	Output	Inputs
Fallahi, Ebrahimi, and Ghaderi (2011)	- CCR - BCC	- Net electricity produced (MWh)	- Labor - Installed capacity (MW) - Fuel (calories) - Electricity (MWh) - Average operational time (h)
Disaggregate Fuel Approach			
Färe, Grosskopf, and Tyteca (1996)	- CCR - Environmental	- Net generation (kWh) - SO_2 (tons) - NO_X (tons) - CO_2 (tons)	- Coal (short tons) - Oil (barrels) - Natural gas (cubic feet) - Installed capacity (MW) - Labor
Liu, Lin, and Lewis (2010)	- CCR - BCC - Scale	- Net electricity produced (MWh)	- Installed capacity (MW) - Electricity used (MWh) - Heating value of total fuels used (calories)
Bi et al. (2014)	- Slack based measure	- Power generated (kWh) - SO_2 (tons) - NO_X (tons) - Soot (tons)	- Installed capacity (kW) - Labor - Coal (tons) - Gas (cubic meters)
Sarica and Or (2007)	- BCC - CCR - Scale	Thermal Plant - Availability Renewable Plant - Production (kWh) - Utilization	Thermal Plant - Fuel cost - Production (kWh) - Thermal efficiency - Environmental cost - CO Renewable Plant - Operating cost
Lynes and Featherstone (2015)	- BCC	- Net Generation (MWh)	- Installed capacity (MW) - Fuel used (BTUs)

Table 2-1 – Literature Review of Production Efficiency Studies of Electric Generation Plants

Study	Model	Output	Inputs
		No Fuel Approach	
Whiteman and Bell (1994)	- Technical	- Generation (MWh) - Sales per customer (GWh)	- Thermal generating capacity (MW) - Other generating capacity (MW) - Labor
Cook et al. (1998)	- Hierarchy DEA	- Capacity operating hours - Outages - Forced deratings	- Total maintenance expenditure - Total occupied hours
Cook and Green (2005)	- Hierarchy DEA	- Capacity operating hours - Outages	- Forced deratings - Total maintenance expenditure - Total occupied hours
Cook and Zhou (2007)	- Hierarchy DEA	- Capacity operating hours - Outages - Forced deratings	- Total maintenance expenditure - Total occupied hours
Barros and Peypoch (2008)	- Technical	- Energy production (MWh) - Capacity utilization	- Labor - Capital ($) - Operation cost - Investment

Table 2-2 – Input and Output Summary Statistics of Electric Generation Plants from 2003 – 2012 for the DEA

	2003 N = 4363	2004 N = 3800	2005 N = 4622	2006 N = 4530	2007 N = 4631	2008 N = 4425	2009 N = 4816	2010 N = 4911	2011 N = 5091	2012 N = 5367
Total Aggregate Fuel Group										
Total Aggregate	7,452,000	9,005,220	7,956,114	7,977,648	8,236,556	6,985,390	7,363,645	7,769,429	6,480,166	6,720,190
	(23,218,713)	(26,462,669)	(24,106,588)	(24,033,666)	(25,094,374)	(23,922,850)	(23,832,990)	(24,043,424)	(21,921,922)	(22,227,412)
Coal										
Coal Fuel Group	3,308,550	4,266,290	3,629,998	3,690,895	4,007,520	2,718,769	3,438,638	3,706,322	2,670,136	2,671,358
	(15,700,367)	(18,733,780)	(16,949,588)	(16,907,855)	(18,429,009)	(15,849,601)	(17,041,551)	(17,944,373)	(15,081,526)	(14,767,302)
Bituminous Coal	1,691,014	2,124,494	1,847,855	1,778,076	1,959,193	1,130,610	1,673,163	1,858,895	1,278,562	1,199,182
	(11,090,226)	(12,885,350)	(11,869,568)	(10,937,609)	(12,361,587)	(10,071,586)	(11,486,377)	(12,506,265)	(9,990,249)	(9,659,928)
Sub-Bituminous Coal	1,285,231	1,820,479	1,499,002	1,583,453	1,702,354	1,372,625	1,575,233	1,644,731	1,223,081	1,286,793
	(9,543,531)	(12,766,320)	(11,274,875)	(11,493,258)	(12,047,527)	(11,076,258)	(11,437,052)	(11,825,684)	(10,371,522)	(10,190,503)
Lignite Coal	236,834	192,040	158,631	188,780	200,188	191,125	170,989	180,559	151,425	170,414
	(4,413,743)	(3,313,501)	(3,013,276)	(3,841,051)	(3,966,086)	(3,805,229)	(3,400,243)	(3,419,308)	(3,186,196)	(3,528,498)
Refined Coal	68,534	96,198	93,198	104,358	122,928	806	-	-	-	-
	(2,001,627)	(1,928,054)	(2,530,187)	(2,653,925)	(3,132,472)	(31,955)				
Waste/Other Coal	26,937	33,079	31,313	36,228	22,856	23,602	19,253	22,137	17,068	14,969
	(439,499)	(485,096)	(612,985)	(709,582)	(652,608)	(689,158)	(606,458)	(651,136)	(552,656)	(393,160)
Natural Gas and Other Gases										
Natural Gas and Other Gases Fuel Group	1,325,493	1,625,093	1,476,134	1,501,346	1,594,570	1,476,947	1,426,030	1,582,819	1,405,097	1,667,664
	(5,055,944)	(5,919,463)	(5,626,955)	(5,856,442)	(6,118,047)	(5,895,327)	(5,915,071)	(6,362,595)	(5,989,099)	(7,078,275)
Natural Gas	1,281,677	1,556,854	1,413,566	1,445,013	1,530,958	1,413,353	1,378,465	1,534,037	1,360,726	1,627,480
	(4,961,529)	(5,790,715)	(5,461,635)	(5,728,715)	(5,982,954)	(5,777,760)	(5,819,273)	(6,264,841)	(5,907,554)	(7,004,962)
Blast Furnace Gas	10,344	23,267	17,645	16,385	15,906	21,932	12,299	14,459	13,059	11,001
	(260,304)	(501,593)	(489,378)	(430,275)	(406,483)	(499,597)	(328,629)	(366,268)	(301,487)	(366,066)

Table 2-2 – Input and Output Summary Statistics of Electric Generation Plants from 2003 – 2012 for the DEA

	2003 N = 4363	2004 N = 3800	2005 N = 4622	2006 N = 4530	2007 N = 4631	2008 N = 4425	2009 N = 4816	2010 N = 4911	2011 N = 5091	2012 N = 5367
Other Gas	33,446	44,645	44,825	39,885	47,635	41,613	35,224	34,255	31,288	29,171
	(601,361)	(627,189)	(636,551)	(548,775)	(614,337)	(517,151)	(452,017)	(456,662)	(455,626)	(404,536)
Gaseous Propane	27	327	98	64	72	50	41	68	23	12
	(787)	(18,215)	(3,871)	(1,770)	(2,549)	(2,330)	(1,631)	(3,322)	(696)	(470)
Petroleum										
Petroleum Fuel Group	259,210	276,103	276,623	136,802	156,467	92,625	77,597	73,325	44,388	40,999
	(2,357,920)	(2,248,415)	(2,458,430)	(1,277,179)	(1,392,452)	(992,163)	(774,152)	(860,332)	(613,552)	(521,071)
Distillate Fuel Oil	30,696	28,706	25,473	13,789	16,562	13,002	13,458	15,894	9,648	8,937
	(200,586)	(199,489)	(181,468)	(72,435)	(84,343)	(135,552)	(80,407)	(140,503)	(66,272)	(107,407)
Jet Fuel	183	702	775	663	1,124	868	845	728	792	645
	(5,871)	(28,248)	(28,859)	(29,377)	(49,453)	(47,048)	(47,215)	(41,062)	(41,074)	(38,249)
Kerosene	1,144	1,367	1,250	401	885	480	798	430	427	198
	(26,489)	(28,582)	(28,543)	(8,033)	(24,527)	(13,895)	(22,725)	(8,440)	(10,633)	(4,976)
Petroleum Coke	25,788	58,916	47,964	43,927	37,803	23,099	21,422	23,056	16,535	21,768
	(450,583)	(886,423)	(836,280)	(786,319)	(672,306)	(476,124)	(413,531)	(555,038)	(384,895)	(467,199)
Petroleum Coke-Derived Synthesis Gas	-	-	-	-	-	-	-	-	-	1,153
										(84,463)
Residual Fuel Oil	198,157	183,482	198,895	75,621	97,561	52,603	39,338	31,795	16,128	7,497
	(2,295,830)	(2,009,414)	(2,269,188)	(952,000)	(1,201,632)	(854,241)	(640,324)	(628,494)	(465,929)	(170,876)
Waste/Other Oil	3,242	2,930	2,266	2,400	2,532	2,572	1,735	1,421	857	801
	(83,188)	(75,017)	(64,243)	(64,076)	(65,835)	(62,801)	(46,890)	(39,756)	(24,035)	(22,761)
Nuclear										
Nuclear Fuel Group	1,719,350	2,058,012	1,663,541	1,650,726	1,564,722	1,732,103	1,482,008	1,452,732	1,341,012	1,364,911
	(15,975,008)	(17,711,720)	(15,899,832)	(15,882,756)	(15,751,100)	(16,579,937)	(15,466,328)	(14,923,158)	(14,433,948)	(14,830,835)

Table 2-2 – Input and Output Summary Statistics of Electric Generation Plants from 2003 – 2012 for the DEA

	2003 N = 4363	2004 N = 3800	2005 N = 4622	2006 N = 4530	2007 N = 4631	2008 N = 4425	2009 N = 4816	2010 N = 4911	2011 N = 5091	2012 N = 5367
Solid Renewable Fuel										
Solid Renewable Fuels Fuel Group	83,720 (635,488)	110,539 (686,349)	110,066 (675,956)	154,422 (811,624)	154,023 (798,835)	142,287 (775,988)	128,086 (720,269)	128,614 (722,140)	114,090 (662,014)	110,524 (630,455)
Agricultural Feedstock	2,921 (108,696)	4,675 (131,858)	5,331 (142,751)	5,222 (151,927)	4,676 (163,090)	6,668 (228,116)	6,667 (219,031)	5,217 (207,618)	5,314 (197,272)	2,491 (105,169)
Municipal Solid Waste	-	-	-	35,307 (337,710)	34,717 (329,036)	36,058 (345,173)	32,464 (326,001)	30,412 (312,257)	28,359 (293,641)	27,805 (290,879)
Other Biomass Solids	1,195 (76,599)	2,695 (92,563)	1,466 (65,436)	495 (16,798)	1,489 (63,723)	3,250 (105,938)	3,093 (113,668)	4,625 (124,034)	3,671 (112,179)	2,737 (117,941)
Wood/Wood Waste Solids	79,603 (607,372)	103,169 (654,415)	103,269 (647,606)	113,397 (716,269)	113,141 (698,486)	96,311 (637,202)	85,862 (584,758)	88,359 (604,514)	76,746 (542,156)	77,490 (530,050)
Liquid Renewable Fuels										
Liquid Renewable Fuels	109,808 (1,036,260)	154,198 (1,274,677)	147,087 (1,270,076)	169,426 (1,345,375)	161,751 (1,300,554)	135,205 (1,309,722)	110,307 (1,053,448)	129,602 (1,158,119)	107,230 (1,039,742)	111,014 (1,067,478)
Other Biomass Liquids	19 (1,116)	54 (1,980)	26 (1,109)	54 (2,098)	38 (1,602)	54 (2,013)	55 (1,789)	41 (1,421)	140 (6,540)	106 (5,642)
Black Liquor	105,844 (1,025,403)	152,033 (1,262,076)	144,702 (1,261,459)	168,048 (1,340,385)	159,720 (1,295,146)	133,525 (1,303,944)	108,831 (1,047,435)	127,971 (1,152,750)	105,751 (1,034,001)	108,655 (1,059,567)
Sludge Waste	1,929 (65,254)	1,945 (38,932)	1,666 (38,322)	1,324 (24,201)	1,388 (25,672)	1,058 (18,988)	881 (18,078)	992 (21,619)	747 (15,880)	779 (15,557)
Wood Waste Liquids	2,017 (65,606)	166 (7,760)	692 (46,764)	-	605 (41,139)	567 (37,738)	540 (37,485)	597 (41,867)	593 (42,198)	1,474 (78,839)

Table 2-2 – Input and Output Summary Statistics of Electric Generation Plants from 2003 – 2012 for the DEA

	2003 N = 4363	2004 N = 3800	2005 N = 4622	2006 N = 4530	2007 N = 4631	2008 N = 4425	2009 N = 4816	2010 N = 4911	2011 N = 5091	2012 N = 5367
Gaseous Renewable Fuels										
Gaseous Renewable Fuels Fuel Group	15,826	19,326	16,955	19,312	18,887	21,268	20,907	15,454	21,874	21,721
	(118,402)	(135,875)	(130,928)	(138,180)	(136,682)	(142,593)	(134,831)	(131,002)	(142,822)	(146,880)
Landfill Gas	13,633	16,905	14,522	16,785	16,848	19,596	19,143	13,611	20,064	19,795
	(110,828)	(127,423)	(123,195)	129,996	(129,654)	(136,909)	(129,367)	(125,501)	(138,006)	(142,331)
Other Biomass Gas	2,192	2,421	2,432	2,527	2,039	1,672	1,765	1,843	1,811	1,926
	(41,856)	(47,834)	(44,562)	(47,100)	(43,344)	(39,960)	(38,194)	(37,634)	(37,186)	(36,973)
Other Renewable Energy Sources										
Other Renewable Energy Fuel Group	628,633	479,735	621,944	641,150	568,618	661,573	673,180	674,841	771,445	727,122
	(4,881,451)	(4,888,557)	(4,851,607)	(5,105,128)	(4,935,157)	(5,167,284)	(4,769,095)	(4,300,409)	(5,365,002)	(5,173,414)
Geothermal	33,023	21,257	29,561	31,865	24,499	31,136	27,321	30,234	28,288	26,425
	(793,918)	(797,828)	(745,816)	(745,975)	(736,883)	(736,535)	(697,252)	(696,544)	(682,592)	(663,977)
Hydroelectric	568,197	428,358	554,642	558,577	476,080	522,650	496,967	464,955	528,566	460,560
	(4,817,336)	(4,818,811)	(4,791,924)	(5,041,039)	(4,862,944)	(5,079,578)	(4,682,248)	(4,190,353)	(5,272,573)	(5,064,729)
Solar	1,253	1,338	1,190	1,112	1,306	1,912	1,789	2,373	3,082	7,265
	(32,291)	(34,234)	(31,020)	(29,388)	(32,549)	(42,256)	(37,935)	(43,255)	(44,400)	(79,127)
Wind	26,159	28,782	36,550	49,597	66,734	105,875	147,103	177,278	211,508	232,872
	(247,102)	(291,085)	(308,779)	(434,199)	(505,106)	(711,904)	(719,071)	(808,912)	(886,308)	(962,938)
Other Energy Sources										
Other Energy Sources Fuel Group	1,410	15,923	13,768	13,569	9,997	4,613	6,892	5,721	4,894	4,877
	(54,035)	(323,492)	(301,589)	(312,374)	(292,214)	(84,365)	(210,714)	(125,157)	(116,102)	(116,630)

Table 2-2 – Input and Output Summary Statistics of Electric Generation Plants from 2003 – 2012 for the DEA

	2003 N = 4363	2004 N = 3800	2005 N = 4622	2006 N = 4530	2007 N = 4631	2008 N = 4425	2009 N = 4816	2010 N = 4911	2011 N = 5091	2012 N = 5367
Capacity										
Installed Capacity (MW)	194 (431)	223 (472)	199 (439)	199 (438)	201 (447)	177 (419)	198 (450)	203 (450)	178 (419)	186 (440)
Output										
Net Generation (MWh)	356,534 (1,653,730)	396,611 (1,833,561)	364,371 (1,672,131)	378,725 (1,701,614)	370,354 (1,696,091)	388,100 (1,777,114)	363,846 (1,681,617)	382,359 (1,651,681)	358,977 (1,630,433)	387,762 (1,718,496)

Standard deviation in parenthesis. All fuel categories are in million BTUs.

Table 2-3 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – All Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2003 N = 4,363									
SCC with Disaggregate	-	0.942***	0.790***	-	0.973***	0.834***	-	0.958***	0.433***
Mean Efficiency	0.640	0.628	0.416	0.573	0.566	0.330	0.795	0.800	0.730
	(0.374)	(0.376)	(0.290)	(0.405)	(0.404)	(0.286)	(0.302)	(0.297)	(0.312)
Number of Efficient Plants[a]	356	168	24	193	80	4	242	112	18
2004 N = 3,800									
SCC with Disaggregate	-	0.969***	0.865***	-	0.988***	0.900***	-	0.937***	0.456***
Mean Efficiency	0.569	0.556	0.421	0.522	0.512	0.361	0.861	0.852	0.832
	(0.373)	(0.371)	(0.286)	(0.374)	(0.373)	(0.255)	(0.243)	(0.248)	(0.239)
Number of Efficient Plants[a]	532	460	27	267	233	3	454	398	6
2005 N = 4,622									
SCC with Disaggregate	-	0.960***	0.795***	-	0.984***	0.838***	-	0.955***	0.312***
Mean Efficiency	0.663	0.652	0.486	0.628	0.619	0.402	0.896	0.896	0.809
	(0.347)	(0.349)	(0.267)	(0.353)	(0.355)	(0.230)	(0.215)	(0.215)	(0.218)
Number of Efficient Plants[a]	953	820	54	595	540	4	621	561	18

Table 2-3 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – All Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2006 N = 4,530									
SCC with Disaggregate	-	0.951***	0.773***	-	0.979***	0.828***	-	0.952***	0.468***
Mean Efficiency	0.666 (0.348)	0.649 (0.351)	0.468 (0.260)	0.613 (0.354)	0.601 (0.356)	0.368 (0.206)	0.875 (0.215)	0.875 (0.217)	0.768 (0.212)
Number of Efficient Plants[a]	977	861	29	632	575	3	991	958	4
2007 N = 4,631									
SCC with Disaggregate	-	0.916***	0.796***	-	0.941***	0.845***	-	0.889***	0.595***
Mean Efficiency	0.556 (0.346)	0.522 (0.331)	0.352 (0.251)	0.471 (0.343)	0.438 (0.320)	0.249 (0.181)	0.799 (0.259)	0.790 (0.262)	0.714 (0.301)
Number of Efficient Plants[a]	345	146	38	189	32	4	317	69	15
2008 N = 4,425									
SCC with Disaggregate	-	0.895***	0.814***	-	0.917***	0.839***	-	0.854***	0.465***
Mean Efficiency	0.605 (0.324)	0.568 (0.306)	0.437 (0.283)	0.533 (0.326)	0.492 (0.298)	0.359 (0.256)	0.830 (0.225)	0.819 (0.229)	0.800 (0.276)
Number of Efficient Plants[a]	519	191	39	288	60	5	357	84	11

Table 2-3 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – All Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2009 N = 4,816									
SCC with Disaggregate	-	0.822***	0.791***	-	0.860***	0.818***	-	0.808***	0.550***
Mean Efficiency	0.608 (0.332)	0.551 (0.303)	0.450 (0.275)	0.524 (0.342)	0.459 (0.295)	0.378 (0.255)	0.814 (0.250)	0.800 (0.251)	0.812 (0.241)
Number of Efficient Plants[a]	595	205	33	369	72	5	450	81	57
2010 N = 4,911									
SCC with Disaggregate	-	0.842***	0.774***	-	0.871***	0.809***	-	0.814***	0.583***
Mean Efficiency	0.623 (0.337)	0.568 (0.311)	0.432 (0.269)	0.530 (0.365)	0.467 (0.321)	0.345 (0.251)	0.782 (0.288)	0.765 (0.284)	0.762 (0.274)
Number of Efficient Plants[a]	734	228	74	444	81	5	536	328	32
2011 N = 5,091									
SCC with Disaggregate	-	0.818***	0.752***	-	0.824***	0.771***	-	0.710***	0.249***
Mean Efficiency	0.711 (0.321)	0.672 (0.310)	0.518 (0.279)	0.669 (0.335)	0.619 (0.317)	0.454 (0.271)	0.898 (0.200)	0.879 (0.208)	0.848 (0.219)
Number of Efficient Plants[a]	682	235	31	445	81	8	529	116	24

Table 2-3 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – All Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2012 N = 5,367									
SCC with Disaggregate	-	0.848***	0.737***	-	0.856***	0.739***	-	0.686***	0.183***
Mean Efficiency	0.733 (0.316)	0.703 (0.310)	0.561 (0.259)	0.703 (0.327)	0.667 (0.315)	0.488 (0.231)	0.928 (0.172)	0.919 (0.176)	0.861 (0.180)
Number of Efficient Plants[a]	729	219	35	501	66	9	790	142	54

Table 2-4 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Coal Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2003 N = 515									
SCC with Disaggregate	-	0.897***	0.839***	-	0.989***	0.985***	-	0.864***	0.625***
Mean Efficiency	0.171 (0.306)	0.133 (0.266)	0.079 (0.183)	0.110 (0.244)	0.098 (0.220)	0.067 (0.156)	0.588 (0.360)	0.617 (0.346)	0.834 (0.233)
Number of Efficient Plants[a]	32	11	2	10	3	1	12	4	15
2004 N = 552									
SCC with Disaggregate	-	0.968***	0.972***	-	0.992***	0.993***	-	0.854***	0.822***
Mean Efficiency	0.146 (0.286)	0.119 (0.247)	0.073 (0.156)	0.103 (0.231)	0.080 (0.185)	0.054 (0.125)	0.599 (0.349)	0.531 (0.324)	0.619 (0.331)
Number of Efficient Plants[a]	25	13	2	11	4	0	14	8	2
2005 N = 570									
SCC with Disaggregate	-	0.942***	0.942***	-	0.952***	0.952***	-	0.854***	0.758***
Mean Efficiency	0.155 (0.279)	0.136 (0.269)	0.086 (0.178)	0.113 (0.226)	0.093 (0.205)	0.067 (0.151)	0.600 (0.347)	0.588 (0.344)	0.619 (0.344)
Number of Efficient Plants[a]	20	12	2	7	2	0	15	11	11

Table 2-4 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Coal Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2006 N = 548									
SCC with Disaggregate	-	0.916***	0.916***	-	0.897***	0.903***	-	0.859***	0.825***
Mean Efficiency	0.156 (0.275)	0.122 (0.247)	0.071 (0.148)	0.111 (0.217)	0.087 (0.193)	0.050 (0.111)	0.632 (0.331)	0.617 (0.343)	0.584 (0.310)
Number of Efficient Plants[a]	16	12	2	5	2	0	26	21	1
2007 N = 547									
SCC with Disaggregate	-	0.937***	0.916***	-	0.934***	0.924***	-	0.871***	0.782***
Mean Efficiency	0.141 (0.270)	0.107 (0.224)	0.050 (0.118)	0.099 (0.212)	0.080 (0.185)	0.026 (0.060)	0.657 (0.325)	0.627 (0.327)	0.563 (0.367)
Number of Efficient Plants[a]	20	7	1	5	2	0	7	3	8
2008 N = 369									
SCC with Disaggregate	-	0.895***	0.879***	-	0.893***	0.901***	-	0.842***	0.793***
Mean Efficiency	0.156 (0.282)	0.129 (0.271)	0.067 (0.146)	0.102 (0.213)	0.074 (0.179)	0.048 (0.117)	0.620 (0.331)	0.568 (0.330)	0.563 (0.363)
Number of Efficient Plants[a]	19	12	1	7	3	0	13	4	1

Table 2-4 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Coal Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2009 N = 511									
SCC with Disaggregate	-	0.905***	0.915***	-	0.915***	0.904***	-	0.865***	0.742***
Mean Efficiency	0.141 (0.271)	0.120 (0.253)	0.056 (0.121)	0.097 (0.210)	0.077 (0.186)	0.039 (0.096)	0.683 (0.308)	0.668 (0.328)	0.680 (0.332)
Number of Efficient Plants[a]	19	17	0	9	6	0	9	8	38
2010 N = 537									
SCC with Disaggregate	-	0.926***	0.918***	-	0.942***	0.931***	-	0.883***	0.762***
Mean Efficiency	0.142 (0.265)	0.120 (0.243)	0.070 (0.153)	0.098 (0.215)	0.087 (0.202)	0.052 (0.118)	0.646 (0.327)	0.631 (0.321)	0.657 (0.353)
Number of Efficient Plants[a]	23	14	4	10	6	0	13	8	4
2011 N = 474									
SCC with Disaggregate	-	0.944***	0.935***	-	0.983***	0.978***	-	0.863***	0.540***
Mean Efficiency	0.152 (0.279)	0.135 (0.261)	0.069 (0.146)	0.110 (0.232)	0.086 (0.190)	0.064 (0.140)	0.678 (0.336)	0.623 (0.335)	0.828 (0.260)
Number of Efficient Plants[a]	22	18	0	11	4	0	15	11	9

Table 2-4 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Coal Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2012 N = 480									
SCC with Disaggregate	-	0.956***	0.948***	-	0.978***	0.981***	-	0.810***	0.611***
Mean Efficiency	0.169 (0.283)	0.136 (0.249)	0.096 (0.179)	0.124 (0.233)	0.105 (0.206)	0.078 (0.155)	0.721 (0.317)	0.712 (0.332)	0.729 (0.331)
Number of Efficient Plants[a]	21	11	2	10	4	0	19	15	31

[a] The number of efficient plants is the number of plants, given the level of aggregation, that have an efficiency score of 1. Standard deviations are in parenthesis. *** implies significance at the 1% level, ** implies significance at the 5% level, and * implies significance at the 10% level.

Table 2-5 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Natural Gas and Other Gases Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2003 N = 1753									
SCC with Disaggregate	-	0.972***	0.935***	-	0.990***	0.978***	-	0.965***	0.809***
Mean Efficiency	0.379 (0.313)	0.367 (0.306)	0.323 (0.283)	0.258 (0.290)	0.252 (0.284)	0.218 (0.247)	0.605 (0.331)	0.612 (0.330)	0.653 (0.326)
Number of Efficient Plants[a]	66	43	14	17	8	1	19	9	5
2004 N = 1750									
SCC with Disaggregate	-	0.975***	0.963***	-	0.990***	0.975***	-	0.909***	0.775***
Mean Efficiency	0.377 (0.299)	0.366 (0.294)	0.336 (0.269)	0.327 (0.275)	0.320 (0.270)	0.288 (0.238)	0.834 (0.263)	0.826 (0.267)	0.824 (0.260)
Number of Efficient Plants[a]	65	44	12	18	10	2	30	16	5
2005 N = 1820									
SCC with Disaggregate	-	0.957***	0.938***	-	0.985***	0.963***	-	0.926***	0.520***
Mean Efficiency	0.455 (0.284)	0.446 (0.279)	0.399 (0.272)	0.407 (0.260)	0.399 (0.255)	0.309 (0.216)	0.855 (0.245)	0.854 (0.246)	0.763 (0.240)
Number of Efficient Plants[a]	61	44	17	20	7	1	25	10	12

Table 2-5 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Natural Gas and Other Gases Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2006 N = 1816									
SCC with Disaggregate	-	0.956***	0.928***	-	0.979***	0.927***	-	0.922***	0.590***
Mean Efficiency	0.464 (0.296)	0.452 (0.292)	0.405 (0.281)	0.382 (0.238)	0.372 (0.232)	0.303 (0.212)	0.812 (0.236)	0.809 (0.240)	0.724 (0.222)
Number of Efficient Plants[a]	59	44	15	15	3	1	69	63	1
2007 N = 1812									
SCC with Disaggregate	-	0.966***	0.903***	-	0.978***	0.942***	-	0.951***	0.664***
Mean Efficiency	0.333 (0.277)	0.317 (0.265)	0.269 (0.256)	0.232 (0.208)	0.220 (0.193)	0.186 (0.177)	0.712 (0.273)	0.706 (0.280)	0.702 (0.300)
Number of Efficient Plants[a]	52	33	18	15	4	2	20	12	11
2008 N = 1657									
SCC with Disaggregate	-	0.968***	0.957***	-	0.989***	0.981***	-	0.923***	0.498***
Mean Efficiency	0.389 (0.296)	0.374 (0.288)	0.322 (0.278)	0.304 (0.267)	0.291 (0.257)	0.268 (0.240)	0.729 (0.253)	0.724 (0.262)	0.800 (0.289)
Number of Efficient Plants[a]	62	38	19	19	7	2	46	26	6

Table 2-5 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Natural Gas and Other Gases Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2009 N = 1723									
SCC with Disaggregate	-	0.961***	0.940***	-	0.987***	0.971***	-	0.953***	0.846***
Mean Efficiency	0.407 (0.304)	0.390 (0.295)	0.324 (0.279)	0.286 (0.266)	0.274 (0.255)	0.258 (0.249)	0.688 (0.289)	0.689 (0.292)	0.764 (0.264)
Number of Efficient Plants[a]	66	44	20	17	7	4	21	9	40
2010 N = 1784									
SCC with Disaggregate	-	0.969***	0.938***	-	0.991***	0.980***	-	0.964***	0.861***
Mean Efficiency	0.417 (0.297)	0.401 (0.288)	0.322 (0.270)	0.273 (0.276)	0.262 (0.266)	0.244 (0.249)	0.621 (0.323)	0.619 (0.323)	0.701 (0.292)
Number of Efficient Plants[a]	74	42	17	19	7	4	61	47	15
2011 N = 1729									
SCC with Disaggregate	-	0.960***	0.917***	-	0.979***	0.956***	-	0.904***	0.244***
Mean Efficiency	0.512 (0.306)	0.498 (0.305)	0.397 (0.302)	0.459 (0.303)	0.445 (0.300)	0.342 (0.274)	0.845 (0.242)	0.835 (0.247)	0.833 (0.227)
Number of Efficient Plants[a]	67	48	14	28	15	4	39	20	15

Table 2-5 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Natural Gas and Other Gases Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2012 N = 1816									
SCC with Disaggregate	-	0.957***	0.929***	-	0.985***	0.971***	-	0.899***	0.432***
Mean Efficiency	0.525 (0.295)	0.512 (0.293)	0.467 (0.293)	0.489 (0.289)	0.479 (0.288)	0.406 (0.261)	0.897 (0.205)	0.897 (0.206)	0.849 (0.204)
Number of Efficient Plants[a]	66	52	18	18	11	4	56	48	29

[a] The number of efficient plants is the number of plants, given the level of aggregation, that have an efficiency score of 1. Standard deviations are in parenthesis. *** implies significance at the 1% level, ** implies significance at the 5% level, and * implies significance at the 10% level.

Table 2-6 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Petroleum Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2003 N = 1536									
SCC with Disaggregate	-	0.937***	0.754***	-	0.993***	0.738***	-	0.943***	0.345***
Mean Efficiency	0.379 (0.315)	0.358 (0.304)	0.199 (0.226)	0.285 (0.294)	0.276 (0.286)	0.096 (0.160)	0.664 (0.334)	0.673 (0.327)	0.548 (0.348)
Number of Efficient Plants[a]	57	27	7	19	8	0	22	12	14
2004 N = 1562									
SCC with Disaggregate	-	0.963***	0.910***	-	0.985***	0.942***	-	0.871***	0.646***
Mean Efficiency	0.344 (0.293)	0.325 (0.279)	0.246 (0.228)	0.282 (0.256)	0.268 (0.242)	0.191 (0.176)	0.777 (0.284)	0.759 (0.287)	0.772 (0.291)
Number of Efficient Plants[a]	46	16	7	19	4	0	28	11	3
2005 N = 1626									
SCC with Disaggregate	-	0.941***	0.906***	-	0.977***	0.949***	-	0.892***	0.605***
Mean Efficiency	0.404 (0.293)	0.385 (0.283)	0.303 (0.238)	0.357 (0.269)	0.342 (0.260)	0.237 (0.183)	0.820 (0.268)	0.821 (0.268)	0.763 (0.275)
Number of Efficient Plants[a]	61	35	13	26	7	1	38	19	10

Table 2-6 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Petroleum Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2006, N = 1534									
SCC with Disaggregate	-	0.923***	0.882***	-	0.964***	0.916***	-	0.893***	0.700***
Mean Efficiency	0.400 (0.294)	0.375 (0.280)	0.289 (0.238)	0.331 (0.252)	0.314 (0.240)	0.207 (0.170)	0.786 (0.259)	0.787 (0.263)	0.694 (0.258)
Number of Efficient Plants[a]	58	30	9	22	5	0	36	17	1
2007, N = 1505									
SCC with Disaggregate	-	0.942***	0.864***	-	0.964***	0.880***	-	0.919***	0.665***
Mean Efficiency	0.305 (0.282)	0.278 (0.261)	0.202 (0.223)	0.204 (0.226)	0.184 (0.200)	0.096 (0.128)	0.676 (0.299)	0.666 (0.304)	0.543 (0.346)
Number of Efficient Plants[a]	37	26	8	17	4	1	20	7	6
2008, N = 1321									
SCC with Disaggregate	-	0.935***	0.772***	-	0.965***	0.752***	-	0.890***	0.411***
Mean Efficiency	0.397 (0.303)	0.371 (0.289)	0.237 (0.232)	0.314 (0.276)	0.291 (0.255)	0.143 (0.164)	0.739 (0.262)	0.728 (0.272)	0.649 (0.352)
Number of Efficient Plants[a]	61	35	6	29	8	1	36	8	2

Table 2-6 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Petroleum Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2009 N = 1432									
SCC with Disaggregate	-	0.927***	0.881***	-	0.970***	0.903***	-	0.919***	0.730***
Mean Efficiency	0.354 (0.305)	0.327 (0.283)	0.235 (0.239)	0.252 (0.262)	0.230 (0.237)	0.147 (0.165)	0.702 (0.290)	0.699 (0.297)	0.687 (0.306)
Number of Efficient Plants[a]	54	29	8	17	5	1	20	8	28
2010 N = 1424									
SCC with Disaggregate	-	0.943***	0.874***	-	0.982***	0.894***	-	0.928***	0.782***
Mean Efficiency	0.344 (0.302)	0.311 (0.275)	0.224 (0.239)	0.223 (0.262)	0.196 (0.228)	0.123 (0.164)	0.634 (0.315)	0.624 (0.310)	0.613 (0.327)
Number of Efficient Plants[a]	60	25	16	24	12	2	28	15	10
2011 N = 1360									
SCC with Disaggregate	-	0.948***	0.879***	-	0.978***	0.905***	-	0.877***	0.469***
Mean Efficiency	0.414 (0.311)	0.398 (0.301)	0.272 (0.255)	0.347 (0.287)	0.327 (0.275)	0.184 (0.211)	0.785 (0.264)	0.767 (0.274)	0.699 (0.309)
Number of Efficient Plants[a]	64	38	6	22	9	2	29	18	14

Table 2-6 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Petroleum Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2012 N = 1326									
SCC with Disaggregate	-	0.949***	0.916***	-	0.976***	0.948***	-	0.838***	0.512***
Mean Efficiency	0.429 (0.302)	0.406 (0.291)	0.333 (0.260)	0.380 (0.285)	0.361 (0.271)	0.271 (0.217)	0.844 (0.237)	0.841 (0.242)	0.802 (0.253)
Number of Efficient Plants[a]	54	31	8	24	8	1	42	30	22

[a] The number of efficient plants is the number of plants, given the level of aggregation, that have an efficiency score of 1. Standard deviations are in parenthesis. *** implies significance at the 1% level, ** implies significance at the 5% level, and * implies significance at the 10% level.

Table 2-7 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Nuclear Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2003, N = 61									
SCC with Disaggregate	-	0.939***	0.227*	-	1.000***	0.452***	-	0.845***	-0.104
Mean Efficiency	0.977 (0.132)	0.975 (0.132)	0.926 (0.155)	0.965 (0.158)	0.965 (0.158)	0.782 (0.130)	0.974 (0.140)	0.974 (0.136)	0.847 (0.020)
Number of Efficient Plants[a]	50	49	4	42	42	0	44	47	0
2004, N = 61									
SCC with Disaggregate	-	0.947***	0.302**	-	1.000***	0.454***	-	0.935***	0.086
Mean Efficiency	0.977 (0.132)	0.975 (0.132)	0.923 (0.160)	0.966 (0.154)	0.964 (0.161)	0.812 (0.147)	0.974 (0.142)	0.972 (0.145)	0.877 (0.063)
Number of Efficient Plants[a]	44	43	7	40	40	0	50	49	0
2005, N = 61									
SCC with Disaggregate	-	1.000***	0.427***	-	1.000***	0.630***	-	0.932***	0.013
Mean Efficiency	0.976 (0.132)	0.965 (0.158)	0.923 (0.160)	0.965 (0.158)	0.965 (0.159)	0.823 (0.148)	0.973 (0.145)	0.984 (0.116)	0.887 (0.049)
Number of Efficient Plants[a]	38	38	6	15	15	0	25	25	0

Table 2-7 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Nuclear Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2006 N = 58									
SCC with Disaggregate	-	0.933***	0.323**	-	1.000***	0.457***	-	0.889***	0.164
Mean Efficiency	0.980 (0.132)	0.968 (0.158)	0.925 (0.158)	0.968 (0.157)	0.968 (0.158)	0.622 (0.114)	0.972 (0.151)	0.984 (0.125)	0.667 (0.060)
Number of Efficient Plants[a]	23	22	4	18	18	0	47	49	0
2007 N = 55									
SCC with Disaggregate	-	0.920***	0.381***	-	1.000***	0.013	-	1.000***	0.097
Mean Efficiency	0.973 (0.144)	0.971 (0.145)	0.916 (0.171)	0.959 (0.171)	0.957 (0.176)	0.435 (0.076)	0.967 (0.154)	0.966 (0.159)	0.470 (0.055)
Number of Efficient Plants[a]	9	10	3	6	6	0	35	35	0
2008 N = 58									
SCC with Disaggregate	-	1.000***	0.341***	-	1.000***	0.148	-	1.000***	0.026
Mean Efficiency	0.990 (0.056)	0.990 (0.056)	0.937 (0.111)	0.981 (0.101)	0.981 (0.101)	0.858 (0.106)	0.988 (0.069)	0.988 (0.069)	0.915 (0.029)
Number of Efficient Plants[a]	42	42	8	26	26	0	31	31	0

Table 2-7 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Nuclear Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2009 N = 55									
SCC with Disaggregate	-	1.000***	0.378***	-	1.000***	0.258*	-	0.949***	-0.282**
Mean Efficiency	0.992	0.989	0.911	0.981	0.979	0.719	0.988	0.988	0.794
	(0.058)	(0.063)	(0.127)	(0.101)	(0.110)	(0.082)	(0.077)	(0.080)	(0.045)
Number of Efficient Plants[a]	43	43	4	37	37	0	44	43	0
2010 N = 57									
SCC with Disaggregate	-	1.000***	0.439***	-	1.000***	0.246*	-	1.000***	-0.118
Mean Efficiency	0.972	0.972	0.906	0.971	0.970	0.774	0.980	0.980	0.841
	(0.143)	(0.144)	(0.158)	(0.148)	(0.149)	(0.138)	(0.129)	(0.130)	(0.119)
Number of Efficient Plants[a]	42	42	6	40	40	0	44	44	0
2011 N = 53									
SCC with Disaggregate	-	0.926***	0.285**	-	1.000***	0.353***	-	1.000***	0.157
Mean Efficiency	0.992	0.999	0.927	0.991	0.991	0.875	0.999	0.992	0.944
	(0.052)	(0.009)	(0.091)	(0.053)	(0.054)	(0.085)	(0.002)	(0.053)	(0.027)
Number of Efficient Plants[a]	39	40	4	36	36	1	45	45	1

Table 2-7 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Nuclear Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
				2012 N = 57					
SCC with Disaggregate	-	1.000***	0.391***	-	1.000***	0.370***	-	0.905***	0.224*
Mean Efficiency	0.990 (0.067)	0.990 (0.067)	0.892 (0.116)	0.986 (0.072)	0.986 (0.072)	0.845 (0.116)	0.996 (0.028)	0.996 (0.028)	0.948 (0.044)
Number of Efficient Plants[a]	24	24	3	21	21	1	35	35	2

[a] The number of efficient plants is the number of plants, given the level of aggregation, that have an efficiency score of 1. Standard deviations are in parenthesis. *** implies significance at the 1% level, ** implies significance at the 5% level, and * implies significance at the 10% level.

Table 2-8 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Solid Renewable Fuel Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2003 N = 161									
SCC with Disaggregate	-	0.969***	0.872***	-	0.992***	0.953***	-	0.915***	0.453***
Mean Efficiency	0.497 (0.357)	0.475 (0.349)	0.286 (0.248)	0.427 (0.339)	0.417 (0.335)	0.249 (0.225)	0.779 (0.294)	0.797 (0.293)	0.849 (0.244)
Number of Efficient Plants[a]	17	13	2	7	5	0	7	5	0
2004 N = 193									
SCC with Disaggregate	-	0.958***	0.891***	-	0.991***	0.971***	-	0.860***	0.625***
Mean Efficiency	0.488 (0.357)	0.450 (0.343)	0.320 (0.264)	0.408 (0.341)	0.393 (0.333)	0.250 (0.223)	0.745 (0.314)	0.770 (0.310)	0.712 (0.296)
Number of Efficient Plants[a]	25	14	3	8	4	0	8	4	0
2005 N = 213									
SCC with Disaggregate	-	0.901***	0.865***	-	0.949***	0.931***	-	0.943***	0.665***
Mean Efficiency	0.480 (0.340)	0.456 (0.335)	0.345 (0.266)	0.395 (0.311)	0.368 (0.299)	0.280 (0.235)	0.746 (0.298)	0.750 (0.293)	0.749 (0.301)
Number of Efficient Plants[a]	17	12	4	8	3	0	8	3	0

Table 2-8 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Solid Renewable Fuel Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2006 N = 281									
SCC with Disaggregate	-	0.883***	0.843***	-	0.932***	0.912***	-	0.844***	0.555***
Mean Efficiency	0.523 (0.336)	0.452 (0.301)	0.282 (0.194)	0.461 (0.333)	0.402 (0.296)	0.225 (0.166)	0.806 (0.288)	0.813 (0.288)	0.737 (0.278)
Number of Efficient Plants[a]	26	10	2	8	3	0	13	10	0
2007 N = 289									
SCC with Disaggregate	-	0.902***	0.776***	-	0.916***	0.910***	-	0.883***	0.464***
Mean Efficiency	0.525 (0.342)	0.443 (0.299)	0.206 (0.187)	0.456 (0.331)	0.384 (0.285)	0.142 (0.124)	0.805 (0.274)	0.799 (0.279)	0.726 (0.356)
Number of Efficient Plants[a]	33	13	1	14	5	1	20	13	1
2008 N = 259									
SCC with Disaggregate	-	0.869***	0.770***	-	0.865***	0.835***	-	0.717***	0.477***
Mean Efficiency	0.584 (0.350)	0.507 (0.324)	0.364 (0.249)	0.524 (0.340)	0.437 (0.299)	0.327 (0.233)	0.828 (0.266)	0.803 (0.273)	0.833 (0.274)
Number of Efficient Plants[a]	41	26	3	16	6	1	21	8	1

Table 2-8 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Solid Renewable Fuel Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2009 N = 266									
SCC with Disaggregate	-	0.890***	0.870***	-	0.909***	0.897***	-	0.770***	0.630***
Mean Efficiency	0.552 (0.350)	0.475 (0.315)	0.280 (0.199)	0.488 (0.333)	0.412 (0.294)	0.244 (0.189)	0.803 (0.275)	0.796 (0.282)	0.777 (0.307)
Number of Efficient Plants[a]	31	16	1	9	4	0	10	6	0
2010 N = 262									
SCC with Disaggregate	-	0.932***	0.858***	-	0.939***	0.901***	-	0.753***	0.446***
Mean Efficiency	0.571 (0.348)	0.519 (0.328)	0.303 (0.213)	0.514 (0.346)	0.454 (0.313)	0.273 (0.198)	0.813 (0.294)	0.798 (0.296)	0.827 (0.311)
Number of Efficient Plants[a]	45	21	3	20	8	0	22	9	9
2011 N = 262									
SCC with Disaggregate	-	0.840***	0.793***	-	0.902***	0.893***	-	0.732***	0.115*
Mean Efficiency	0.589 (0.339)	0.514 (0.314)	0.314 (0.213)	0.516 (0.334)	0.446 (0.301)	0.297 (0.203)	0.809 (0.280)	0.807 (0.283)	0.903 (0.180)
Number of Efficient Plants[a]	33	18	1	12	4	0	20	19	13

Table 2-8 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Solid Renewable Fuel Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
				2012 N = 262					
SCC with Disaggregate	-	0.920***	0.844***	-	0.922***	0.907***	-	0.789***	0.496***
Mean Efficiency	0.584 (0.344)	0.507 (0.312)	0.354 (0.240)	0.519 (0.338)	0.441 (0.301)	0.321 (0.224)	0.821 (0.280)	0.811 (0.280)	0.846 (0.282)
Number of Efficient Plants[a]	35	15	4	15	8	0	20	23	2

[a] The number of efficient plants is the number of plants, given the level of aggregation, that have an efficiency score of 1. Standard deviations are in parenthesis. *** implies significance at the 1% level, ** implies significance at the 5% level, and * implies significance at the 10% level.

Table 2-9 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Liquid Renewable Fuel Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2003 N = 72									
SCC with Disaggregate	-	0.977***	0.857***	-	0.997***	0.942***	-	0.917***	0.430***
Mean Efficiency	0.340 (0.295)	0.328 (0.292)	0.161 (0.191)	0.275 (0.259)	0.267 (0.249)	0.108 (0.086)	0.761 (0.304)	0.789 (0.294)	0.826 (0.259)
Number of Efficient Plants[a]	7	6	2	3	2	0	3	2	0
2004 N = 78									
SCC with Disaggregate	-	0.973***	0.933***	-	0.996***	0.980***	-	0.850***	0.489***
Mean Efficiency	0.323 (0.302)	0.281 (0.264)	0.234 (0.259)	0.277 (0.264)	0.260 (0.253)	0.153 (0.151)	0.753 (0.303)	0.798 (0.275)	0.655 (0.248)
Number of Efficient Plants[a]	3	1	1	1	1	0	2	1	0
2005 N = 87									
SCC with Disaggregate	-	0.991***	0.920***	-	0.995***	0.962***	-	0.970***	0.657***
Mean Efficiency	0.311 (0.283)	0.300 (0.285)	0.263 (0.264)	0.275 (0.259)	0.259 (0.247)	0.188 (0.178)	0.758 (0.306)	0.761 (0.303)	0.687 (0.296)
Number of Efficient Plants[a]	5	4	3	2	2	0	2	2	0

Table 2-9 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Liquid Renewable Fuel Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2006 N = 95									
SCC with Disaggregate	-	0.922***	0.943***	-	0.997***	0.982***	-	0.734***	0.663***
Mean Efficiency	0.321 (0.278)	0.312 (0.275)	0.189 (0.175)	0.261 (0.229)	0.250 (0.218)	0.151 (0.135)	0.726 (0.307)	0.741 (0.322)	0.707 (0.315)
Number of Efficient Plants[a]	5	6	1	2	1	0	3	3	0
2007 N = 100									
SCC with Disaggregate	-	0.990***	0.746***	-	0.996***	0.891***	-	0.935***	0.547***
Mean Efficiency	0.280 (0.278)	0.252 (0.248)	0.086 (0.124)	0.224 (0.229)	0.213 (0.221)	0.047 (0.041)	0.717 (0.313)	0.738 (0.315)	0.652 (0.405)
Number of Efficient Plants[a]	7	4	1	3	3	0	5	5	0
2008 N = 80									
SCC with Disaggregate	-	0.978***	0.903***	-	0.996***	0.940***	-	0.836***	0.519***
Mean Efficiency	0.349 (0.316)	0.341 (0.313)	0.277 (0.266)	0.308 (0.295)	0.297 (0.283)	0.230 (0.222)	0.755 (0.316)	0.756 (0.321)	0.746 (0.316)
Number of Efficient Plants[a]	7	6	2	4	3	0	5	4	0

Table 2-9 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Liquid Renewable Fuel Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2009 N = 80									
SCC with Disaggregate	-	0.992***	0.956***	-	0.995***	0.958***	-	0.952***	0.801***
Mean Efficiency	0.322 (0.302)	0.290 (0.262)	0.172 (0.193)	0.274 (0.268)	0.258 (0.248)	0.108 (0.102)	0.733 (0.314)	0.759 (0.321)	0.610 (0.330)
Number of Efficient Plants[a]	3	1	1	1	1	0	1	2	0
2010 N = 90									
SCC with Disaggregate	-	0.987***	0.921***	-	0.996***	0.952***	-	0.870***	0.516***
Mean Efficiency	0.353 (0.301)	0.323 (0.276)	0.207 (0.194)	0.320 (0.291)	0.301 (0.273)	0.178 (0.158)	0.758 (0.334)	0.779 (0.325)	0.755 (0.356)
Number of Efficient Plants[a]	4	0	1	3	1	0	4	2	8
2011 N = 79									
SCC with Disaggregate	-	0.968***	0.910***	-	0.979***	0.930***	-	0.813***	0.299***
Mean Efficiency	0.394 (0.332)	0.359 (0.321)	0.221 (0.200)	0.346 (0.312)	0.312 (0.288)	0.209 (0.185)	0.759 (0.312)	0.767 (0.307)	0.887 (0.208)
Number of Efficient Plants[a]	7	6	1	4	3	0	7	3	11

Table 2-9 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Liquid Renewable Fuel Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2012 N = 82									
SCC with Disaggregate	-	0.982***	0.904***	-	0.979***	0.941***	-	0.876***	0.619***
Mean Efficiency	0.389 (0.333)	0.350 (0.309)	0.262 (0.254)	0.346 (0.312)	0.312 (0.286)	0.222 (0.202)	0.775 (0.310)	0.781 (0.311)	0.770 (0.322)
Number of Efficient Plants[a]	6	4	3	2	1	0	4	9	1

[a] The number of efficient plants is the number of plants, given the level of aggregation, that have an efficiency score of 1. Standard deviations are in parenthesis. *** implies significance at the 1% level, ** implies significance at the 5% level, and * implies significance at the 10% level.

Table 2-10 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Gaseous Renewable Fuel Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2003 N = 196									
SCC with Disaggregate	-	0.927***	0.758***	-	0.997***	0.923***	-	0.905***	0.821***
Mean Efficiency	0.720 (0.248)	0.697 (0.248)	0.544 (0.220)	0.620 (0.269)	0.614 (0.271)	0.524 (0.231)	0.852 (0.217)	0.863 (0.215)	0.938 (0.153)
Number of Efficient Plants[a]	22	18	1	8	5	1	8	5	1
2004 N = 203									
SCC with Disaggregate	-	0.942***	0.869***	-	0.991***	0.973***	-	0.960***	0.685***
Mean Efficiency	0.724 (0.263)	0.699 (0.261)	0.583 (0.228)	0.644 (0.274)	0.627 (0.275)	0.520 (0.228)	0.862 (0.219)	0.864 (0.215)	0.861 (0.200)
Number of Efficient Plants[a]	16	11	1	6	5	0	7	5	0
2005 N = 216									
SCC with Disaggregate	-	0.935***	0.860***	-	0.979***	0.955***	-	0.935***	0.730***
Mean Efficiency	0.667 (0.278)	0.644 (0.274)	0.568 (0.240)	0.580 (0.284)	0.564 (0.282)	0.506 (0.240)	0.848 (0.224)	0.851 (0.225)	0.863 (0.209)
Number of Efficient Plants[a]	21	16	3	8	4	2	8	5	3

Table 2-10 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Gaseous Renewable Fuel Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2006 N = 237									
SCC with Disaggregate	-	0.883***	0.791***	-	0.940***	0.935***	-	0.949***	0.540***
Mean Efficiency	0.662 (0.250)	0.634 (0.245)	0.515 (0.214)	0.573 (0.255)	0.550 (0.251)	0.431 (0.198)	0.849 (0.223)	0.848 (0.225)	0.818 (0.203)
Number of Efficient Plants[a]	20	11	1	8	4	1	8	4	1
2007 N = 245									
SCC with Disaggregate	-	0.942***	0.674***	-	0.981***	0.807***	-	0.950***	0.519***
Mean Efficiency	0.664 (0.263)	0.645 (0.262)	0.399 (0.178)	0.571 (0.275)	0.559 (0.274)	0.308 (0.138)	0.838 (0.234)	0.842 (0.238)	0.789 (0.271)
Number of Efficient Plants[a]	17	13	0	7	5	0	7	5	1
2008 N = 251									
SCC with Disaggregate	-	0.937***	0.878***	-	0.979***	0.950***	-	0.952***	0.711***
Mean Efficiency	0.729 (0.240)	0.715 (0.239)	0.602 (0.225)	0.657 (0.258)	0.647 (0.258)	0.533 (0.244)	0.881 (0.202)	0.883 (0.202)	0.857 (0.222)
Number of Efficient Plants[a]	21	15	0	7	4	0	7	4	1

Table 2-10 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Gaseous Renewable Fuel Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2009 N = 283									
SCC with Disaggregate	-	0.893***	0.814***	-	0.964***	0.897***	-	0.918***	0.603***
Mean Efficiency	0.750 (0.224)	0.730 (0.224)	0.559 (0.180)	0.699 (0.245)	0.686 (0.246)	0.510 (0.193)	0.918 (0.173)	0.923 (0.167)	0.894 (0.196)
Number of Efficient Plants[a]	26	17	1	10	6	0	10	6	0
2010 N = 208									
SCC with Disaggregate	-	0.878***	0.825***	-	0.988***	0.959***	-	0.870***	0.511***
Mean Efficiency	0.701 (0.265)	0.669 (0.260)	0.556 (0.233)	0.615 (0.276)	0.601 (0.276)	0.479 (0.246)	0.867 (0.217)	0.885 (0.211)	0.840 (0.244)
Number of Efficient Plants[a]	26	17	1	7	5	0	7	5	0
2011 N = 309									
SCC with Disaggregate	-	0.864***	0.796***	-	0.956***	0.921***	-	0.897***	0.215***
Mean Efficiency	0.744 (0.219)	0.721 (0.220)	0.632 (0.201)	0.689 (0.232)	0.672 (0.235)	0.598 (0.214)	0.921 (0.157)	0.925 (0.155)	0.936 (0.142)
Number of Efficient Plants[a]	24	15	3	9	5	1	10	5	1

Table 2-10 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Gaseous Renewable Fuel Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2012 N = 314									
SCC with Disaggregate	-	0.927***	0.862***	-	0.976***	0.973***	-	0.972***	0.580***
Mean Efficiency	0.740 (0.230)	0.721 (0.228)	0.643 (0.211)	0.666 (0.242)	0.646 (0.247)	0.593 (0.219)	0.895 (0.173)	0.889 (0.177)	0.919 (0.164)
Number of Efficient Plants[a]	27	18	1	9	7	2	9	7	2

[a] The number of efficient plants is the number of plants, given the level of aggregation, that have an efficiency score of 1. Standard deviations are in parenthesis. *** implies significance at the 1% level, ** implies significance at the 5% level, and * implies significance at the 10% level.

Table 2-11 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Other Renewable Sources Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2003 N = 1545									
SCC with Disaggregate	-	0.651***	0.574***	-	0.664***	0.620***	-	0.809***	-0.283***
Mean Efficiency	0.979 (0.116)	0.976 (0.122)	0.603 (0.175)	0.976 (0.126)	0.974 (0.129)	0.541 (0.195)	0.990 (0.081)	0.990 (0.078)	0.882 (0.174)
Number of Efficient Plants[a]	156	27	3	95	9	1	140	36	1
2004 N = 931									
SCC with Disaggregate	-	0.949***	0.200***	-	0.994***	0.284***	-	0.921***	0.398***
Mean Efficiency	0.970 (0.149)	0.968 (0.154)	0.642 (0.166)	0.967 (0.161)	0.965 (0.165)	0.570 (0.158)	0.987 (0.096)	0.988 (0.095)	0.889 (0.152)
Number of Efficient Plants[a]	341	329	3	170	165	1	335	313	1
2005 N = 1614									
SCC with Disaggregate	-	0.915***	0.177***	-	0.997***	0.252***	-	0.975***	0.098***
Mean Efficiency	0.980 (0.123)	0.979 (0.126)	0.644 (0.149)	0.978 (0.129)	0.978 (0.131)	0.547 (0.139)	0.993 (0.063)	0.993 (0.064)	0.855 (0.141)
Number of Efficient Plants[a]	759	683	19	517	502	1	523	503	1

Table 2-11 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Other Renewable Sources Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2006 N = 1574									
SCC with Disaggregate	-	0.900***	0.306***	-	0.932***	0.384***	-	0.849***	-0.027
Mean Efficiency	0.978 (0.130)	0.976 (0.134)	0.610 (0.136)	0.975 (0.138)	0.975 (0.140)	0.509 (0.094)	0.991 (0.074)	0.992 (0.072)	0.847 (0.136)
Number of Efficient Plants[a]	804	754	4	559	536	1	827	829	1
2007 N = 1680									
SCC with Disaggregate	-	0.609***	0.554***	-	0.616***	0.611***	-	0.701***	0.472***
Mean Efficiency	0.831 (0.182)	0.784 (0.183)	0.481 (0.166)	0.774 (0.206)	0.718 (0.194)	0.385 (0.097)	0.920 (0.149)	0.907 (0.155)	0.833 (0.201)
Number of Efficient Plants[a]	206	55	12	128	2	1	220	2	1
2008 N = 1715									
SCC with Disaggregate	-	0.601***	0.539***	-	0.589***	0.589***	-	0.600***	0.516***
Mean Efficiency	0.802 (0.194)	0.745 (0.177)	0.575 (0.201)	0.749 (0.209)	0.677 (0.176)	0.492 (0.179)	0.929 (0.123)	0.910 (0.131)	0.872 (0.178)
Number of Efficient Plants[a]	308	45	8	191	3	2	224	3	3

Table 2-11 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Other Renewable Sources Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2009 N = 1943									
SCC with Disaggregate	-	0.286***	0.300***	-	0.255***	0.253***	-	0.471***	0.035
Mean Efficiency	0.816 (0.189)	0.710 (0.176)	0.613 (0.155)	0.764 (0.211)	0.635 (0.168)	0.547 (0.148)	0.930 (0.119)	0.899 (0.136)	0.893 (0.145)
Number of Efficient Plants[a]	381	52	4	273	6	0	341	6	1
2010 N = 2054									
SCC with Disaggregate	-	0.288***	0.284***	-	0.213***	0.210***	-	0.378***	0.103***
Mean Efficiency	0.853 (0.177)	0.757 (0.178)	0.574 (0.162)	0.810 (0.204)	0.688 (0.183)	0.491 (0.155)	0.943 (0.121)	0.909 (0.141)	0.859 (0.180)
Number of Efficient Plants[a]	503	78	38	335	4	0	378	205	11
2011 N = 2223									
SCC with Disaggregate	-	0.206***	0.292***	-	0.093***	0.090***	-	0.246***	-0.036*
Mean Efficiency	0.928 (0.134)	0.865 (0.158)	0.675 (0.127)	0.912 (0.151)	0.823 (0.179)	0.615 (0.131)	0.977 (0.079)	0.947 (0.111)	0.910 (0.116)
Number of Efficient Plants[a]	471	85	10	332	5	2	390	5	2

Table 2-11 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Other Renewable Sources Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2012 N = 2438									
SCC with Disaggregate	-	0.265***	0.363***	-	0.163***	0.155***	-	0.212***	-0.086***
Mean Efficiency	0.955 (0.114)	0.913 (0.132)	0.687 (0.122)	0.945 (0.123)	0.888 (0.143)	0.599 (0.095)	0.987 (0.055)	0.970 (0.074)	0.880 (0.109)
Number of Efficient Plants[a]	535	87	12	409	5	2	647	23	4

[a] The number of efficient plants is the number of plants, given the level of aggregation, that have an efficiency score of 1. Standard deviations are in parenthesis. *** implies significance at the 1% level, ** implies significance at the 5% level, and * implies significance at the 10% level.

Table 2-12 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Other Energy Source Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2003 N = 7									
SCC with Disaggregate	-	0.964***	0.964***	-	0.964***	0.893***	-	0.857**	0.786**
Mean Efficiency	0.280 (0.46)	0.279 (0.46)	0.147 (0.25)	0.225 (0.39)	0.224 (0.39)	0.138 (0.24)	0.473 (0.39)	0.482 (0.38)	0.824 (0.17)
Number of Efficient Plants[a]	1	1	0	1	1	0	1	1	0
2004 N = 31									
SCC with Disaggregate	-	0.993***	0.891***	-	0.999***	0.959***	-	0.988***	0.756***
Mean Efficiency	0.563 (0.44)	0.558 (0.45)	0.356 (0.31)	0.496 (0.44)	0.495 (0.44)	0.314 (0.30)	0.705 (0.37)	0.723 (0.36)	0.714 (0.33)
Number of Efficient Plants[a]	7	7	0	4	4	0	4	4	0
2005 N = 36									
SCC with Disaggregate	-	0.995***	0.927***	-	0.998***	0.967***	-	0.995***	0.491***
Mean Efficiency	0.560 (0.43)	0.555 (0.43)	0.424 (0.34)	0.514 (0.42)	0.511 (0.42)	0.364 (0.30)	0.822 (0.26)	0.828 (0.25)	0.802 (0.25)
Number of Efficient Plants[a]	6	6	0	3	3	0	3	3	1

Table 2-12 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Other Energy Source Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2006, N = 30									
SCC with Disaggregate	-	0.872***	0.778***	-	0.997***	0.947***	-	0.997***	0.562***
Mean Efficiency	0.575 (0.45)	0.541 (0.45)	0.343 (0.31)	0.494 (0.44)	0.492 (0.44)	0.266 (0.25)	0.702 (0.39)	0.708 (0.38)	0.644 (0.35)
Number of Efficient Plants[a]	9	7	0	3	3	0	3	3	0
2007, N = 25									
SCC with Disaggregate	-	0.999***	0.723***	-	0.995***	0.940***	-	0.992***	0.869***
Mean Efficiency	0.424 (0.40)	0.423 (0.40)	0.155 (0.14)	0.368 (0.42)	0.368 (0.42)	0.098 (0.14)	0.645 (0.40)	0.629 (0.41)	0.571 (0.43)
Number of Efficient Plants[a]	5	5	0	4	4	0	4	4	0
2008, N = 30									
SCC with Disaggregate	-	0.945***	0.920***	-	0.970***	0.916***	-	0.969***	0.819***
Mean Efficiency	0.551 (0.46)	0.518 (0.46)	0.329 (0.31)	0.512 (0.47)	0.490 (0.48)	0.292 (0.30)	0.771 (0.33)	0.726 (0.37)	0.720 (0.35)
Number of Efficient Plants[a]	10	9	1	6	6	0	6	6	0

Table 2-12 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Other Energy Source Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2009 N = 31									
SCC with Disaggregate	-	0.990***	0.950***	-	0.980***	0.937***	-	0.926***	0.689***
Mean Efficiency	0.427 (0.44)	0.401 (0.44)	0.244 (0.28)	0.345 (0.43)	0.338 (0.43)	0.194 (0.27)	0.579 (0.39)	0.547 (0.39)	0.525 (0.39)
Number of Efficient Plants[a]	6	6	0	3	3	0	3	3	1
2010 N = 30									
SCC with Disaggregate	-	0.982***	0.959***	-	0.997***	0.972***	-	0.990***	0.916***
Mean Efficiency	0.436 (0.44)	0.403 (0.44)	0.266 (0.28)	0.355 (0.46)	0.354 (0.46)	0.217 (0.29)	0.578 (0.40)	0.586 (0.41)	0.559 (0.41)
Number of Efficient Plants[a]	6	7	0	5	6	0	9	9	0
2011 N = 25									
SCC with Disaggregate	-	0.983***	0.898***	-	0.993***	0.983***	-	0.981***	0.630***
Mean Efficiency	0.419 (0.42)	0.409 (0.42)	0.255 (0.33)	0.324 (0.43)	0.318 (0.43)	0.230 (0.31)	0.547 (0.42)	0.536 (0.41)	0.735 (0.36)
Number of Efficient Plants[a]	8	8	0	6	6	0	6	6	0

Table 2-12 – Spearman Correlation Coefficients and Mean Production Efficiency Score by Aggregation Level of Electric Generation Plants in the U.S. between 2003 and 2012 – Other Energy Source Inputs

	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
2012 N = 24									
SCC with Disaggregate	-	0.995***	0.963***	-	0.992***	0.962***	-	0.991***	0.857***
Mean Efficiency	0.401 (0.44)	0.394 (0.45)	0.279 (0.31)	0.373 (0.46)	0.366 (0.46)	0.239 (0.30)	0.629 (0.41)	0.621 (0.41)	0.595 (0.40)
Number of Efficient Plants[a]	6	6	0	5	6	0	7	8	0

[a] The number of efficient plants is the number of plants, given the level of aggregation, that have an efficiency score of 1. Standard deviations are in parenthesis. *** implies significance at the 1% level, ** implies significance at the 5% level, and * implies significance at the 10% level.

Table 2-13 – Ranking of the Most Efficient Fuel Input Category by Aggregation Level for All Years

Ranking by Fuel Category[a]	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
1	Nuclear	Nuclear	Nuclear	Nuclear	Nuclear	Nuclear	Nuclear	Nuclear	Gaseous Renewable Fuels
2	Other Renewable Sources	Other Renewable Sources	Other Renewable Sources	Other Renewable Sources	Other Renewable Sources	Other Renewable Sources	Other Renewable Sources	Other Renewable Sources	Other Renewable Sources
3	Gaseous Renewable Fuels	Gaseous Renewable Fuels	Gaseous Renewable Fuels	Gaseous Renewable Fuels	Gaseous Renewable Fuels	Gaseous Renewable Fuels	Gaseous Renewable Fuels	Gaseous Renewable Fuels	Nuclear
4	Solid Renewable Fuels	Solid Renewable Fuels	Natural Gas and Other Gases	Solid Renewable Fuels	Solid Renewable Fuels	Natural Gas and Other Gases	Solid Renewable Fuels	Solid Renewable Fuels	Solid Renewable Fuels
5	Other Energy Sources	Other Energy Sources	Solid Renewable Fuels	Other Energy Sources	Other Energy Sources	Solid Renewable Fuels	Natural Gas and Other Gases	Liquid Renewable Fuels	Natural Gas and Other Gases
6	Natural Gas and Other Gases	Natural Gas and Other Gases	Other Energy Sources	Natural Gas and Other Gases	Natural Gas and Other Gases	Other Energy Sources	Liquid Renewable Fuels	Natural Gas and Other Gases	Liquid Renewable Fuels
7	Petroleum	Petroleum	Petroleum	Petroleum	Petroleum	Petroleum	Petroleum	Petroleum	Petroleum
8	Liquid Renewable Fuels	Liquid Renewable Fuels	Liquid Renewable Fuels	Liquid Renewable Fuels	Liquid Renewable Fuels	Liquid Renewable Fuels	Other Energy Sources	Other Energy Sources	Coal

Table 2-13 – Ranking of the Most Efficient Fuel Input Category by Aggregation Level for All Years

Ranking by Fuel Category[a]	Pure Technical Efficiency			Overall Technical Efficiency			Scale Efficiency		
	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate	Disaggregate	Aggregate Fuel Group	Total Aggregate
9	Coal	Coal	Coal	Coal	Coal	Coal	Coal	Coal	Other Energy Sources

[a] 1 represents the most efficient fuel input category for the given efficiency and aggregation level and 9 represents the least efficient fuel input category for the given efficiency and aggregation level.

Figure 2-1 Input-oriented DEA Graph

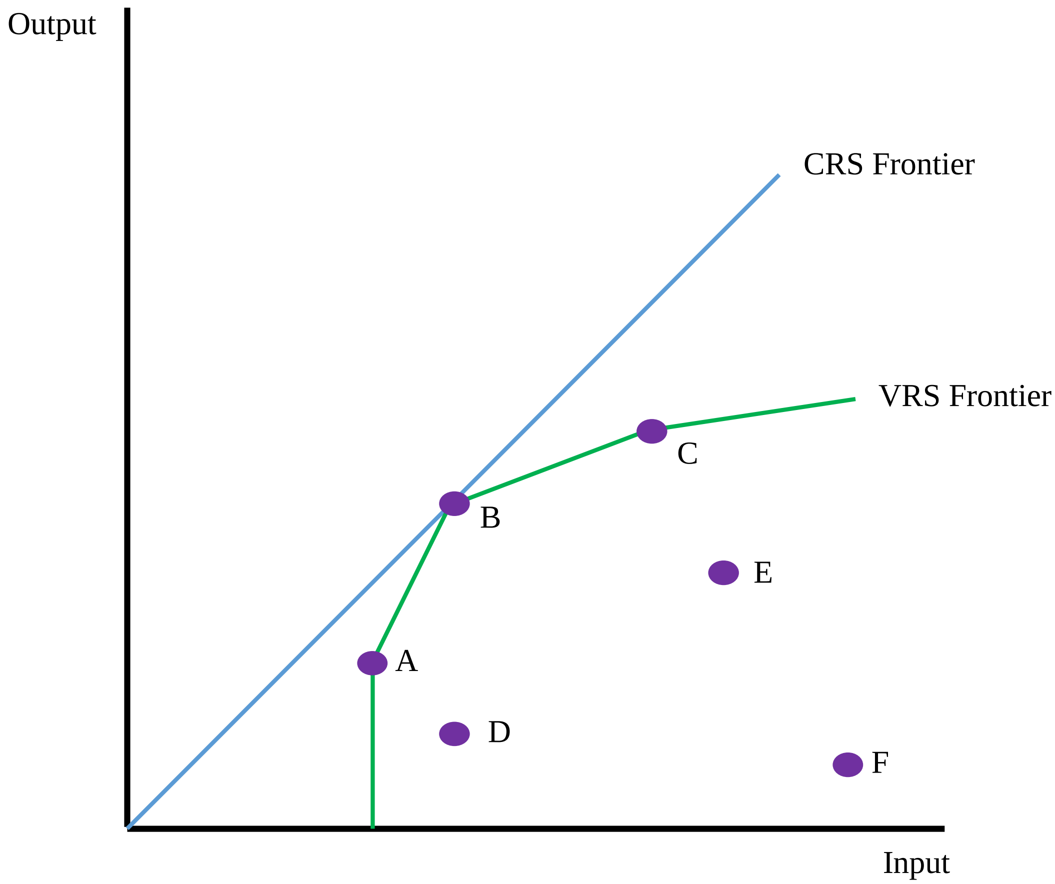


Figure 2-2 Input-oriented DEA Graph Example 1

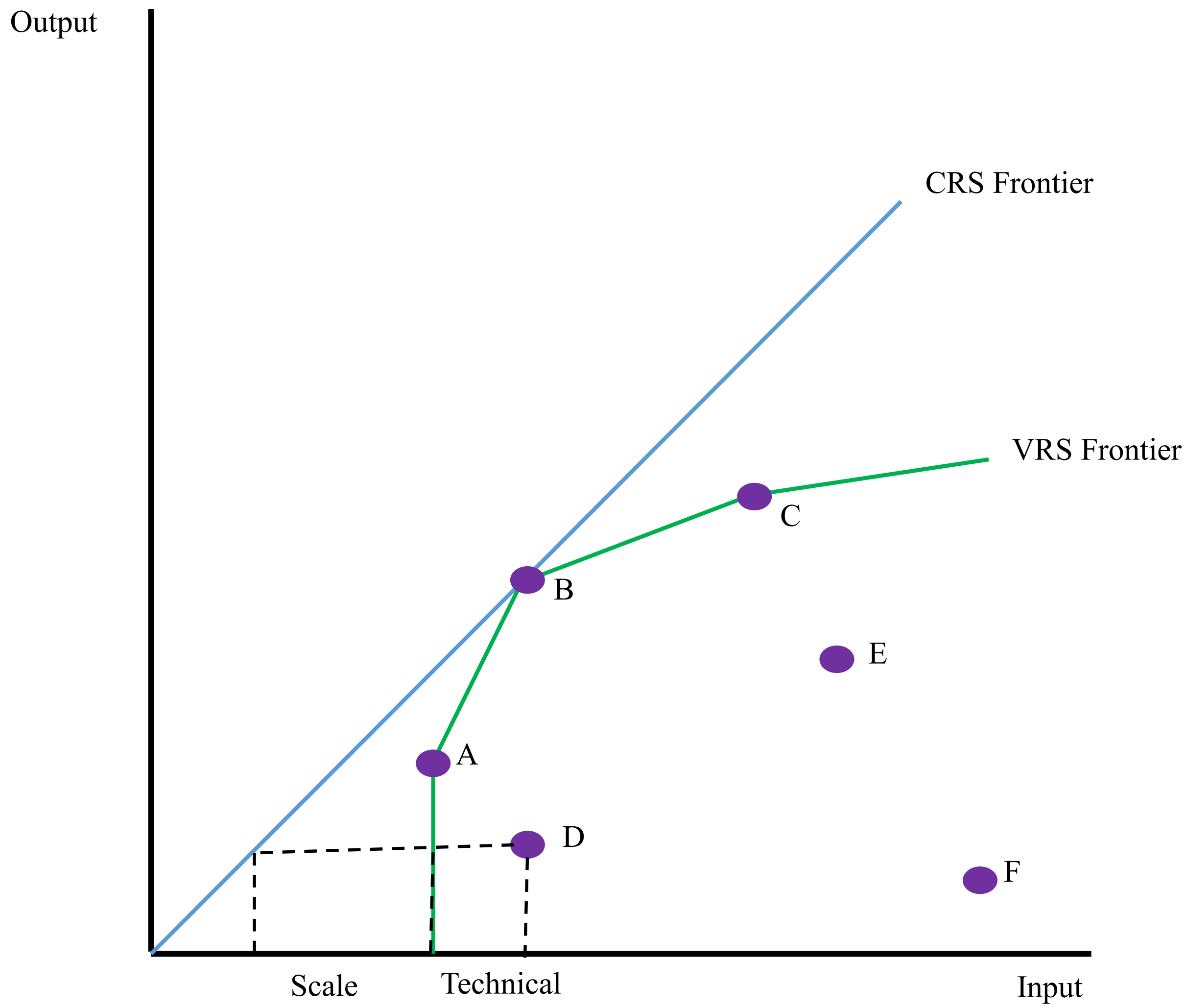


Figure 2-3 Input-oriented DEA Graph Example 2

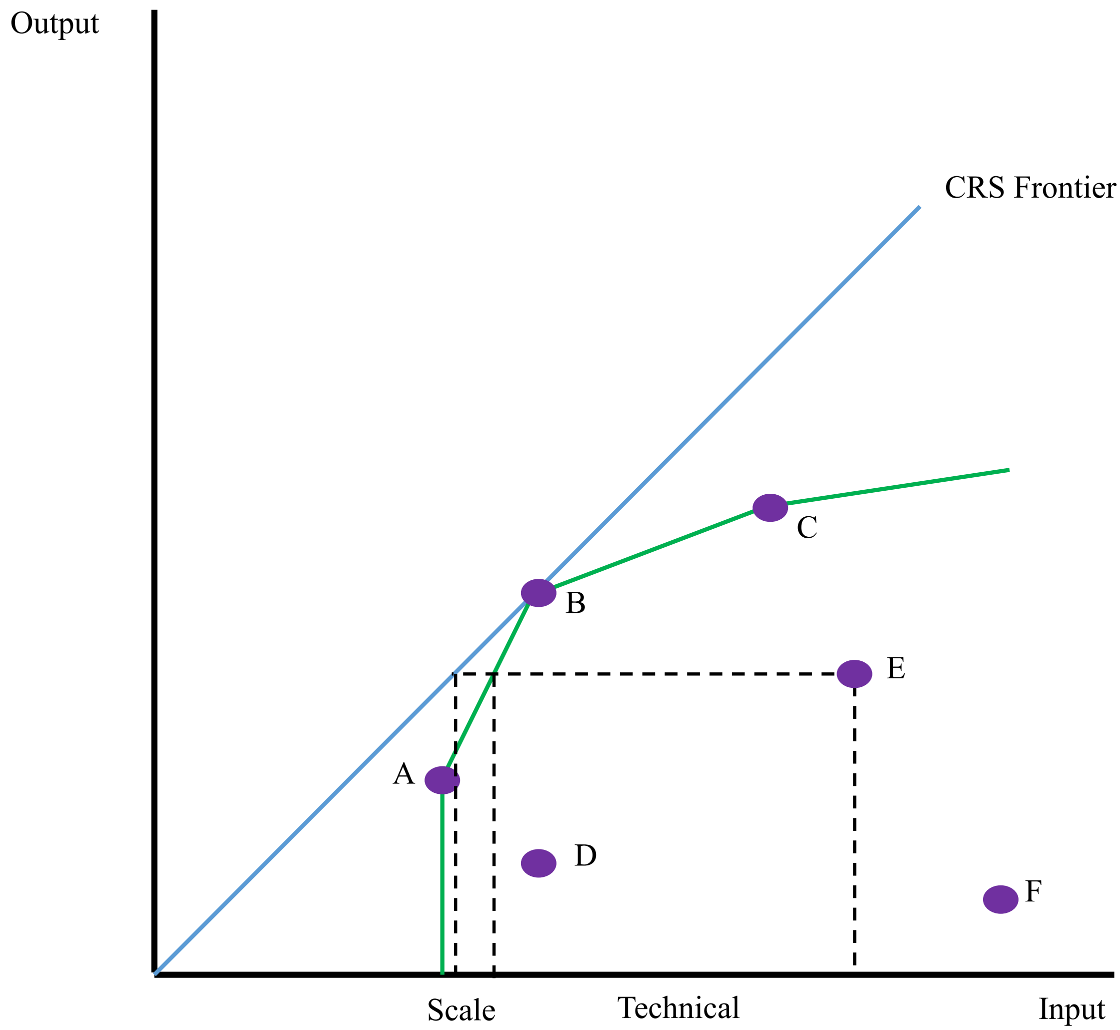


Figure 2-4 Cumulative Distribution Function of the Pure Technical Efficiency Scores for All Fuel Inputs for 2012

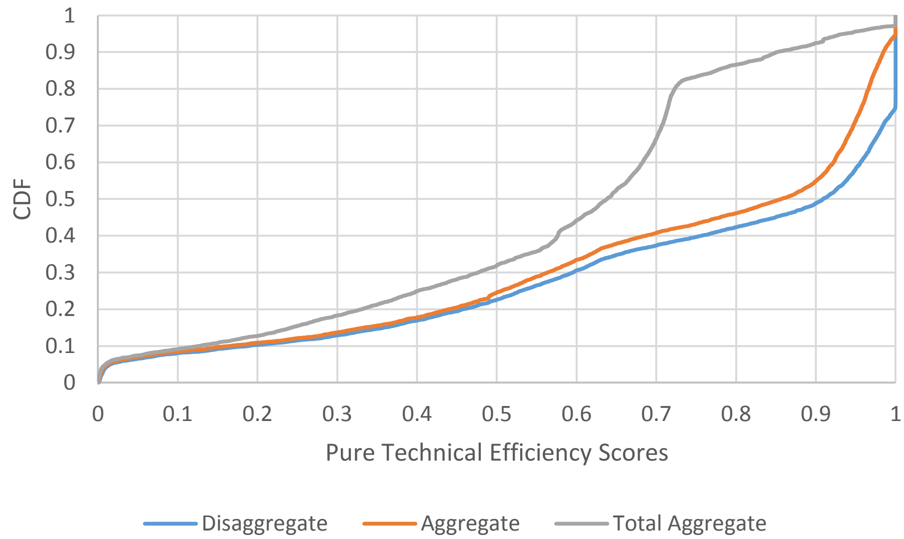


Figure 2-5 Cumulative Distribution Function of the Overall Technical Efficiency Scores for All Fuel Inputs for 2012

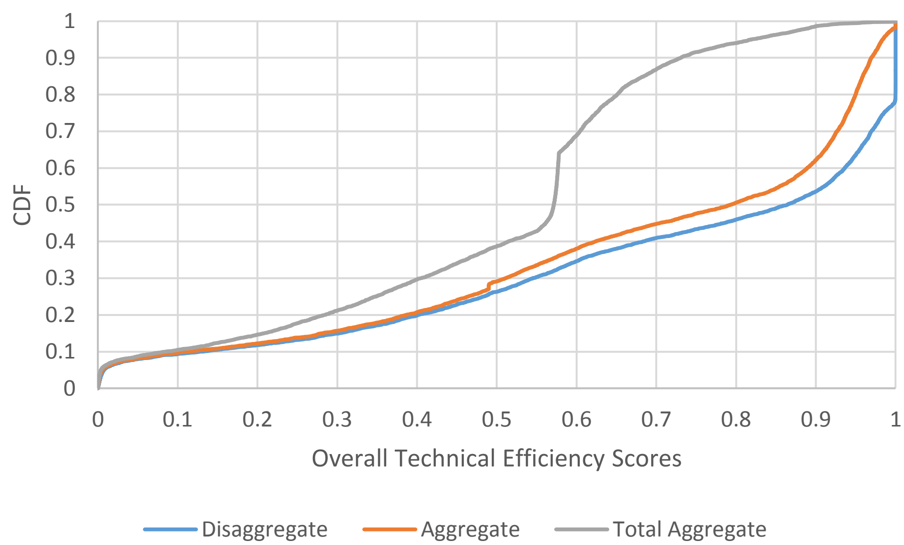


Figure 2-6 Cumulative Distribution Function of the Pure Technical Efficiency Scores for All Fuel Inputs for 2012

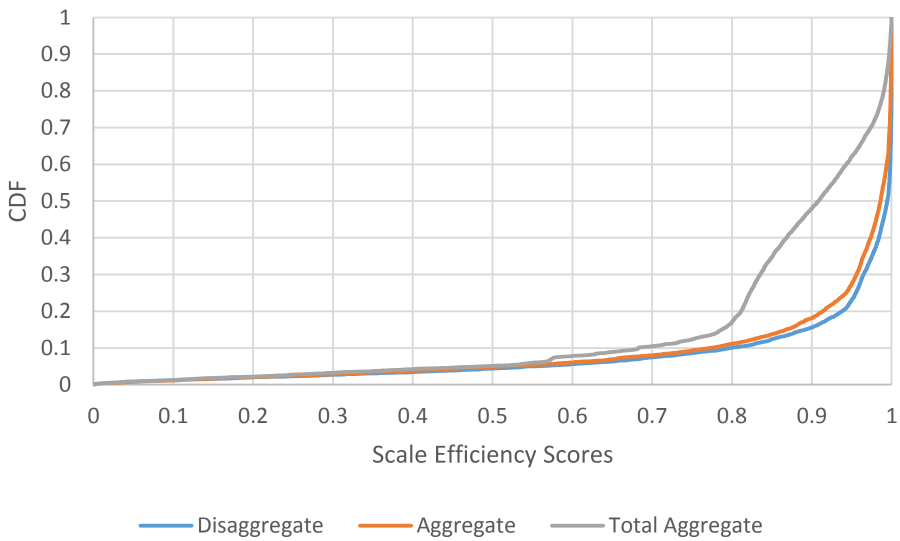


Figure 2-7 Cumulative Distribution Function of the Pure Technical Efficiency Scores for Coal Inputs for 2012

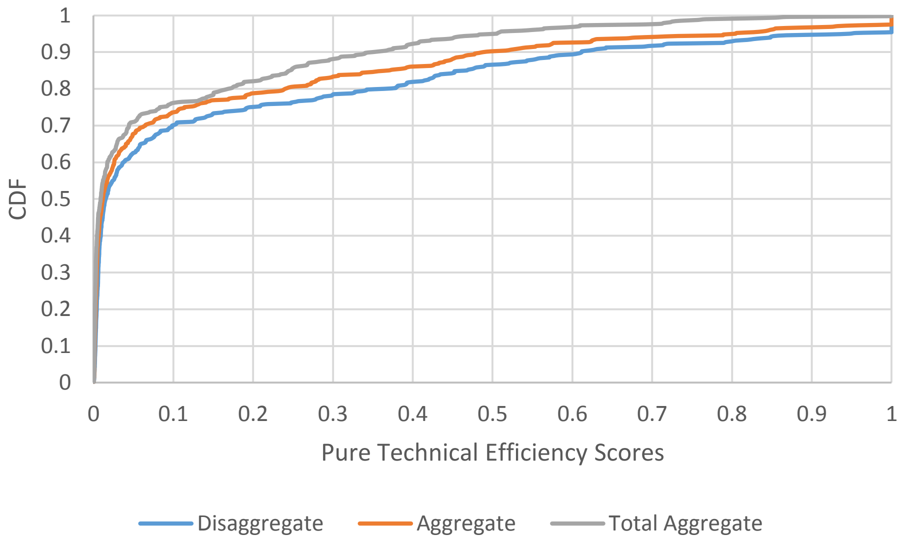


Figure 2-8 Cumulative Distribution Function of the Overall Technical Efficiency Scores for Coal Inputs for 2012

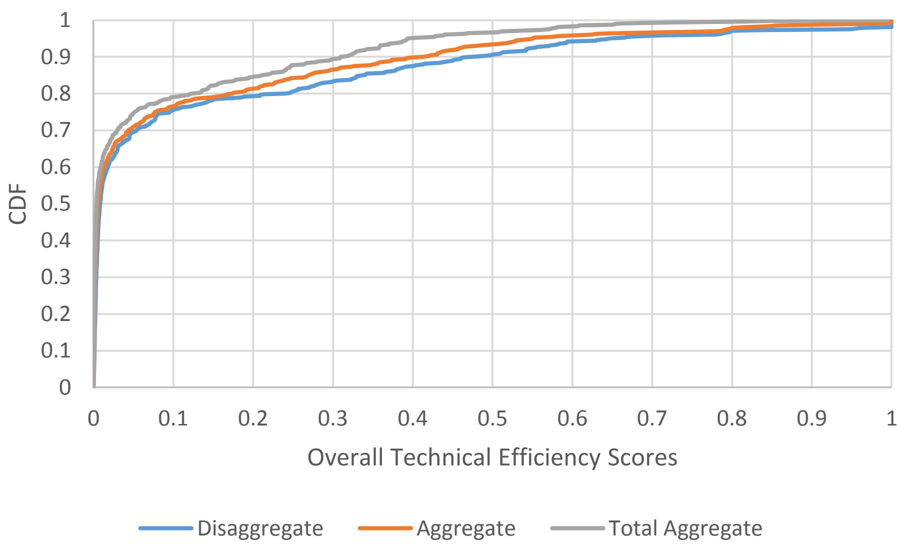


Figure 2-9 Cumulative Distribution Function of the Scale Efficiency Scores for Coal Inputs for 2012

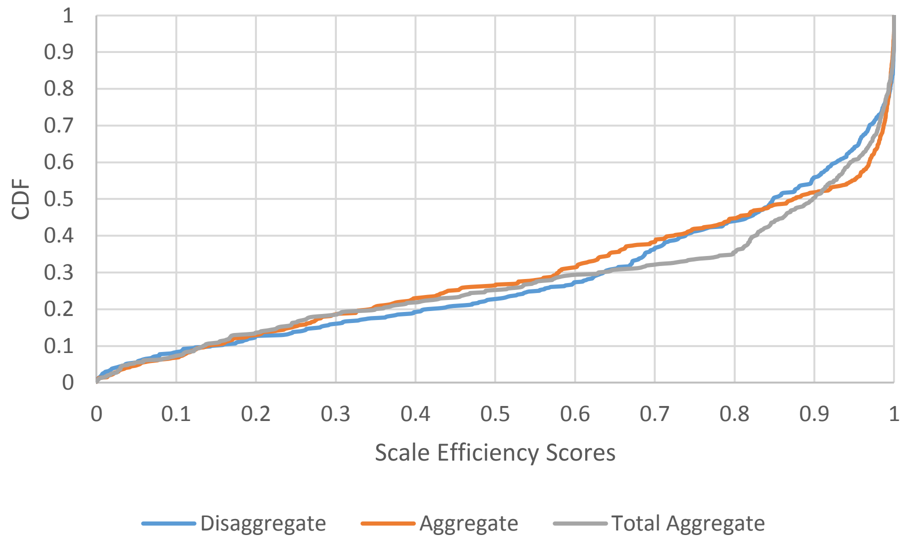


Figure 2-10 Cumulative Distribution Function of the Pure Technical Efficiency Scores for Natural Gas and Other Gases Inputs for 2012

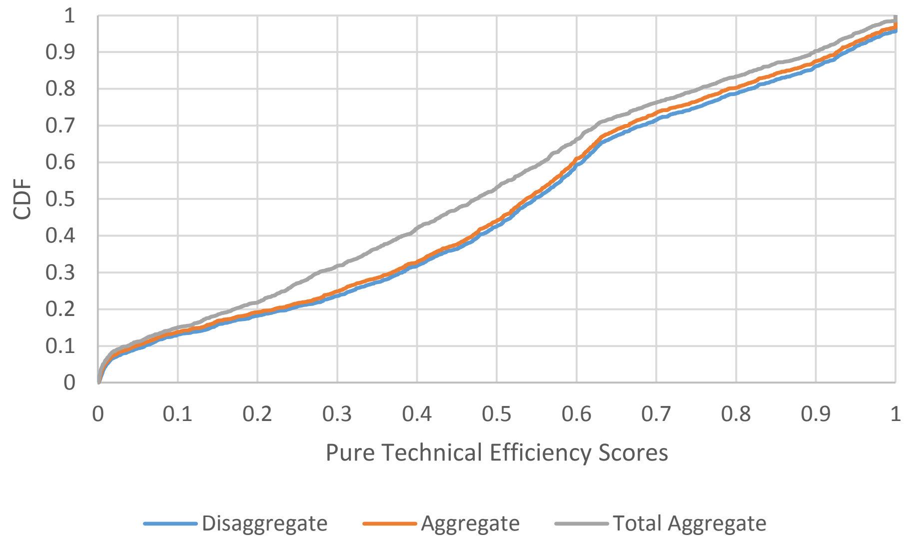


Figure 2-11 Cumulative Distribution Function of the Overall Technical Efficiency Scores for Natural Gas and Other Gases Inputs for 2012

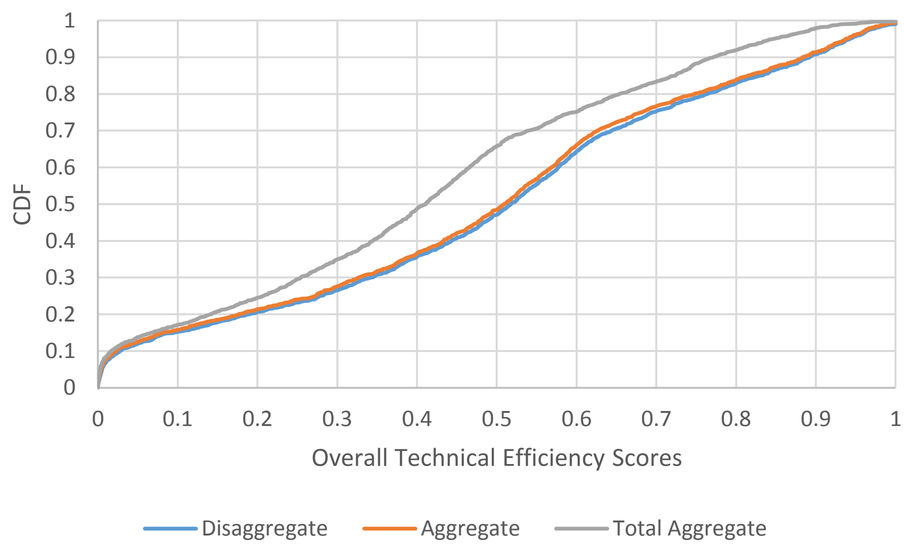


Figure 2-12 Cumulative Distribution Function of the Scale Efficiency Scores for Natural Gas and Other Gases Inputs for 2012

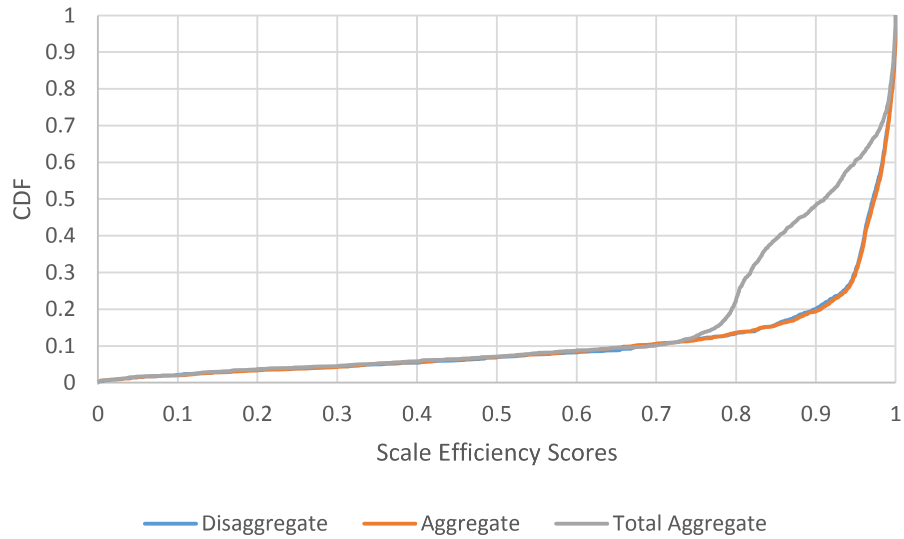


Figure 2-13 Cumulative Distribution Function of the Pure Technical Efficiency Scores for Petroleum Inputs for 2012

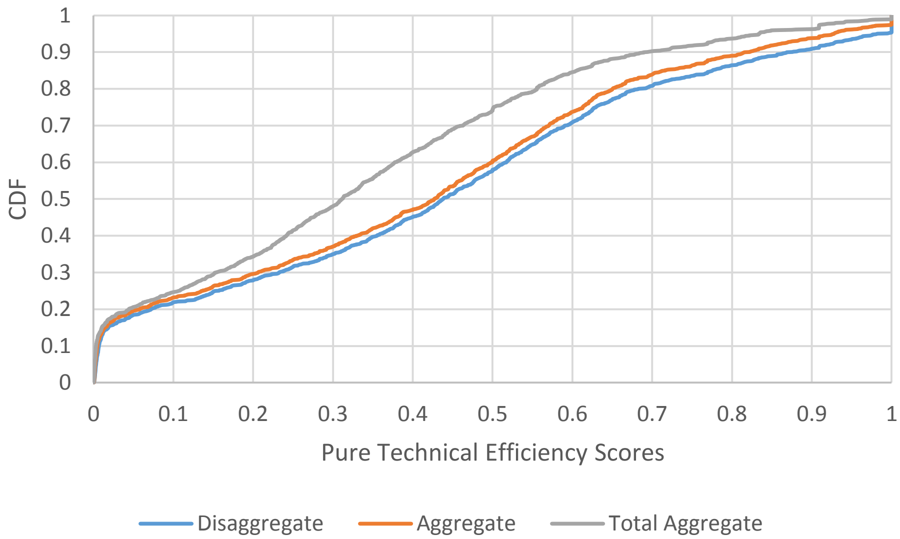


Figure 2-14 Cumulative Distribution Function of the Overall Technical Efficiency Scores for Petroleum Inputs for 2012

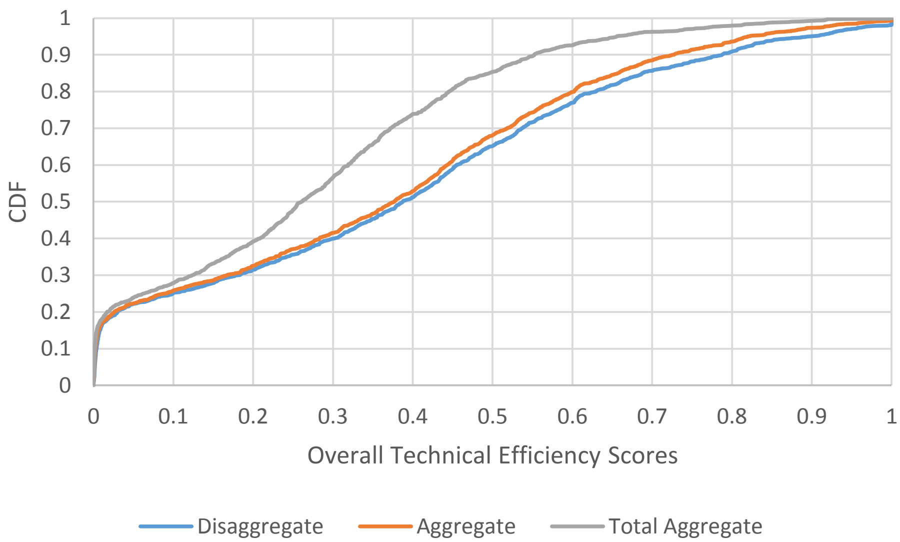


Figure 2-15 Cumulative Distribution Function of the Scale Efficiency Scores for Petroleum Inputs for 2012

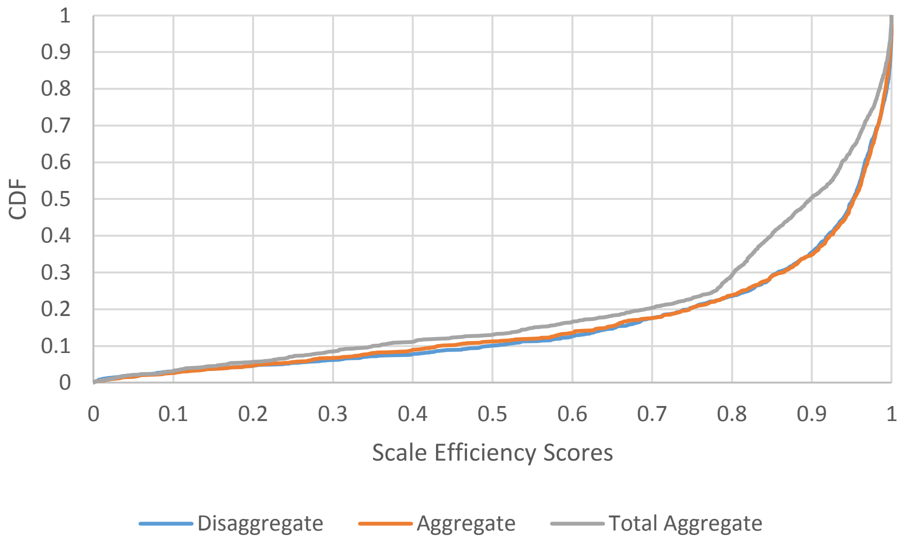


Figure 2-16 Cumulative Distribution Function of the Pure Technical Efficiency Scores for Nuclear Inputs for 2012

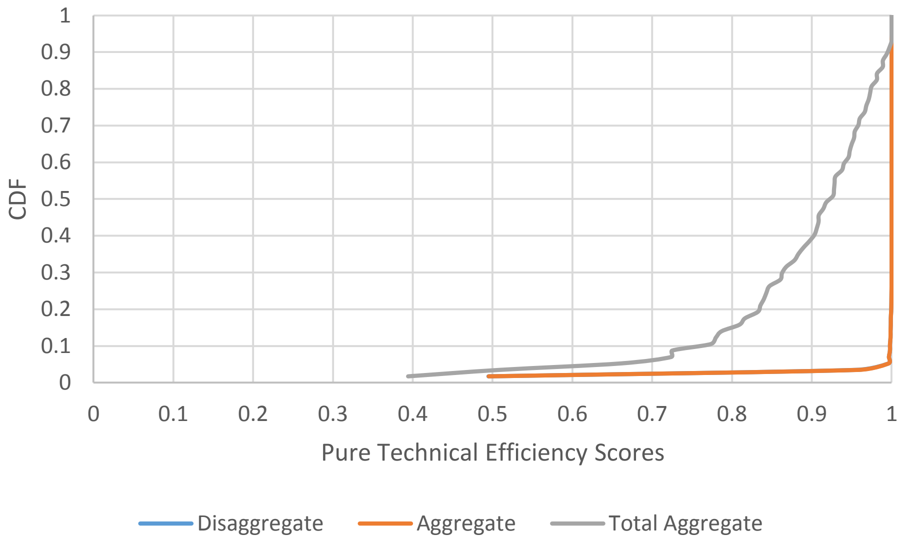


Figure 2-17 Cumulative Distribution Function of the Overall Technical Efficiency Scores for Nuclear Inputs for 2012

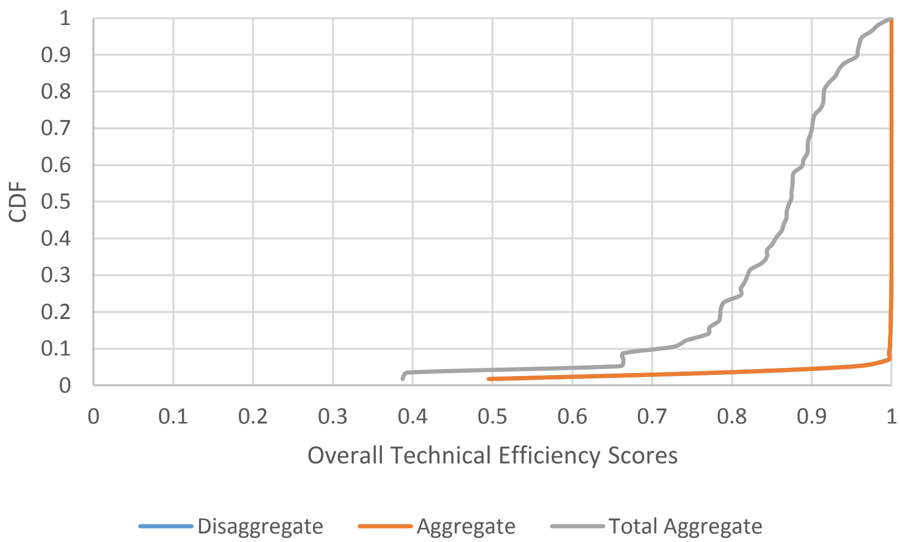


Figure 2-18 Cumulative Distribution Function of the Scale Efficiency Scores for Nuclear Inputs for 2012

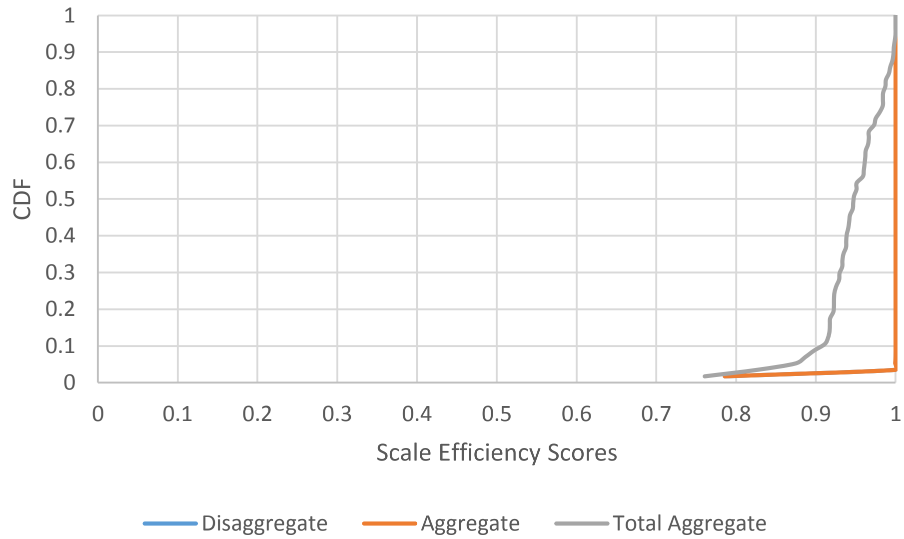


Figure 2-19 Cumulative Distribution Function of the Pure Technical Efficiency Scores for Solid Renewable Fuel Inputs for 2012

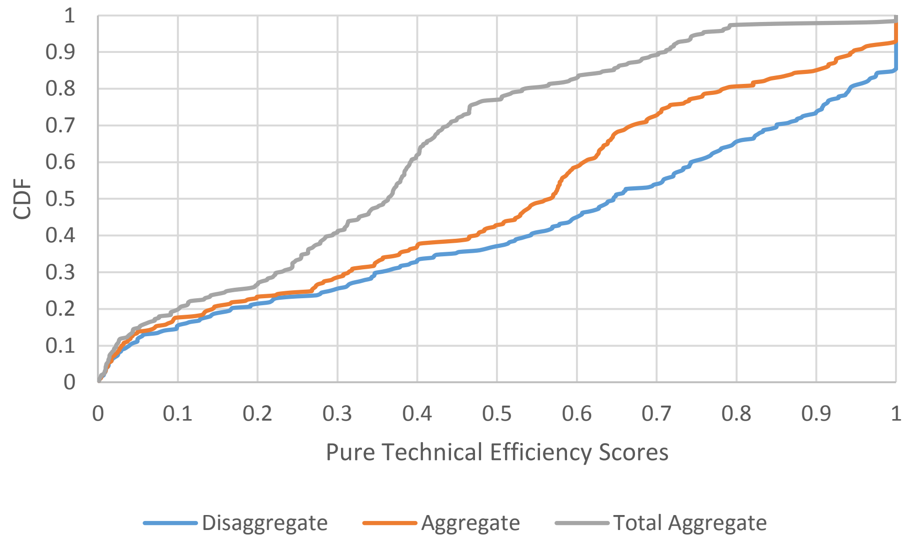


Figure 2-20 Cumulative Distribution Function of the Overall Technical Efficiency Scores for Solid Renewable Fuel Inputs for 2012

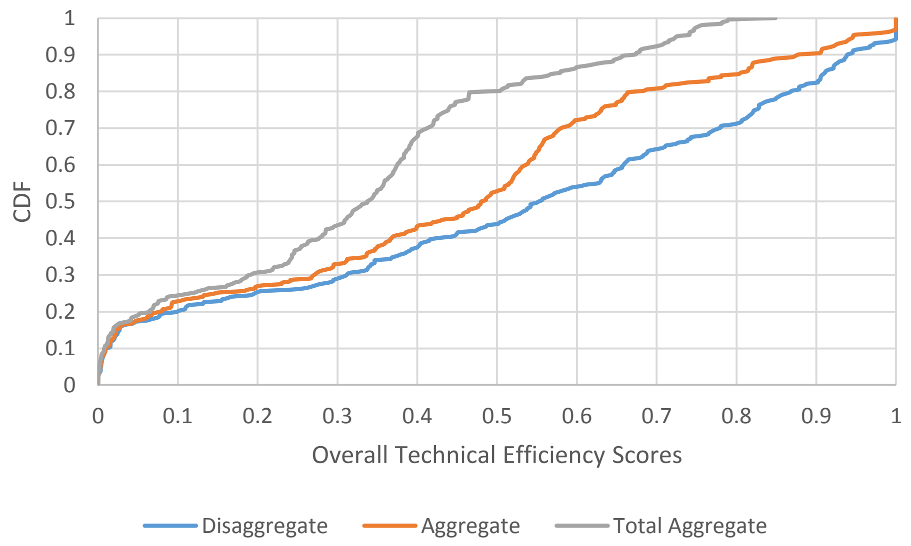


Figure 2-21 Cumulative Distribution Function of the Scale Efficiency Scores for Solid Renewable Fuel Inputs for 2012

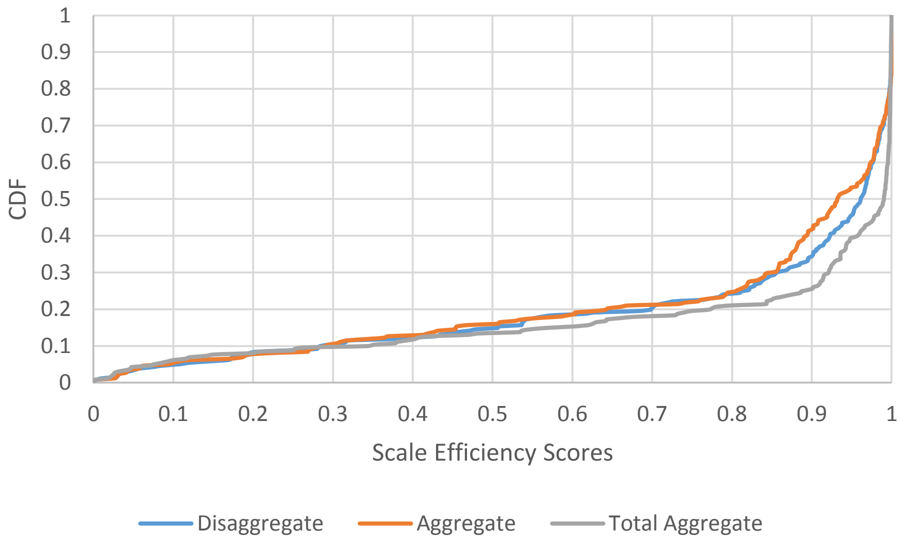


Figure 2-22 Cumulative Distribution Function of the Pure Technical Efficiency Scores for Liquid Renewable Fuel Inputs for 2012

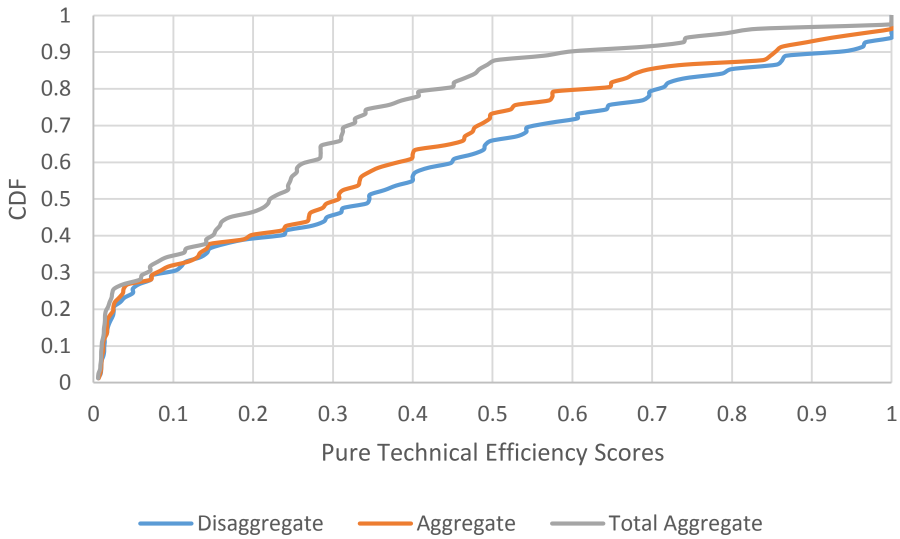


Figure 2-23 Cumulative Distribution Function of the Overall Technical Efficiency Scores for Liquid Renewable Fuel Inputs for 2012

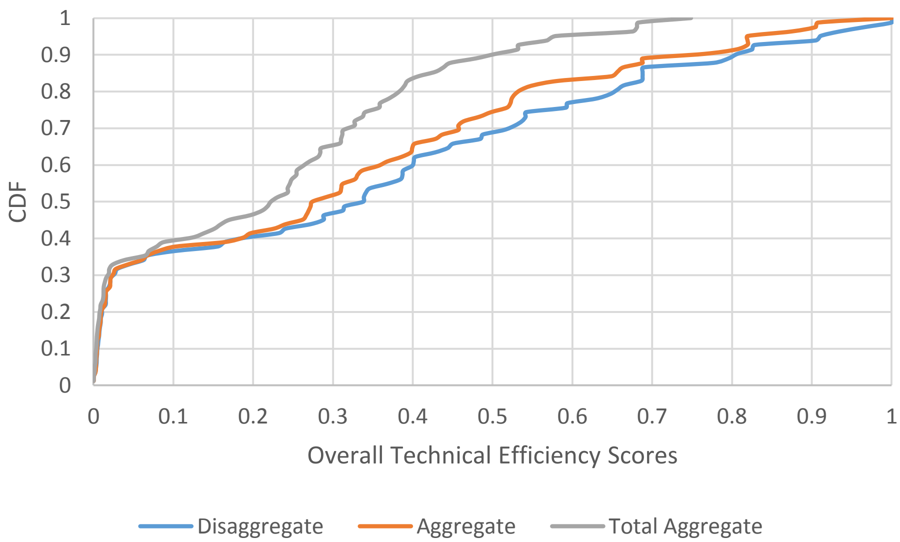


Figure 2-24 Cumulative Distribution Function of the Scale Efficiency Scores for Liquid Renewable Fuel Inputs for 2012

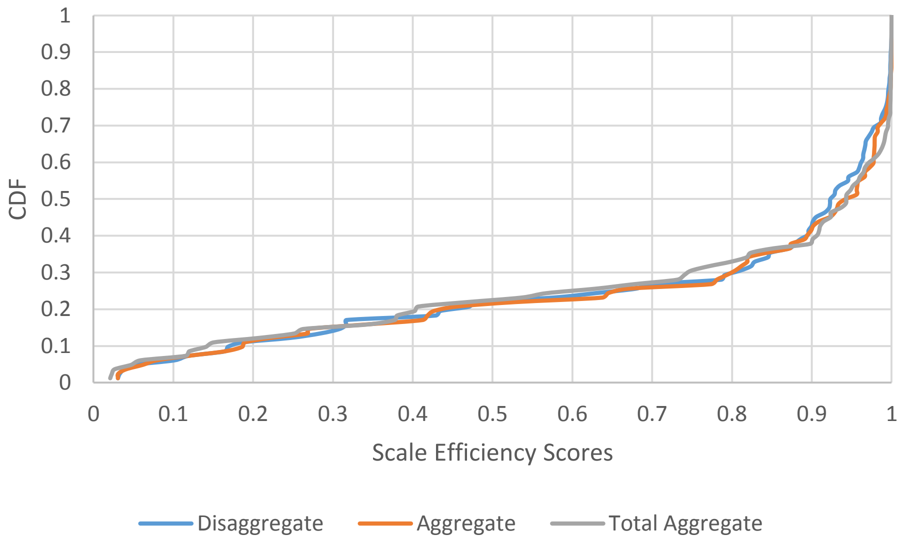


Figure 2-25 Cumulative Distribution Function of the Pure Technical Efficiency Scores for Gaseous Renewable Fuel Inputs for 2012

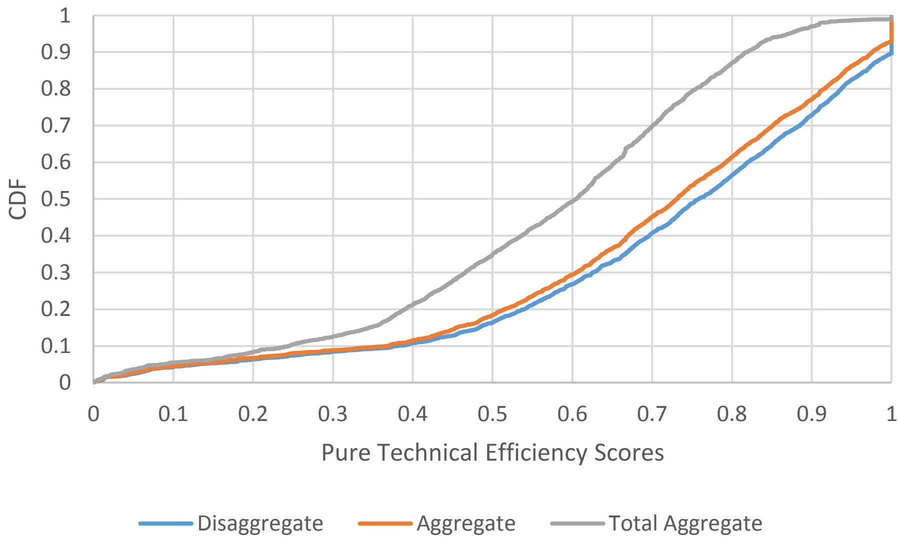


Figure 2-26 Cumulative Distribution Function of the Overall Technical Efficiency Scores for Gaseous Renewable Fuel Inputs for 2012

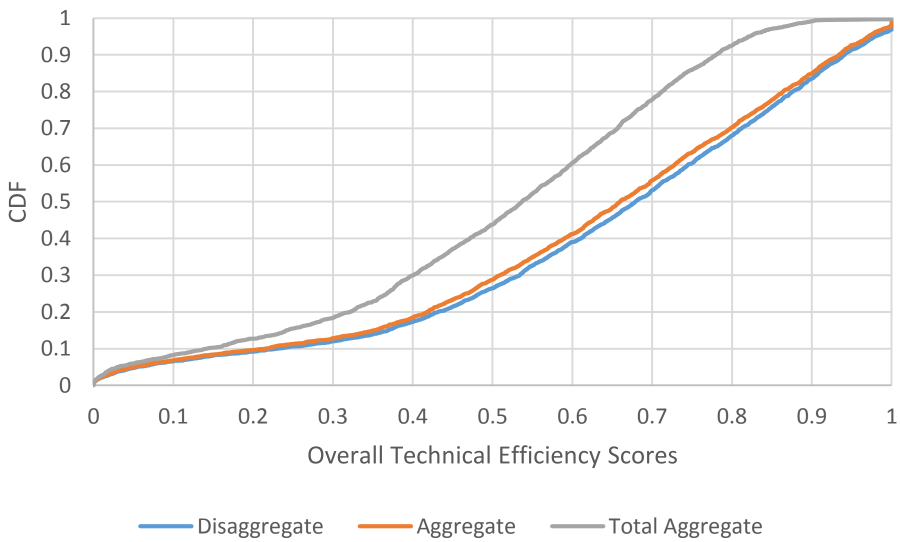


Figure 2-27 Cumulative Distribution Function of the Scale Efficiency Scores for Gaseous Renewable Fuel Inputs for 2012

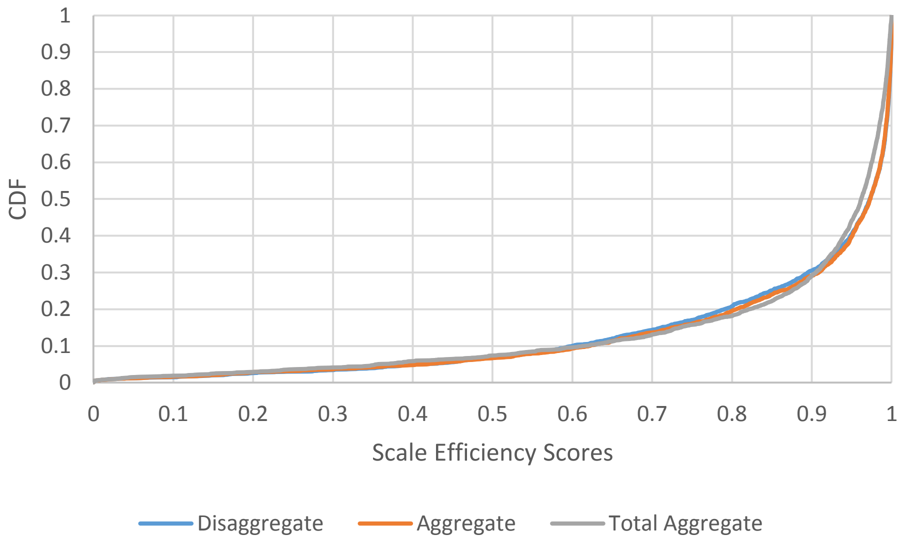


Figure 2-28 Cumulative Distribution Function of the Pure Technical Efficiency Scores for Other Renewable Sources Inputs for 2012

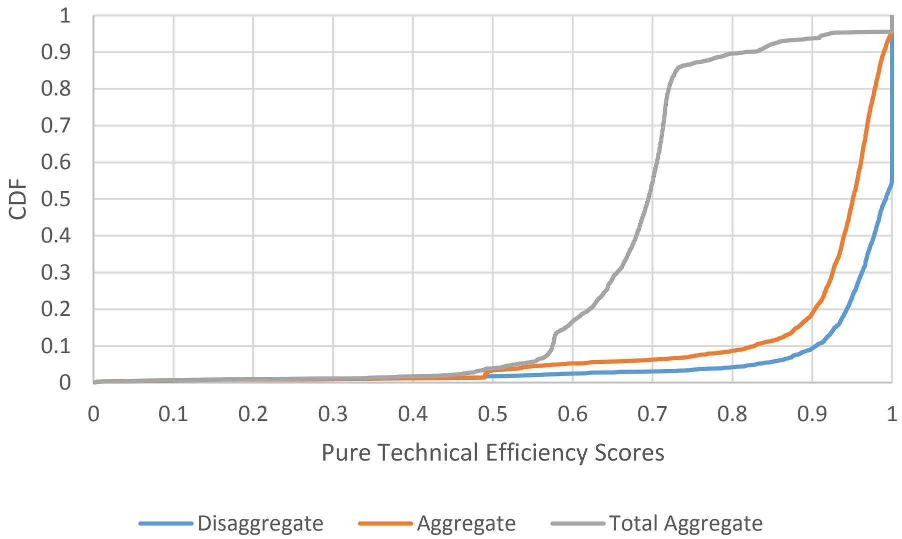


Figure 2-29 Cumulative Distribution Function of the Overall Technical Efficiency Scores for Other Renewable Sources Inputs for 2012

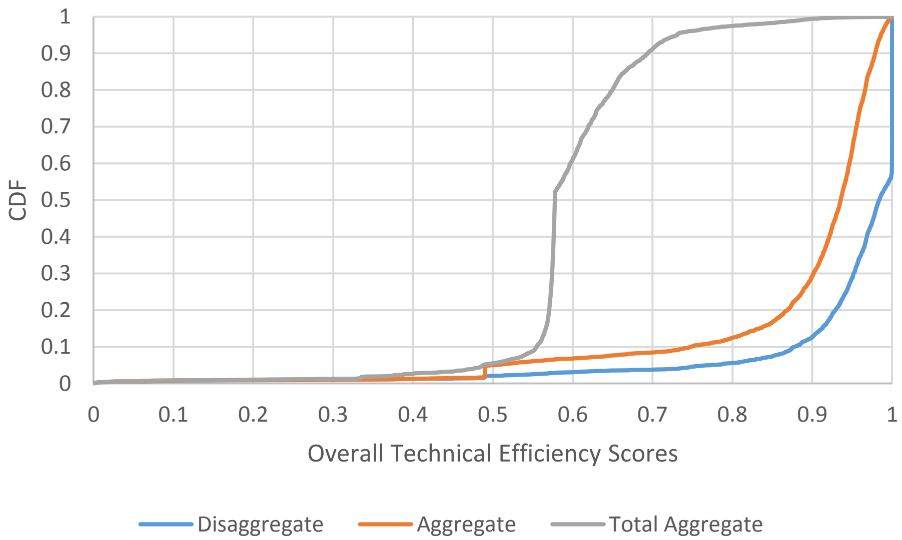


Figure 2-30 Cumulative Distribution Function of the Scale Efficiency Scores for Other Renewable Sources Inputs for 2012

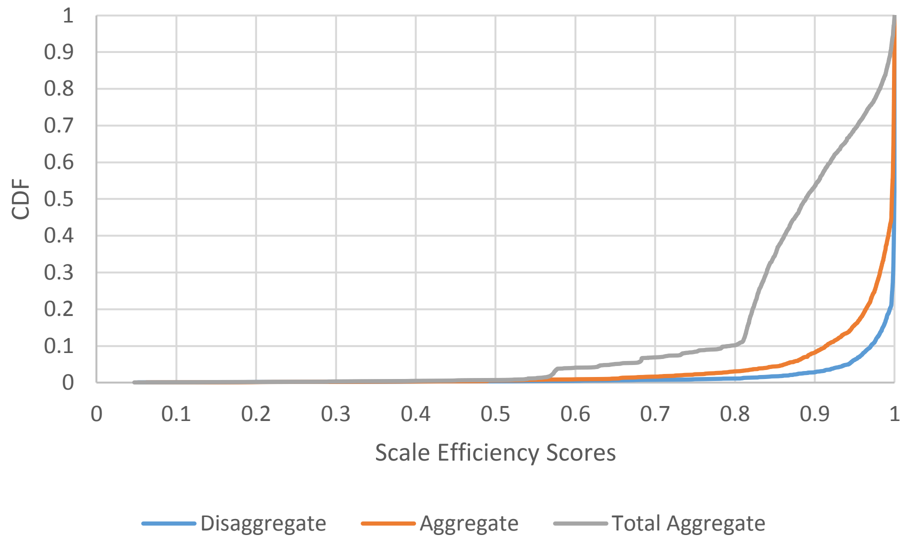


Figure 2-31 Cumulative Distribution Function of the Pure Technical Efficiency Scores for Other Energy Sources Inputs for 2012

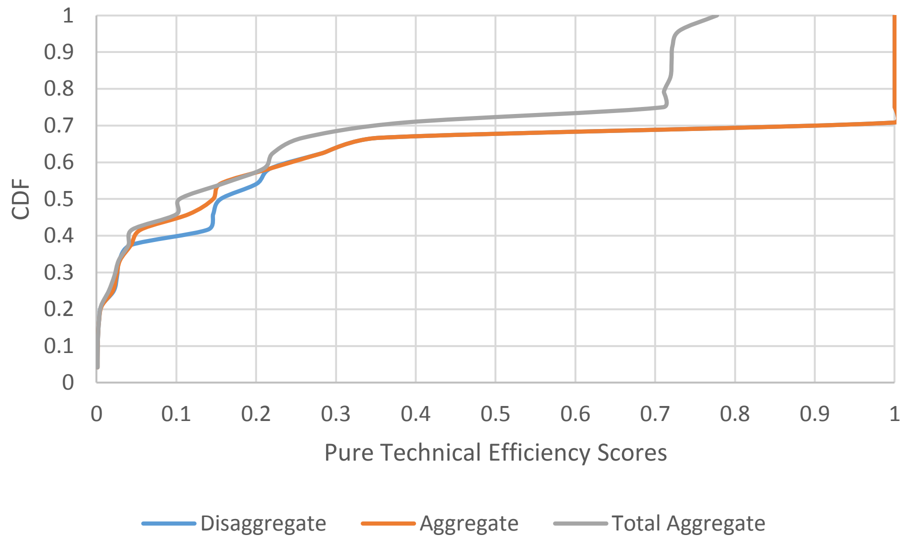


Figure 2-32 Cumulative Distribution Function of the Overall Technical Efficiency Scores for Other Energy Sources Inputs for 2012

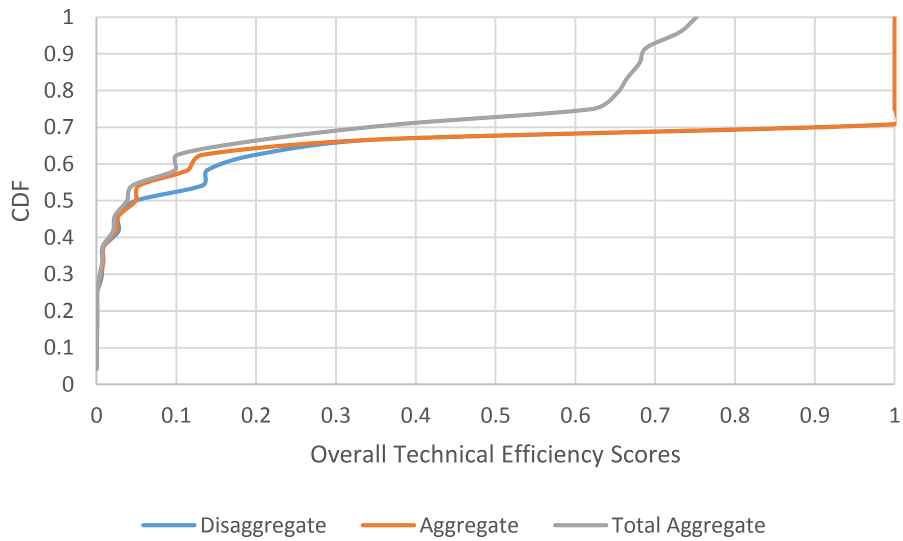
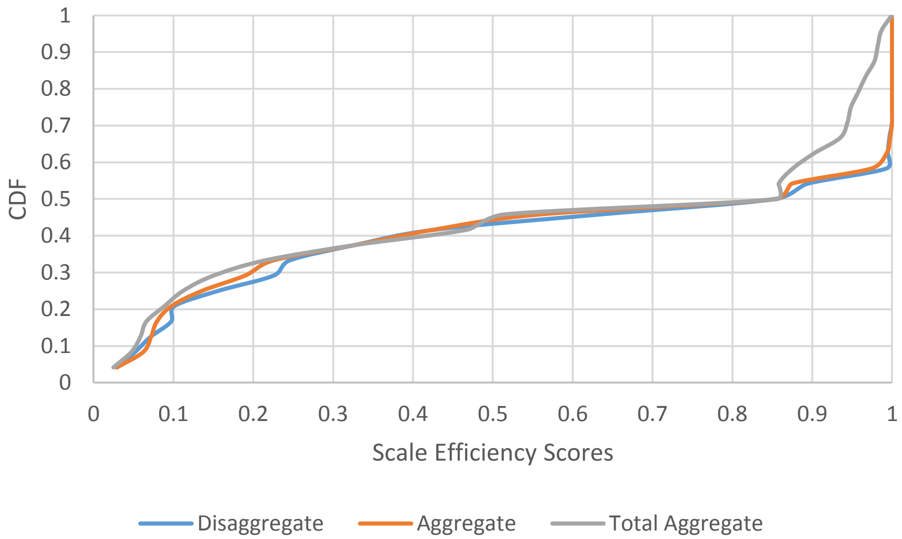


Figure 2-33 Cumulative Distribution Function of the Scale Efficiency Scores for Other Energy Sources Inputs for 2012



Chapter 3 - Greenhouse Gas Policy Effects on U.S. Electric Generation Plant Production Efficiencies

3.1 Introduction

The demand for clean energy sources is on the rise. Gone are the times of unregulated power plants polluting the air. Since the 1950s, policies have been implemented and updated to control the emissions of certain pollutants that result from electricity production. In 1990, the Clean Air Act was updated to address pollutants associated with acid rain, ozone depletion, and toxic gases. Across the United States, this amendment was effective at reducing the intended pollutants. The main focus of policy makers has now shifted from pollutants that cause acid rain to pollutants that are responsible for climate change – greenhouse gases (GHGs). Nationwide policies to specifically control greenhouse gases have not been implemented, as of 2015. Instead, regional and state level polices have been adopted in an attempt to reduce greenhouse gas emissions. The regional policies are designed to directly limit the quantity of greenhouse gases emitted by power plants, while the state policies are designed to promote the adoption of energy sources that do not emit GHGs.

Currently there are two regional organizations that have polices designed to reduce the amount of greenhouse gas emissions emitted. Both of these are regional market-based policies. The first organization was the Regional Greenhouse Gas Initiative (RGGI). RGGI began in 2009 and currently is comprised of nine states in the northeast and mid-Atlantic regions. There are two ways that firms can become compliant under this system. The first, and most common, is a firm can purchase carbon dioxide (CO_2) permits in a quarterly auction. With this system, if a firm is a low emitter, they will not have to spend much money on permits. However, if they are a high emitter, they have the option to buy enough permits to offset their pollution, or reducing their emissions through technology improvement, renewable energy deployment, or reduced production. This allows firms to decide what makes the most sense from an operational perspective. The second option allows companies to reduce their permit obligation by creating CO_2 offsets. This is a project-based greenhouse gas reduction program. There are strict limitations on what type of projects a power plant can participate in. In addition, only 3.3% of the power plants obligation can be offset by this program. The second regional organization is the Western Climate Initiative. The Western Climate Initiative began auctions in 2014. Currently, California is the only state in the U.S. that is a member, the remaining members are Canadian provinces.

There are four main renewable energy policies implemented on a state by state basis that encourage the deployment of renewable energies. The state level policies are: renewable portfolio standard (RPS), net metering, public benefit fund, and mandatory green power option. At the state level, the main policy is RPS. The RPS requires utilities within a state to generate a certain percent or quantity of electricity from renewable energy sources. The percent or quantity that the utility is required to produce, the attainment year, and whether or not the utility faces a penalty for noncompliance, varies greatly across states. Net metering has been adopted in more states than any of the other renewable energy policies. Net metering allows customers to produce their own electricity from a renewable resource (most commonly solar) and sell it to the utility company. Under net metering if the customer is not able to produce enough electricity they can purchase what they need from the utility. Public benefit funds charge utility consumers a small surcharge on their electricity bill to help support the development of renewable energy in the state. The least used policy is mandatory green power option. Under the mandatory green power option the state requires utility companies to give their customers the option to purchase electricity generated by renewable energy sources.

Two of the four state policies – RPS and mandatory green power option – require power plants to make long term decisions about whether they should build new renewable energy plants to meet their requirements or if they should purchase renewable power from the grid. While the public benefit fund is designed to ensure that renewable energy is developed by the power plant. Net metering is less likely to affect the deployment of renewable energy by the power plants since the power plants cannot offset how much renewable energy they must purchase under net metering by producing electricity from their own renewable energy sources. Numerous studies have been conducted that show renewable energy policies have at least partially led to the deployment of renewable energy within the states (Chen, et al. 2009, Shrimali and Kniefel 2011, Shrimali, Lynes and Indvik 2015, Yin and Powers 2010, O. Bespalova 2014, O. G. Bespalova 2011, Carley 2009, Kneifel 2008). In most studies, net metering was not found to affect renewable energy deployment, however it is likely that increasing the quantity of electricity the power plant receives from net metering will affect overall production decisions and emissions by the plant.

There are three types of greenhouses gases that are a direct result of the production of electricity – carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4). CO_2 and N_2O are byproducts of burning fossil fuels and biofuels for electricity production. CO_2 has the greatest impact on climate change of the GHG because it is the most prevalent. However, the global warming potential of N_2O is over 300 times that of CO_2. CH_4 comes from the production of coal, natural gas, and petroleum, as well as incomplete fossil fuel combustion.

A percentage of greenhouse gases in the atmosphere can be attributed to the production of electricity. Coal, natural gas, petroleum, and some renewable fuel power plants produce greenhouse gas emissions as a by-product of producing electricity. The by-product – greenhouse gas emissions – is often referred to as an undesirable output. In order to combat greenhouse gas emissions a number of policies that directly or indirectly focus on reducing greenhouse gas emissions have been developed. These policies are necessary to reduce greenhouse gas emissions because electric generation plants act myopically focusing on their bottom line rather than what is best for the environment. This implies that they make production decisions based on what will generate the highest level of profit or lowest costs with a disregard for the environment unless policies with financial or production burdens dictate otherwise. The objective of this study is twofold. The first is to determine the production efficiencies of electric generation plants that produce greenhouse gas emissions (an undesirable output). The second is to determine if policies focused on directly or indirectly reducing greenhouse gas emissions have had an effect on the efficiency of electric generation plants. A two-stage analysis is used to determine if policies geared toward reducing greenhouse gas emissions affect the efficiencies of greenhouse gas emitting electric generation plants. The first stage uses firm level input and output data to determine the pure technical, overall technical, and scale efficiency scores of greenhouse gas emitting electric power plants. The second stage uses the estimated efficiency scores from the first stage as the dependent variable of a tobit regression.

3.2 Literature Review

DEA is a linear programming, non-parametric model that is commonly used to determine production, cost, and revenue efficiencies of firms. Farrell (1957) laid the ground work for the DEA analysis. However it is not until the late 1970s and early 1980s that production oriented

DEA analysis is truly developed. Charnes, Cooper, and Rhodes (1978) developed the overall technical efficiency analysis which is often referred to as CCR and Banker, Charnes, and Cooper (1984) developed the pure technical efficiency which is often referred to as BCC.

There have been two different schools of thought developed to address undesirable outputs, depending on the research question at hand. The first school of thought builds on the work of Charnes, Cooper, and Rhodes (1978) and Banker, Charnes, and Cooper (1984). This work is focused on the production of a polluting firm. While the second school of thought builds on the work of Färe et al. (1989), which focuses on determining the environmental efficiency of a firm determined by the undesirable outputs. Färe et al. (1989) expanded upon the work of Farrell (1957) to develop a DEA model that allows for undesirable outputs to be incorporated into the model as weakly disposable. An overview of all the studies is presented in Table 3-1.

3.2.1 Production Studies

One of the first studies to include undesirable outputs in a DEA analysis of electricity plants was Golany, Roll, and Rybak (1994). They determined the overall technical efficiency (CCR) of 87 Israeli power plants operating in a closed market. Four outputs and three inputs are considered. The four outputs considered are generated power (MWh), operational availability, deviation from operational parameters, and sulfur dioxide (SO_2) emissions. SO_2 is measured in three levels as a set of binary codes. The three levels are good, medium, and bad. Good implied that the plant is polluting at an acceptable emissions rate which meant there is one or less violation per quarter. Medium implied that there are between two and four violations per quarter. Lastly, bad implied that there are five or more violations per quarter.

Yaisawarng and Klein (1994) considered how SO_2 control policies affect the efficiency of power plants in the U.S. They used overall technical (CCR), pure technical (BCC), and scale efficiencies to analyze the impact of these policies on approximately 60 coal-fired plants from 1985-1989. They find that plants with scrubbers experience lower overall technical and pure technical efficiency levels than plants without scrubbers.

In another study, using a two-stage model, Raczka (2001) determines why 41 heat plants in Poland are technically (in)efficient. The pure technical efficiency score is determined in the first stage analysis using one output and three inputs. Instead of including pollution as an undesirable output, it is included as an input. The pollution variable is represented by how much the utility has to pay in penalties due to polluting. Average age and average capacity of the boilers are included in the second stage analysis, neither are found to be statistically significant.

Arocena and Waddams Price (2002) determine the efficiency change, technological change, scale index, and graphyperbolic Malmquist index of electricity producers in Spain from 1984-1997. Five outputs and three inputs are used in the analysis. The five outputs include annual net power produced (GWh), availability, SO_2 (tons), NO_X (tons), and particulates (tons).

Nag (2006) used DEA to help create a trajectory of emissions for coal based thermal power generation for utility plants in India. A slack-based input-oriented pure technical efficiency is determined for the plants. By calculating the slack it allows the researchers to determine if there is an excess of inputs even after a proportional reduction in inputs has been made.

Sarica and Or (2007) determined the efficiencies of thermal power plants in Turkey using overall technical (CCR) and pure technical (BCC) efficiencies and assurance region type DEA. The model includes four outputs and two inputs. The four outputs are availability, thermal efficiency, environmental cost, and carbon monoxide (CO) (tons). The two inputs include fuel cost and production (kWh). Three of the four output variables relate to pollution. Thermal efficiency reflects the effects of CO emissions by relating heat dissipated is converted into electric energy. When the thermal efficiency is maximized, it implies that emissions are minimized. The environmental cost is the monetary value that is determined using dollars per ton of the annual SO_2, NO_x, and particulate emissions of each plant.

Welch and Barnum (2009) evaluate what it would take for steam powered plants to move from the cost efficient point to the environmental efficient point. They find as a whole it could be very costly to move from the cost efficient point to the environmental efficient point, however for select firms they could improve both their cost and environmental efficiencies by simply reducing the amount of inputs used.

Sozen, Alp, and Ozdemir (2010) created two efficiency indexes for state owned thermal plants in Turkey. One analysis focused on the slack-based overall technical efficiencies while the other focuses on environmental performance. The environmental performance model included emissions as outputs. The outputs taken into consideration are CH_4, N_2O, non-methane volatile organic compounds (NMVOC), CO, CO_2, mono-nitrogen oxide (NO_X), and SO_2 (all in tons).

In another study, Majumder and Marcus (2001) used a two-stage model to determine if the change in the 1970 Clean Air Act affected the overall technical (CCR) and pure technical (BCC) efficiencies of 150 of the largest investor-owned utilities in the U.S. in 1990. Instead of including pollution variables in the DEA analysis, they included numerous pollution variables in a second-stage tobit model. The pollution variables included were: air pollution, water pollution, waste pollution, noise pollution, and esthetic pollution. Several other plant variables were also included: size, research and development, residential customers, nuclear power, proportion generated, and regional control effects. They found that air pollution had a positive and statistically significant impact on efficiencies while waste pollution had a negative and statistically significant impact.

3.2.2 Environmental Studies

In addition to looking at overall technical, pure technical, and scale efficiencies several other DEA analysis have been used. Färe, Grosskopf, and Tyteca (1996) use a distance function and include the bad outputs SO_2, NO_X, and CO_2 in their DEA analysis. Tyteca (1997) compares three different approaches to analyzing the environmental efficiency of coal-fired power plants. There is one desirable and three undesirable outputs considered in the analysis – net generation (kWh), and SO_2, NO_X, and CO_2 (all in tons). The inputs considered include installed capacity (MW), coal (1,000 short tons), oil (100 bbls), gas (mmcf), and labor. They find that there are considerable differences between the ranking of firms based on the model that is used. However, they say that in order to decide which model is best, it likely depends on what the model is going to be used for. Since all of these models are designed to show which power plants are most environmentally efficient, simply showing a ranking might be sufficient enough to encourage the least environmentally efficient firms to reevaluate their production process and increase their environmental efficiency by decreasing their undesirable outputs.

Korhonen and Luptacik (2004) develop several different models to deal with undesirable outputs. The models used include: all outputs as a weighted sum where the bad outputs are negative; the bad outputs enter the analysis as inputs; the ratio of the weighted sum of desirable inputs minus the inputs of the undesirable outputs; and an output-oriented version of the aforementioned models. In order to test the models, 24 European power plants were studied. The desirable output included is electricity generation (MW) and the input is costs. The undesirable outputs include dust, NO_x, and SO_2. Comparing the results of the first three models, they find that similar results are obtained regardless of which model is used.

Xie, Fan, and Qu (2012) use a network DEA to determine the environmental efficiencies of 30 provincial administrative regions in China. They find that the percentage of thermal power versus clean energy power effects the environmental efficiency of a plant. In most years of the study, the electric generation plants that used at least 25% clean energy power were the most efficient plants. They also find that policies developed to incentivize clean energy development has achieved its objective. A single undesirable output is used in the analysis – CO_2.

Zhou et al. (2013) introduces a non-radial DEA approach that uses entropy weights to determine the environmental efficiency of the power industry in China. The three inputs are labor, investment, and energy. The three undesirable outputs are SO_2, NO_X, and CO_2. The energy and environmental efficiencies of 28 provinces' thermal power plants in China are determined by Bi et al. (2014) using a slack-based model. Four outputs and four inputs are considered. The four outputs include one good output – power generated (10^8 kWh), and three bad outputs – SO_2, NO_X, and soot (all in tons).

There are a series of studies by Sueyoshi and Goto that have two overarching goals. The first goal is to determine if the Clean Air Act has helped curtail SO_2 and NO_x pollution. The second goal is to determine an appropriate model to calculate the environmental efficiency of a firm in a given year or over a series of years. Analyzing coal-fired plants in the U.S., the three undesirable outputs analyzed are SO_2 (tons), NO_X (tons), and CO_2 (1000 tons). The one desirable output considered is net generation (MWh). Sueyoshi, Goto, and Ueno (2010) and Sueyoshi and Goto (2010) evaluate the plants' operational, environmental, and unified performance, where unified performance takes into account both operational and environmental aspects. The DEA model of choice is a range-adjusted measure model. They find that the Clean Air Act has helped to curtail SO_2 and NO_x pollution and conclude that the policy should be extended to also include CO_2.

Sueyoshi and Goto (2012) compare the results of radial and non-radial DEA analysis for the unified efficiencies of coal-fired power plants in the U.S. Both quantities and prices are used as input variables. The input variables include number of employees, total cost of the plant, total non-fuel operation and management cost, and fuel consumption (1000 tons). They find that there is not a large difference in using either the radial or non-radial models, however, the number of decision making units (DMUs) used can make a significant difference in the analysis. They recommend, whenever possible, it is better to use more DMUs. Two regional transmission organizations in the U.S. were compared by Sueyoshi and Goto (2013) to determine both their environmental and operational performances.

In 2013 two different time series analysis were conducted by Sueyoshi and Goto. One study creates a Malmquist index to take into account improvements in technology with respect to CO_2 emissions (Sueyoshi and Goto 2013). They find that there is a time lag with respect to technology innovation for electricity production and CO_2 emission reduction. The second proposes a DEA window analysis in order to capture the frontier shift for environmental assessment (Sueyoshi, Goto and Sugiyama 2013). Over the time frame of the study, the efficiency of coal-fired power plants has increased implying that the Clean Air Act has succeed in reducing pollution by coal-fired power plants. They suggest that a policy like the Clean Air Act should be implemented or extended to also control for CO_2 emissions.

The previous studies have taken one of two approaches when considering undesirable outputs in an efficiency analysis. The first is to include undesirable outputs as a component of a traditional production DEA analysis. The second approach is to develop an environmental efficiency that is less concerned with the production of the firm and more concerned with the emissions of the firm. Several of these studies have also determined if policies focused on reducing emissions have been successful. The current study follows the first approach by focusing on the production efficiencies of electric generation plants while incorporating undesirable outputs. This study contributes to the literature in a couple ways. First, this is the first DEA study in the U.S. to only include greenhouse gas emissions as undesirable outputs since other emissions like SO_2 are currently heavily regulated and have been for decades. Whereas greenhouse gas emissions are not regulated in most states but may become regulated in the future. Second this study determines if the policies designed to reduce greenhouse gas emissions have been effective.

3.3 Methods

Electric generation plants, like other firms operating in a market that is not perfectly competitive, will try to maximize their profits. This could mean maximizing revenue while minimizing costs, or simply minimizing costs depending on if the electric generation plant is operating in a regulated or an unregulated market. However, even for unregulated firms the flexibility to affect input or output prices is relatively low. This implies that these firms should try to produce the highest level of output using the lowest level of inputs. However, these managers realize that with the production of electricity from coal, natural gas, and petroleum, they produce a desirable output – electricity, as well as undesirable outputs like greenhouse gas emissions. It is likely that electric generation plants will not curtail their production of undesirable outputs until there is a policy in place telling them to control the undesirable outputs.

Due to the myopic nature of electric generation plants, it is important to not view them as firms that are trying to maximize their environmental efficiencies, instead they are firms that are trying to maximize their production efficiencies conditional on state and federal policies. This is especially true since there are not any policies in place that directly cap the quantity of greenhouse gases emitted by a particular plant. Instead the greenhouse gas emissions of a firm should be considered in the efficiency measure as firms will have to decide if and how they could change their greenhouse gas emissions.

Three different input-oriented efficiency models are used in this study – overall technical efficiency, pure technical efficiency, and scale efficiency. By considering all three types of production efficiencies, a firm is able to determine how best to adjust their production practices to become more efficient. In order to take into account the undesirable outputs in the model, the negative of the undesirable quantities are used. This has the same effect as the firm trying to minimize the undesirable output.

All three efficiency scores range from zero to one, where one implies the firm is efficient. For every type of efficiency, at least one DMU must have an efficiency score of one, however no DMU has to have an efficiency score of zero. In most DEA analysis multiple firms will have an efficiency of one. Those with an efficiency of one create the production frontier that all other firms try to reach. Input-oriented DEA is used in this analysis. If a firm has an overall technical or pure technical efficiency score of less than one, this implies that the firm could become more efficient by using less inputs to reach the same level of output. If the scale efficiency is less than one, this implies that the firm is operating at an inappropriate scale.

Charnes, Cooper, and Rhodes (1978) first introduced how to solve for the overall technical efficiency (CCR) of a firm under constant returns to scale. The model determines how far a producer is from producing at the level of constant returns to scale. The model is as follows:

3.1 $$\min_{\theta_i, z_i} \theta_i$$

Subject to:

$$\sum_{k=1}^{K} z_k x_{mk} \leq \theta_i x_{mi} \quad \text{for } m = 1, \ldots, M$$

$$\sum_{k=1}^{K} y_k z_k \geq y_i$$

$$-\sum_{k=1}^{K} b_k z_k \geq -b_i$$

$$(z_1, \ldots, z_K) \geq 0$$

where z is an intensity (or weight) of each electric generation plant k, x_{mk} are the inputs, y_k is the desirable output and b_k are the undesirable "bad" outputs of each electric generating plant k. There are M different inputs. θ_i is the measure of overall technical efficiency (CCR). If θ_i is equal to one then the power plant is efficient.

The pure technical efficiency (BCC) which measures how far a producer is from the production function, allowing for variable returns to scale, was first introduce by Banker, Charnes, and Cooper (1984). Using the pure technical efficiency analysis researchers are able to determine how to reduce inputs to make firms more efficient. The model is as follows:

3.2 $$\min_{\lambda_i, z_i} \lambda_i$$

Subject to:

$$\sum_{k=1}^{K} z_k x_{mk} \leq \lambda_i x_{mi} \quad \text{for } m = 1, \dots, M$$

$$\sum_{k=1}^{K} y_k z_k \geq y_i$$

$$-\sum_{k=1}^{K} b_k z_k \geq -b_i$$

$$\sum_{k=1}^{K} z_k = 1$$

$$(z_1, \dots, z_K) \geq 0$$

where the same definition exists as in the overall technical efficiency model – z is an intensity (or weight) vector, x_{mk} are the inputs, y_k is the desirable output and b_k are the undesirable "bad" outputs. The number of electric plants is K. There are M different inputs. λ_i is the measure of pure technical efficiency (BCC). If λ_i is equal to one then the power plant is efficient.

The scale efficiency can be derived using the efficiency scores of the overall technical and pure technical efficiency scores. The scale efficiency is:

3.3 $$\gamma_i = \frac{\theta_i}{\lambda_i}$$

where γ_i is the scale efficiency, θ_i is the overall technical efficiency, and λ_i is the pure technical efficiency for power plant i.

If the scale efficiency score equals one this implies that the firm is operating at constant returns to scale (implying $\theta_i = \lambda_i$). If the scale efficiency score equals the overall technical efficiency (CCR) score and is not equal to one then increasing returns to scale exists ($\lambda_i \neq 1$, $\gamma_i = \theta_i$). If the scale efficiency does not equal one or the overall technical efficiency score then decreasing returns to scale exists ($\lambda_i \neq 1,\ \gamma_i \neq \theta_i$).

Once the overall technical (CCR), pure technical (BCC) and scale efficiency scores are determined a second stage regression model is used to determine how policies designed to reduce greenhouse gas emissions affect the efficiencies of power plants. A censored tobit model is used rather than an OLS model since the dependent variable, the efficiency scores, range from 0 to 1. Building on the censored tobit model from Greene (2007) the model used in the analysis is:

3.4 $$\delta_i^* = \alpha + \beta X_i + \gamma Z_s + \varepsilon_i \qquad \varepsilon_i \sim N[0, \sigma^2]$$

$$\delta_i = \delta_i^* \qquad \text{if } \delta_i^* < 1$$

$$\delta_i = 1 \qquad \text{if } \delta_i^* \geq 1$$

where $\delta_i = \lambda_i, \theta_i,$ and γ_i are the observed pure technical (BCC), overall technical (CCR), and scale efficiency scores and δ_i^* is the latent variable for plant i; α is the intercept; X_i is a vector of plant specific explanatory variables; and Z_s is a vector of state specific policies for state s. X_i is made up of fuel inputs that are aggregated to the category level for the econometric analysis: coal, natural gas, petroleum, and non-emitting sources and other plant specific variables. The error term, ε_i, is distributed normally with mean 0 and variance σ^2.

3.4 Data

A two-stage analysis is used to determine if policies geared toward reducing greenhouse gas emissions affect the efficiencies of greenhouse gas emitting electric generation plants. The first stage uses firm level input and output data to determine the pure technical, overall technical, and scale efficiency scores. The second stage uses the estimated efficiency scores from the first stage as the dependent variable of a tobit regression.

3.4.1 DEA Data

Plant level data is used to determine the overall technical (CCR), pure technical (BCC), and scale efficiencies for coal, natural gas, and petroleum power plants from 2010 to 2012 in the U.S. The inputs used in the analysis are fuel and capital. There are up to 17 different types of fuel included in the analysis (Table 3-2). The fuel sources are measured by total fuel consumption MMBTU (million British Thermal Units) annually. Capital is represented by net capacity in megawatts (MW) at a power plant. One desirable and three undesirable outputs are included in the analysis (Table 3-2). The one desirable output is net generation in megawatt hours (MWh). The three undesirable outputs are CO_2, NH_4, and N_2O measured in metric tons. There are, on average, 950 plants per year considered in the analysis. The analysis is conducted using cross-sectional data for three years. The number of power plants in each year varies depending on the number of plants included in the survey for a given year and completeness of the data for each plant during a given year.

The production data comes from the U.S. Energy Information Administration (EIA) Form 923 (EIA 2015) and the greenhouse gas data comes from the U.S. Environmental Protection Agency (EPA) Greenhouse Gas Reporting Program (EPA 2015) that began collecting data in 2010. Since the study is focused on power plants that emit greenhouse gases, only power plants that used coal, natural gas, and/or petroleum are used in the analysis. Currently the EPA does not report information on greenhouse gas emissions from plants that use solid, liquid, or gaseous biofuel sources. Since these fuel inputs emit greenhouse gas emissions, any plant that used a biofuel source in addition to coal, natural gas, and/or petroleum was removed from the analysis. If the plant was not removed it would result in higher efficiency scores for the plant and possibly more efficient firms overall. Despite removing any plants that use biofuel from the analysis, power plants that used coal, natural gas, and/or petroleum as well as nuclear or a non-biofuel renewable energy source are included in the study. These sources do not affect the quantity of emissions by the firm but do affect the capacity and generation of the plant. Power plants that only produced electricity from nuclear power or a non-biofuel renewable energy source are not included in the study since they do not emit any greenhouse gases directly.

When deciding the variables to include in the DEA, it is important to consider three factors: 1) availability of data; 2) the body of literature; and 3) professional opinion of relevant individuals. A key variable that is missing from this analysis is labor. However, due to a lack of availability of a labor variable for the entire data set, it was not included in the analysis. Despite not including labor in the analysis, the results may not be significantly affected. A study conducted by Fallahi, Ebrahimi, and Ghaderi (2011) found the most important inputs are the installed capacity and fuel that described 91% of the full model. In addition, Welch and Barnum (2009) did not include labor for a number of reasons. First their study, like this study, was not focused on labor decisions, instead it was focused on fuel choice decisions. Second, labor makes up a very small portion of the input resources. Lastly, fuel and labor are not substitutes for one another in the electric generation industry, instead they are compliments so only one complimentary variable needs to be included. According to the EIA for the duration of this study, expenditures related to labor make up approximately 10% or less of total expenditures for the utility (EIA 2015). It is important to make sure there are enough degrees of freedom to estimate the DEA model. In general, there are enough degrees of freedom if the number of DMUs is greater than or equal to three times the number of inputs plus the number of outputs (C. P. Barros 2008). Given that the minimum number of observations is 915, degrees of freedom is not an issue for even the disaggregate analysis (915 > 3(18+4)).

3.4.2 Econometric Data

For the econometric analysis, the estimated efficiency scores obtained in the first stage of the analysis are used as the dependent variables. To determine if the type of fuel used affects the efficiency scores, dummy variables are created for the fuel inputs groups. The fuel groups are coal, natural gas, petroleum, and non-emitters. This implies that if a power plant used any type of coal during a given year then coal is equal to ‘1’ and ‘0’ otherwise. Two other plant specific variables are included in the analysis. The first additional plant specific variable is plant capital – installed capacity (in MW/10); and the second is the average age of the plant (in decades). The average age of the plant is used since some plants are made up of multiple units that began operating at different times. In this case, the average age of all the units is used as the average age of the plant.

To determine how the policies affect the efficiencies of power plants five policy are included in the tobit model. Since there is a large variation in RPS policies across states, three different dummy variables are included in the analysis. The first dummy variable is equal to ‘1’ if the policy was enacted by the current year and ‘0’ otherwise. The second variable is equal to ‘1’ if there was a voluntary RPS in place during the current year and ‘0’ otherwise. The third variable is equal to ‘1’ if there was a noncompliance penalty associated with the RPS and ‘0’ otherwise. The other three state policies – net metering, public benefits funds, and mandatory green power option – are equal to ‘1’ if the policy was in place during a given year and ‘0’ otherwise (DSIRE 2013). One regional variable is included in the analysis – RGGI. If a state is participating in RGGI during a given year, then RGGI is equal to ‘1’ and ‘0’ otherwise (RGGI 2015). Note, the Western Climate Initiative is not included in the analysis since the program did not go into effect until after 2012, the last year in this analysis. Table 3-3 contains variable means and standard deviations for the variables included in the second stage analysis that are not included in the first stage.

3.4.2.a Hypotheses Concerning Econometric Analysis

It is believed that coal will have a negative effect on the overall technical and pure technical efficiency scores. This is because coal plants produce the most greenhouse gas emissions. In addition, due to the regulations placed on electricity production by coal, it is likely that the use of coal by a power plant will have a negative effect on the efficiency scores. Since natural gas produces less greenhouse gas emissions, it is likely that natural gas will have a positive effect on the efficiency scores. Clean energy sources (non-emitters) are typically more efficient than non-clean energy sources (Lynes and Featherstone 2015, Xie, Fan and Qu 2012) so this might imply that non-emitters will have a positive effect on the efficiency score. However, since only non-emitters that are part of an emitting electric power plant are included in the analysis, non-emitters may not have a positive effect.

Several studies have considered variations of capacity in their second stage analysis (Lam and Shiu 2001, Raczka 2001) and find it to have a positive and statistically significant effect on the efficiency scores. However, Lynes and Featherstone (2015) find capacity to have a negative and statistically significant effect. Age of the boiler is included in Raczka (2001) is found not to be statistically significant. However, it is likely the age of the plant will have a negative effect on the efficiency scores for two reasons. First, new technology that enhances productivity of a power plant develops more quickly than old plants are retired. This implies that newer power plants will be operating with more efficient equipment. Second, new technology can also mean cleaner technology as power plants plan for stricter government regulations.

RGGI will likely have a positive effect on the pure technical and overall technical efficiency scores. This is because RGGI encourages firms to reduce their greenhouse gas emissions the most efficient way possible. If a firm believes they will become more inefficient then they can elect to buy extra permits rather than change the production mix to meet the requirements. However, if a firm believes it can decrease its emissions by using new technology or production process, then it will efficiently cut its emissions.

Since the other policies focus on decreasing greenhouse gas emissions by increasing the quantity of renewable energy used in the fuel mix, which can often be intermittent, it is possible that the other policies could have a negative effect on the efficiency scores. However, since these policies are designed to encourage the reduction of greenhouse gas emissions, they may have a positive effect.

3.5 Results

The results of the DEA and econometric analysis are reported in Table 3-4 and Table 3-5. The estimated efficiency scores determined in the DEA analysis are used in the second stage regression analysis.

3.5.1 DEA Results

Mean pure technical, overall technical, and scale efficiency scores are in Table 3-4. The efficiency scores reported in the table are the mean scores for power plants that use the particular input during a given year. The results reveal that there is variation in the efficiencies within the categories of fuel. For instance, the range of mean pure technical efficiency scores for types of coal range from 0.263 (*Sub-Bituminous Coal*) to 0.619 (*Waste/Other Coal*) in 2010. *Sub-Bituminous Coal* has the lowest mean pure technical and overall technical efficiency scores for all three years, compared to other types of coal. It also has the lowest scale efficiency score in

2010 and 2011. *Lignite Coal* has the highest overall technical efficiency and scale efficiency scores during all three years, compared to other types of coal. It also has the highest pure technical efficiency scores in 2011 and 2012. *Waste/Other Coal* has the highest pure technical efficiency score in 2010. The efficiency score decreases dramatically (by more than half) in 2011 and 2012. It is likely that this decrease is a result of an almost efficient firm that was in the study in 2010, was not in the study in 2011 and 2012.

Petroleum fuel inputs have the highest mean efficiency scores of all fuel categories. The mean pure technical efficiency scores range from 0.434, 0.359, and 0.469 (*Distillate Fuel Oil*) to 0.624, 0.725, (*Kerosene*) and 0.911 (*Jet Fuel*) in 2010, 2011, and 2012, respectively. *Kerosene* has the highest overall technical efficiency scores of the petroleum inputs in all three years 0.545, 0.607, and 0.543 in 2010, 2011, and 2012, respectively. The lowest mean overall technical efficiency score in 2010 is 0.237 (*Petroleum Coke*); in 2011 is 0.192 (*Jet Fuel*); and in 2012 is 0.006 (*Waste/Other Oil*). *Kerosene* has the highest mean scale efficiency scores in 2010 and 2012 – 0.871 and 0.887, respectively. Since their scale efficiency scores are relatively high, this implies that on average, these firms could improve their efficiencies more by focusing on their technical efficiency instead of their scale efficiencies. The highest scale efficiency score in 2011 is 0.836 (*Residual Fuel Oil*). *Petroleum Coke* has the lowest scale efficiency score in 2010 – 0.489 while *Waste/Other Oil* has the lowest efficiency in 2011 and 2012 – 0.493 and 0.039, respectively.

Natural Gas has the highest mean pure technical, overall technical, and scale efficiency scores in all three years in the Natural Gas and Other Gases category of inputs. The remaining three types of fuel have limited observations and in most cases have low mean pure technical and overall technical efficiency scores. However the scale efficiency for *Blast Furnace* is above 0.970 in 2010 and 2012.

The only non-emitting fuel inputs that were included in the analysis were inputs that were used at an electric generating plant that also used emitting inputs. Because of this, there is a limited number of plants that use non-emitting inputs in this study. *Nuclear* power has the highest mean pure technical, overall technical, and scale efficiencies in all three years of the study. Whereas S*olar* as the lowest pure technical, overall technical, and scale efficiency scores in the study. Depending on the year and efficiency score the range between the mean low and high efficiency scores is as large as 0.002 to 1.000.

Figure 3-1, Figure 3-2, and Figure 3-3 show the cumulative distribution functions (CDF) for the 2010, 2011, and 2012 efficiency scores, respectively. The efficiency scores for all firms for each year are included in the graphs. In 2010 (Figure 3-1), almost 20% of electric generating facilities have a scale efficiency of approximately 1 or 80% less than 1.0. More than 55% of electric generating facilities have a scale efficiency of greater than 0.900 or 45% less than 0.90. Just over 10% of firms have a pure technical efficiency score of approximately 1 or about 89% have and score less than 1.0. Less than 5% of firms have an overall technical efficiency score of approximately 1 or 95% have a score less than 1.0. This graph shows that a majority of firms have high scale efficiencies which may imply that a majority of firms should focus on improving their technical efficiency instead of their scale efficiencies. Similar results are shown in Figure 3-2 and Figure 3-3, for 2011 and 2012, respectively. In 2011 (Figure 3-2) 50% of electric generating plants have a scale efficiency of greater than 0.900 and 20% have a scale efficiency of approximately 1. Approximately 20% of electric generating plants have a pure technical efficiency of greater than 0.900 and approximately 10% have a pure technical efficiency score of approximately 1. While approximately 12% of electric generating plants have an overall technical efficiency score of greater than 0.900 and 5% of an overall technical efficiency score of approximately 1. Like in 2010, since a large number of firms are almost scale efficient, this implies that a majority of firms could benefit more from improving their technical efficiency than their scale efficiency. In 2012 (Figure 3-3) even more firms have high scale efficiencies. 65% of firms have a scale efficiency of 0.900 or higher and 30% of firms have a scale efficiency of approximately 1. Approximately 11% of firms have a pure technical efficiency score of approximately 1 and 5% have an overall technical efficiency score of approximately 1. Again this implies that firms would improve their efficiency score more by improving their technical efficiency instead of their scale efficiency.

3.5.2 Econometric Results

Using the efficiency scores as dependent variables, several results are found to hold across every year and type of efficiency (Table 3-5). While others only hold for the pure technical and overall technical efficiencies and not for the scale efficiency or not for every year in the study. Table 3-5 reports the coefficient estimates from the tobit regression. These are not the marginal effects which implies that coefficient estimates cannot be directly interpreted. Instead inference can be drawn from the sign and significance of the coefficient.

First looking at plant characteristics, the age of the plant is negative and statistically significant for all three efficiencies in every year of the study. This implies that older plants are less efficient than newer plants. This inefficiency is likely due to equipment wearing out over time as well as new technology being developed that helps the plants operate more efficiently. Installed capacity is positive and statistically significant for the overall technical and scale efficiencies for all three years. This implies that larger plants are able to operate more efficiently than smaller plants. However, installed capacity is negative and statistically significant in the pure technical efficiency model in 2010 which is in line with the findings of Lynes and Featherstone (2015) since they only looked at the pure technical efficiency scores. Coal is negative and statistically significant for all three efficiencies in every year. This is not surprising since coal, as a whole, emits the most greenhouse gas emissions. Natural gas and other gases are negative and statistically significant for the overall technical efficiency in 2010 and 2011 and for the scale efficiency in 2011. However, the magnitude of these effects is smaller than the effects from coal. Natural gas and other gases likely has a negative and statistically significant effect during certain years since gaseous propane has very low efficiency scores for these instances. No plants in 2012 used gaseous propane as an input which is likely why natural gas did not have any statistically significant effect in 2012. If electric generation facilities that use gaseous propane were removed from the analysis it is likely that natural gas would not have a statistically significant effect on these efficiency scores. Despite experiencing a negative and statistically significant overall technical efficiency, the scale efficiency is positive and statistically significant in 2010. This implies that even though firms are inefficient they would likely benefit more from decreasing their inputs than changing the size of their plant. The pure technical and overall technical efficiencies are negative and statistically significant for petroleum for all three years. However, the scale efficiencies for petroleum are positive and statistically significant for 2011 and 2012. This implies that the firms should focus on reducing their inputs, potentially through better management practices or better equipment, to increase their efficiencies rather than adjusting the scale of the plant.

The regional and state policies geared toward reducing greenhouse gas emissions have mixed effects on the pure technical, overall technical, and scale efficiencies. RGGI is positive and statistically significant for all three efficiencies in every year except the scale efficiency for 2012. This implies that states that are a part of RGGI are more efficient than states that are not. This could be because the RGGI has successfully encouraged electric generation plants to reduce their greenhouse gas emissions while still efficiently generating electricity[1].

RPS in Effect has a negative and statistically significant effect on the overall technical and pure technical efficiencies in 2011 and 2012. This is expected because RPS encourages the deployment of renewable energy that can often be intermittent and rely on traditional energy sources to ramp up generation. This excessive ramp up production may decrease the efficiency of these plants. Volunteer RPS is positive and statistically significant in the pure technical and overall technical efficiencies in 2010. It is likely that it is statistically significant in 2010 and not in 2011 and 2012 because the states that have a voluntary policy in place in 2010 are more efficient states. However as new states adopt the policy in subsequent years, these states are less efficient which results in the policy no longer having an effect on the efficiencies. Non-compliance penalty is positive and statistically significant for the pure technical efficiency in 2011 and 2012 and for the overall technical efficiency in 2012. It is likely that the non-compliance penalty has a positive effect because it sets an upper limit on how much a utility plant will have to pay to become compliant. If a company is operating fairly efficiently to begin with they may be able to make small adjustments and implementations of technology to become compliant, which will likely reduce their greenhouse gas emission, while not greatly affecting

[1] To determine if RGGI is the cause of the higher efficiency scores, the DEA analysis was rerun without the bad outputs and the same regression was run on the new efficiency scores. These results indicate that states that participate in RGGI are more efficient, from a production standpoint, than states that do not. However, without accurate emissions data before and after RGGI began it is unknown if these state became more efficient due to RGGI or not.

their net generation. However, if a firm knows it will take drastic changes to become compliant, they may elect to pay the penalty and remain operating at the same efficiency level.

Mandatory green power option is positive and statistically significant in the pure technical and overall technical efficiency models in 2011 as well as the pure technical efficiency model in 2012. Like with the voluntary RPS, it is likely the positive effect is due to the states that have adopted a mandatory green power option are more efficient to begin with then states that do not. Public benefits fund is negative and statistically significant for the 2012 scale efficiency. Net metering is negative and statistically significant for all three efficiencies in 2010 and 2012. Since power plants cannot control how much power they received from net metering it is likely they have more capacity that is not being fully used. Since the capacity is not being fully used the plants are less efficient.

3.6 Summary and Conclusions

Electric generation plants are profit maximizing firms that produce undesirable outputs including greenhouse gas emissions. Over the last decade there has been an increase in adoption of policies focused on directly or indirectly reducing greenhouse gas emission by power plants. These policies have resulted in mixed results on the production efficiencies of electric generating plants.

RGGI has a positive and statistically significant effect on the production efficiencies of the power plants. This may be due to the fact that states that participate in RGGI are naturally more efficient from a production standpoint it could also be due to the policy itself. RGGI is designed to penalize electric generation plants for producing large quantities of CO_2. However, it lets the electric generation plants decide if and how they reduce their emissions of CO_2. The other policies do not have a large effect on the efficiency of electric generation plants instead they may have a greater effect on the deployment of renewable energy which will offset the use of emitting energy sources, since they are designed to encourage renewable energy deployment instead of reduction of greenhouse gases.

Despite RPS having a negative and statistically significant effect on the overall technical and pure technical efficiencies in 2011 and 2012, that does not necessarily mean the policy is bad for the overall utility, from a production standpoint. The policy does not require every electric generating plant to produce a certain quantity of electricity from renewable energy at the plant, rather the utilities have to produce or purchase a certain quantity of electricity from renewable energy. Other studies have shown that renewable energy is typically an efficient way to produce electricity, from a production standpoint. The negative impact of the policy on the electric generating plants in 2011 and 2012 could be the result of beginning to underuse the conventional electric generation plants as more intermittent renewable energy is used for electricity production. However, since renewable energy is typically efficient, the efficiency of the utility may not be negatively impacted.

To determine if RGGI has had a direct effect on the production efficiencies of electric generation plants some additional analysis should be done. Since the EPA did not start collecting data on greenhouse gas pollutants until 2010 it might be hard to determine if the RGGI states have been able to reduce their greenhouse gas pollution while maintaining high production efficiencies. Instead an analysis should be done to see if there has been a change in the production efficiency scores without bad outputs of the RGGI states before and after RGGI began. Another check is using propensity matching between electric generation plants in RGGI states and electric generation plants in non-RGGI states to determine if the results are due to

RGGI or if electric power generation plants are more efficient in states with RGGI regardless of the policy.

To effectively reduce greenhouse gas emissions it might be beneficial to have more policies like RGGI. These policies should not replace the policies that focus on increasing renewable energy deployment, instead they should be developed alongside these policies like RGGI has been. The renewable energy polices will encourage new energy development to come from clean sources while programs like RGGI directly encourage the reduction of greenhouse gas emissions from power plants that are already established. In addition, not all new power plant development will come from clean energy sources. By creating policies like RGGI, any new coal, natural gas, and petroleum power plants will likely be developed with lower emission levels than in previous years.

Table 3-1 – Literature Review of Production Efficiency Studies of Emitting Electric Generation Plants

Study	Model	Output	Inputs
		Production Studies	
Golany, Roll, and Rybak (1994)	- CCR	- Total generated power (GWh)	- Installed capacity - Fuel consumption - Manpower
Yaisawarng and Klein (1994)	- Malmquist Index	- Net generation (kWh) - SO_2 (tons)	- Fuel (BTUs) - Labor - Capital ($) - Sulfur
Raczka (2001)	- Technical - Scale efficiency	- Heat production (terajoules)	- Labor - Fuel (terajoules) - Pollution
Arocena and Waddams Price (2002)	- Efficiency change - Technology change - Scale index - Graphyperbolic matrix	- Net power produced (MWh) - Availability - SO_2 - NO_x - Particulates	- Capacity (MW) - Labor - Fuel (therms)
Nag (2006)	- Slack-based BCC	- Net power generation	- Coal consumption - Oil consumption - Auxiliary consumption
Sarica and Or (2007)	- BCC - CCR - Assurance region	Thermal Plant - Availability Renewable Plant - Production (kWh) - Utilization	Thermal Plant - Fuel cost - Production (kWh) - Thermal efficiency - Environmental cost - CO Renewable Plant - Operating cost
Welch and Barnum (2009)	- Technical efficiency - Cost efficiency - Environmental efficiency	- Electricity generated (MWh)	- Coal consumed (MBTU) - Gas consumed (MBTU) - Oil consumed (MBTU)

Table 3-1 – Literature Review of Production Efficiency Studies of Emitting Electric Generation Plants

Study	Model	Output	Inputs
Sozen, Alp, and Ozdemir (2010)	- Slack-based CCR - Environmental efficiency	- Fuel cost - Production - CH_4 - N_2O - NMVOC - CO - CO_2 - NO_X - SO_2	- Capacity use factors - Thermal efficiency - Average operational time - Project production capacity
Majumder and Marcus (2001)	- BCC - CCR	- Total sales - Dispositions of energy (MWh)	- Spending on total production - Transmission - Distribution - Total number of employees - Amount of power purchased
		Environmental Studies	
Färe, Grosskopf, and Tyteca (1996)	- CCR - Environmental Efficiency	- Net generation (kWh) - SO_2 (tons) - NO_X (tons) - CO_2 (tons)	- Coal (short tons) - Oil (barrels) - Natural gas (cubic feet) - Installed capacity (MW) - Labor
Tyteca (1997)	- CCR - Undesirable output-oriented - Output only model	- Net generation (MWh) - SO_2 (tons) - NO_X (tons) - CO_2 (tons)	- Installed capacity (MW) - Coal (short tons) - Oil (bbls) - Gas (MMcf) - Labor

Table 3-1 – Literature Review of Production Efficiency Studies of Emitting Electric Generation Plants

Study	Model	Output	Inputs
Korhonen and Luptacik (2004)	- All outputs as a weighted sum - Undesirable outputs as inputs - Ratio of weighted sum of desirable inputs minus the inputs of the undesirable outputs - Output-oriented model	- Electricity generation (MW) - Dust - NO_X - SO_2	- Cost ($)
Xie, Fan, and Qu (2012)	- 2-stage Network DEA	- Electricity generated (TWh) - CO_2 (tons) - Auxiliary power (TWh) - On-grid electricty (TWh)	- Labor - Installed capacity (MW) - Fuel (tons)
Zhou et al. (2013)	- Non-radial DEA	- SO_2 - NO_X - CO_2	- Labor - Investment - Energy
Bi et al. (2014)	- Slack based measure	- Power generated (kWh) - SO_2 (tons) - NO_X (tons) - Soot (tons)	- Installed capacity (kW) - Labor - Coal (tons) - Gas (cubic meters)
Sueyoshi, Goto, and Ueno (2010)	- Range-adjusted model - Operational - Environmental - Unified	- Net generation (MWh) - SO_2 (ton) - NO_X (ton) - CO_2 (ton)	- Employees - Total cost of plant ($) - Total non-fuel O&M ($) - Fuel consumption (ton)
Sueyoshi and Goto (2010)	- Range-adjusted model - Operational - Environmental - Unified	- Net generation (MWh) - SO_2 (ton) - NO_X (ton) - CO_2 (ton)	- Employees - Total cost of plant ($) - Total non-fuel O&M ($) - Fuel consumption (ton)

Table 3-1 – Literature Review of Production Efficiency Studies of Emitting Electric Generation Plants

Study	Model	Output	Inputs
Sueyoshi and Goto (2012)	- Radial and non-radial unified efficiencies	- Total amount of sales (JPY) - CO_2 (ton)	- Total assets (JPY) - Total amount of energy inputs (GJ) - Total number of employees
Sueyoshi and Goto (2013)	- Operational - Environmental	- Net generation (MWh) - SO_2 (ton) - CO_2 (ton) - CH_4 (lbs) - N_2O (lbs)	- Plant capacity (MW) - Annual heat input (BTU)
Sueyoshi and Goto (2013)	- Malmquist Index	- Electricity (GWh) - CO_2 (ton)	- Combustible (MWe) - Nuclear (MWe) - Hydro and renewables (MWe)
Sueyoshi, Goto, and Sugiyama (2013)	- Window analysis DEA	- Net generation (MWh) - SO_2 (ton) - NO_X (ton) - CO_2 (ton)	- Employees - Total cost of plant ($) - Total non-fuel O&M ($) - Fuel consumption (ton)

Table 3-2 – Input and Output Summary Statistics of Electric Generation Plants from 2010 – 2012 for the DEA

	2010 N = 954		2011 N = 915		2012 N = 988	
Emitting Inputs						
Bituminous Coal	6,516,815	(22,506,517)	6,236,363	(21,596,695)	4,719,381	(18,715,483)
Sub-Bituminous Coal	7,118,542	(22,869,348)	7,451,758	(23,680,841)	6,074,480	(20,950,498)
Lignite Coal	853,003	(7,541,997)	978,249	(8,446,944)	876,246	(8,045,204)
Waste/Other Coal	69,639	(1,366,794)	59,311	(1,206,549)	41,710	(771,712)
Distillate Fuel Oil	48,665	(144,764)	36,044	(105,695)	23,905	(65,184)
Jet Fuel	21	(319)	12	(219)	9	(220)
Kerosene	1,180	(15,312)	1,454	(23,680)	747	(11,020)
Petroleum Coke	95,636	(1,349,668)	122,094	(1,540,685)	75,437	(1,049,913)
Residual Fuel Oil	66,276	(656,690)	19,695	(159,310)	7,245	(57,240)
Waste/Other Oil	1,185	(18,754)	339	(4,553)	275	(5,960)
Natural Gas	5,456,532	(11,429,263)	5,234,704	(11,340,098)	7,052,317	(13,247,748)
Blast Furnace Gas	6,923	(213,823)	--	--	7,030	(220,955)
Other Gas	15,475	(330,261)	15,398	(363,382)	19,324	(409,847)
Gaseous Propane	47	(1,053)	39	(920)	0	0
Non-Emitting Inputs						
Nuclear	368,781	(7,503,452)	72,777	(2,201,425)	280,844	(6,775,844)
Hydroelectric	2,571	(71,778)	2,312	(68,535)	25	(783)
Solar	71	(1,849)	109	(3,103)	858	(26,744)
Installed Capacity	632	(620)	634	(624)	636	(629)
Outputs						
Net Generation	670,364	(1,605,115)	619,746	(1,484,655)	863,785	(1,777,602)
Carbon Dioxide (CO_2)	2,756,937	(10,177,936)	2,941,673	(9,517,245)	1,524,895	(2,747,048)
Methane (CH_4)	237	(1,156)	255	(1,068)	106	(284)
Nitrous Oxide (N_2O)	41	(172)	44	(159)	20	(47)

Standard deviations are in parenthesis. Note: Firms enter and leave the dataset from year to year which can cause large differences in mean and standard deviation values.

Table 3-3 – Summary Statistics of State Policies and Plant Variables from 2003 – 2012 Used in the Econometric Model

	2010 N = 47[2]	2011 N = 48	2012 N = 47
Mandatory Green Power Option	0.170	0.167	0.170
Net Metering	0.830	0.854	0.851
Public Benefits Funds	0.319	0.313	0.319
RPS in Effect	0.468	0.542	0.596
RPS Penalty	0.277	0.313	0.319
Voluntary RPS	0.106	0.125	0.128
RGGI	0.191	0.188	0.170[3]
	N = 954	N = 915	N = 988
Average Age of Plant (in decades)	2.491 (1.675)	2.553 (1.655)	2.428 (1.636)

Standard deviations are in parenthesis.

[2] Not all states are included in the analysis because emission information was not available for every state.

[3] New Jersey left RGGI beginning January 1, 2012, decreasing the percent of states involved in RGGI.

Table 3-4 – Mean Production Efficiency Scores of Electric Generation Plants in the U.S. 2010 through 2012

	2010			2011			2012		
	Pure Technical Efficiency	Overall Technical Efficiency	Scale Efficiency	Pure Technical Efficiency	Overall Technical Efficiency	Scale Efficiency	Pure Technical Efficiency	Overall Technical Efficiency	Scale Efficiency
All Inputs									
All Fuel Inputs	N = 954			N = 913			N = 988		
	0.488	0.399	0.697	0.497	0.412	0.739	0.563	0.511	0.817
	(0.287)	(0.295)	(0.397)	(0.345)	(0.338)	(0.326)	(0.335)	(0.336)	(0.302)
Emitting Inputs									
Bituminous Coal	N = 183			N = 178			N = 155		
	0.388	0.079	0.182	0.268	0.103	0.453	0.469	0.139	0.259
	(0.358)	(0.193)	(0.266)	(0.359)	(0.230)	(0.365)	(0.397)	(0.280)	(0.316)
Sub-Bituminous Coal	N = 161			N = 154			N = 154		
	0.263	0.053	0.152	0.164	0.042	0.311	0.213	0.076	0.342
	(0.291)	(0.169)	(0.254)	(0.271)	(0.139)	(0.347)	(0.320)	(0.214)	(0.350)
Lignite Coal	N = 17			N = 17			N = 17		
	0.585	0.466	0.630	0.713	0.362	0.550	0.689	0.426	0.630
	(0.401)	(0.366)	(0.414)	(0.408)	(0.404)	(0.438)	(0.448)	(0.327)	(0.303)
Waste/Other Coal	N = 5			N = 4			N = 4		
	0.619	0.204	0.221	0.272	0.255	0.547	0.270	0.253	0.557
	(0.433)	(0.445)	(0.436)	(0.486)	(0.497)	(0.435)	(0.487)	(0.498)	(0.512)
Distillate Fuel Oil	N = 425			N = 406			N = 380		
	0.434	0.280	0.508	0.359	0.290	0.668	0.461	0.338	0.609
	(0.313)	(0.302)	(0.433)	(0.346)	(0.323)	(0.364)	(0.351)	(0.341)	(0.414)
Jet Fuel	N = 5			N = 3			N = 2		
	0.532	0.433	0.566	0.635	0.192	0.543	0.911	0.285	0.347
	(0.453)	(0.435)	(0.472)	(0.540)	(0.319)	(0.505)	(0.126)	(0.403)	(0.490)
Kerosene	N = 18			N = 16			N = 22		
	0.624	0.545	0.871	0.725	0.607	0.813	0.644	0.543	0.887
	(0.248)	(0.243)	(0.232)	(0.229)	(0.259)	(0.217)	(0.264)	(0.238)	(0.225)

Table 3-4 – Mean Production Efficiency Scores of Electric Generation Plants in the U.S. 2010 through 2012

	2010			2011			2012		
	Pure Technical Efficiency	Overall Technical Efficiency	Scale Efficiency	Pure Technical Efficiency	Overall Technical Efficiency	Scale Efficiency	Pure Technical Efficiency	Overall Technical Efficiency	Scale Efficiency
Petroleum Coke		N = 13			N = 11			N = 9	
	0.573	0.273	0.489	0.592	0.375	0.633	0.716	0.528	0.669
	(0.347)	(0.281)	(0.363)	(0.284)	(0.332)	(0.389)	(0.364)	(0.381)	(0.365)
Residual Fuel Oil		N = 52			N = 45			N = 38	
	0.522	0.394	0.739	0.527	0.435	0.836	0.548	0.440	0.825
	(0.289)	(0.261)	(0.352)	(0.295)	(0.289)	(0.258)	(0.244)	(0.263)	(0.318)
Waste/Other Oil		N = 5			N = 7			N = 3	
	0.579	0.351	0.589	0.649	0.312	0.493	0.671	0.006	0.039
	(0.342)	(0.320)	(0.485)	(0.450)	(0.380)	(0.454)	(0.570)	(0.005)	(0.052)
Natural Gas		N = 762			N = 731			N = 816	
	0.568	0.472	0.793	0.595	0.485	0.758	0.677	0.598	0.843
	(0.251)	(0.256)	(0.331)	(0.294)	(0.315)	(0.326)	(0.254)	(0.287)	(0.298)
Blast Furnace Gas		N = 1			N = 0			N = 1	
	0.142	0.142	0.999	--	--	--	0.104	0.102	0.979
	--	--	--				--	--	--
Other Gas		N = 6			N = 5			N = 4	
	0.293	0.033	0.401	0.048	0.041	0.532	0.089	0.073	0.565
	(0.382)	(0.041)	(0.432)	(0.049)	(0.052)	(0.409)	(0.086)	(0.094)	(0.478)
Gaseous Propane		N = 4			N = 3			N = 0	
	0.514	0.002	0.009	0.176	0.005	0.015	--	--	--
	(0.458)	(0.003)	(0.014)	(0.222)	(0.008)	(0.015)			
Non-Emitting Inputs									
Nuclear		N = 4			N = 1			N = 2	
	0.657	0.605	0.696	1	1	1	0.750	0.748	0.996
	(0.466)	(0.439)	(0.468)	--	--	--	(0.354)	(0.357)	(0.006)

Table 3-4 – Mean Production Efficiency Scores of Electric Generation Plants in the U.S. 2010 through 2012

	2010			2011			2012		
	Pure Technical Efficiency	Overall Technical Efficiency	Scale Efficiency	Pure Technical Efficiency	Overall Technical Efficiency	Scale Efficiency	Pure Technical Efficiency	Overall Technical Efficiency	Scale Efficiency
	N = 2			N = 2			N = 1		
Hydroelectric	0.625	0.277	0.505	0.516	0.317	0.418	0.102	0.009	0.088
	(0.136)	(0.287)	(0.570)	(0.684)	(0.439)	(0.297)	--	--	--
	N = 4			N = 4			N = 4		
Solar	0.078	0.007	0.077	0.060	0.002	0.076	0.066	0.003	0.272
	(0.031)	(0.007)	(0.065)	(0.053)	(0.001)	(0.096)	(0.043)	(0.002)	(0.486)

Standard deviation in parenthesis.

Table 3-5 – Second Stage Tobit Model Regression Results for the Production Efficiencies for 2010 – 2012

	2010			2011			2012		
	Pure Technical Efficiency	Overall Technical Efficiency	Scale Efficiency	Pure Technical Efficiency	Overall Technical Efficiency	Scale Efficiency	Pure Technical Efficiency	Overall Technical Efficiency	Scale Efficiency
Intercept	0.845***	0.743***	0.912***	0.861***	0.824***	0.997***	0.883***	0.846***	0.918***
	(0.053)	(0.036)	(0.044)	(0.057)	(0.046)	(0.050)	(0.056)	(0.043)	(0.047)
Policies									
RPS in Effect (RPS)	-0.027	-0.016	-0.040	-0.116***	-0.083***	-0.039	-0.110***	-0.053**	0.005
	(0.029)	(0.022)	(0.024)	(0.030)	(0.026)	(0.030)	(0.029)	(0.0230	(0.025)
Voluntary RPS	0.068*	0.077**	0.060	0.033	0.036	0.022	-0.018	-0.021	-0.011
	(0.040)	(0.036)	(0.039)	(0.040)	(0.034)	(0.035)	(0.040)	(0.030)	(0.029)
Non-compliance Penalty	-0.036	-0.016	0.004	0.061**	0.022	0.000	0.054**	0.033*	0.003
	(0.025)	(0.017)	(0.022)	(0.025)	(0.022)	(0.025)	(0.023)	(0.018)	(0.019)
RGGI	0.091***	0.081***	0.051**	0.173***	0.142***	0.077***	0.121***	0.099***	0.031
	(0.026)	(0.019)	(0.025)	(0.029)	(0.027)	(0.029)	(0.025)	(0.020)	(0.021)
Mandatory Green Power Option (MGPO)	0.006	0.004	0.006	0.115***	0.069***	0.005	0.071**	0.032	-0.021
	(0.033)	(0.025)	(0.025)	(0.035)	(0.027)	(0.031)	(0.033)	(0.023)	(0.025)
Public Benefits Fund (PBF)	0.039	0.018	0.005	0.019	0.023	-0.009	-0.007	-0.023	-0.037*
	(0.028)	(0.022)	(0.026)	(0.030)	(0.025)	(0.030)	(0.027)	(0.020)	(0.023)
Net Metering (NM)	-0.050*	-0.043**	-0.043*	-0.103**	-0.107***	-0.051*	-0.013	-0.002	0.016
	(0.029)	(0.021)	(0.026)	(0.033)	(0.027)	(0.029)	(0.029)	(0.022)	(0.024)
Power Plant Characteristics									
Installed Capacity	-0.00065***	0.00020*	0.00033**	-0.00004	0.00050***	0.00090***	0.00021	0.00040***	0.00038**
	(0.00019)	(0.00011)	(0.00014)	(0.00019)	(0.00014)	(0.00018)	(0.00018)	(0.00013)	(0.00016)
Age of Plant	-0.037***	-0.043***	-0.022***	-0.042***	-0.040***	-0.016***	-0.045***	-0.047***	-0.021***
	(0.007)	(0.004)	(0.006)	(0.007)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)

Table 3-5 – Second Stage Tobit Model Regression Results for the Production Efficiencies for 2010 – 2012

	2010			2011			2012		
	Pure Technical Efficiency	Overall Technical Efficiency	Scale Efficiency	Pure Technical Efficiency	Overall Technical Efficiency	Scale Efficiency	Pure Technical Efficiency	Overall Technical Efficiency	Scale Efficiency
Fuel									
Coal	-0.180***	-0.397***	-0.641***	-0.251***	-0.434***	-0.572***	-0.236***	-0.471***	-0.613***
	(0.034)	(0.023)	(0.030)	(0.036)	(0.026)	(0.030)	(0.036)	(0.028)	(0.032)
Natural Gas & Other Gases	-0.058	-0.068**	0.079**	0.027	-0.068**	-0.105***	0.004	-0.047	0.041
	(0.039)	(0.028)	(0.033)	(0.040)	(0.031)	(0.036)	(0.045)	(0.034)	(0.039)
Petroleum	-0.062***	-0.060***	-0.005	-0.142***	-0.074***	0.081***	-0.103***	-0.079***	0.046**
	(0.021)	(0.016)	(0.019)	(0.023)	(0.020)	(0.020)	(0.020)	(0.018)	(0.019)
Non-polluting Inputs	0.035	0.006	-0.119	0.042	0.017	-0.285	-0.305**	-0.335**	-0.405**
	(0.144)	(0.135)	(0.167)	(0.204)	(0.192)	(0.199)	(0.150)	(0.153)	(0.170)
Sigma	0.267***	0.193***	0.221***	0.280***	0.244***	0.261***	0.268***	0.209***	0.222***
	(0.008)	(0.009)	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Observations	954			915			988		
Censored	81	27	30	73	33	42	89	29	62
Log Likelihood	-190.87	164.71	49.83	-216.89	-51.45	-108.31	-201.47	97.21	14.22

Standard errors are in parenthesis. *** implies significance at the 1% level, ** implies significance at the 5% level, and * implies significance at the 10% level.

Figure 3-1 Cumulative Distribution Function for 2010 Production Efficiency Scores

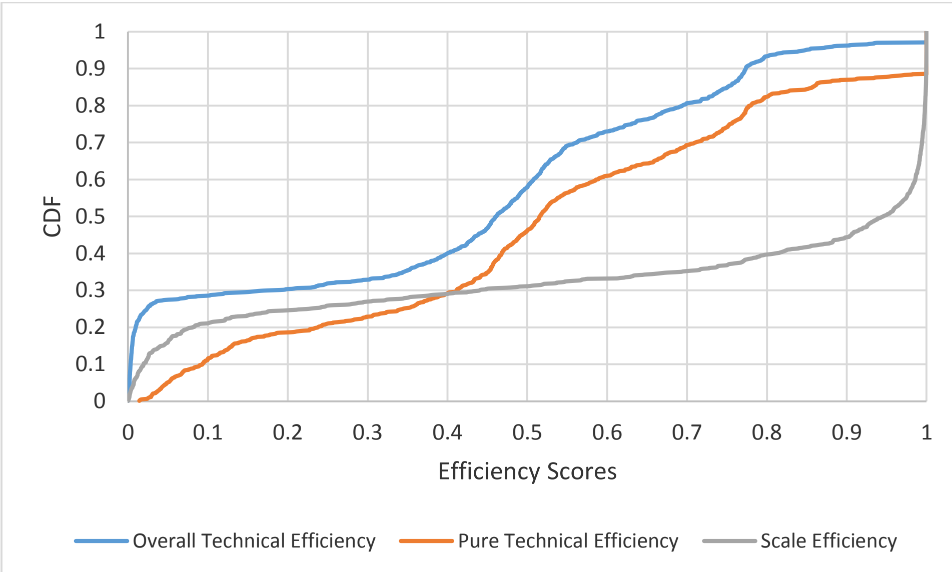


Figure 3-2 Cumulative Distribution Function for 2011 Production Efficiency Scores

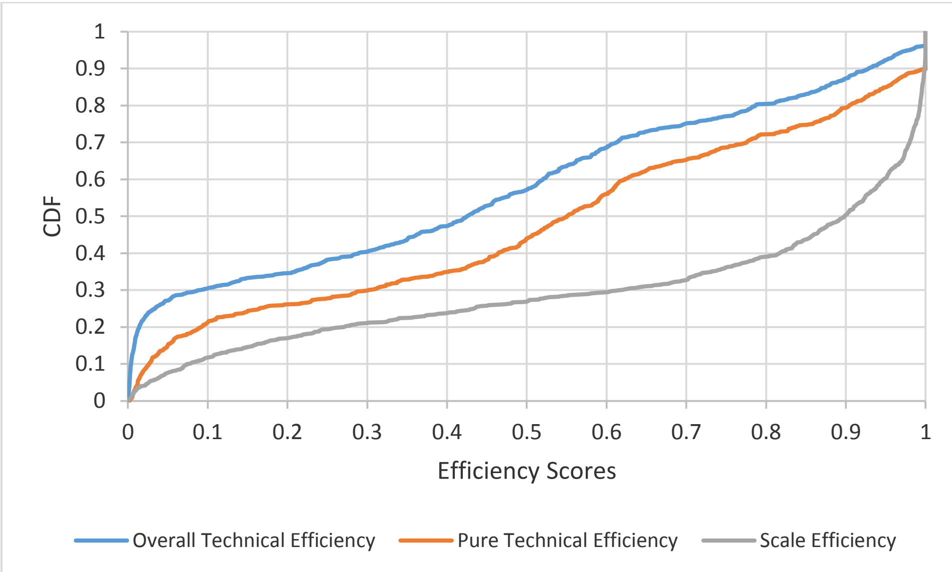
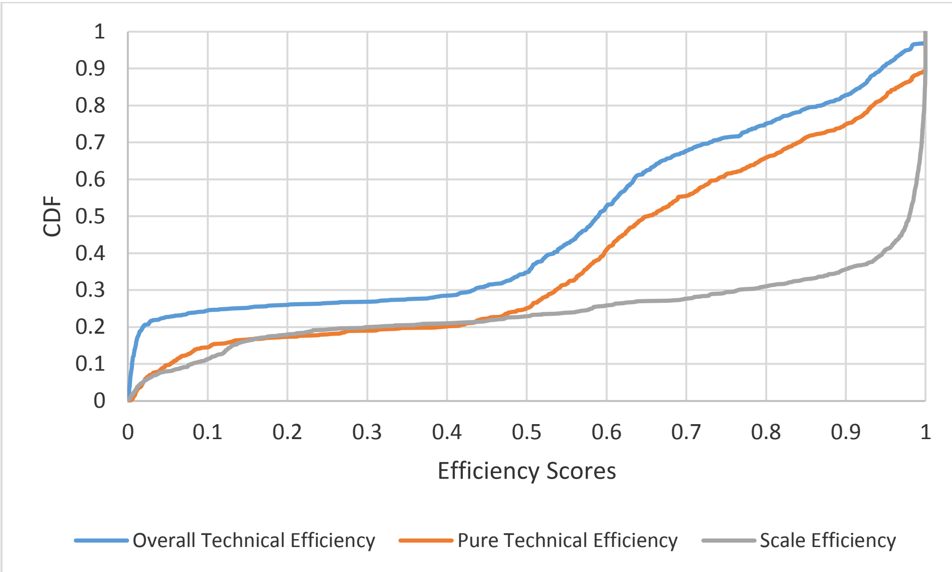


Figure 3-3 Cumulative Distribution Function for 2012 Production Efficiency Scores



Appendix

Table 3-6 Statistically Significant Policy Variables in Regression Model with Bad Outputs

	2010	2011	2012
Policies	**Pure Technical Efficiency**		
	Voluntary RPS (+) RGGI (+) Net Metering (-)	RPS in Effect (-) Non-compliance Penalty (+) RGGI (+) Mandatory Green Power Option (+) Net Metering (-)	RPS in Effect (-) Non-compliance Penalty (+) RGGI (+) Mandatory Green Power Option (+)
	Overall Technical Efficiency		
	Voluntary RPS (+) RGGI (+) Net Metering (-)	RPS in Effect (-) RGGI (+) Mandatory Green Power Option (+) Net Metering (-)	RPS in Effect (-) RGGI (+)
	Scale Efficiency		
	RGGI (+) Net Metering (-)	RGGI (+) Net Metering (-)	Public Benefits Fund (-)

Table 3-7 Statistically Significant Plant Characteristic Variables in Regression Model with Bad Outputs

	2010	2011	2012
Power Plant Characteristics	**Pure Technical Efficiency**		
	Installed Capacity (-) Age of Plant (-) Coal (-) Petroleum (-)	Installed Capacity (-) Age of Plant (-) Coal (-) Natural Gas and Other Gases (-) Petroleum (-)	Age of Plant (-) Coal (-) Petroleum (-) Non-emitting Inputs (-)
	Overall Technical Efficiency		
	Installed Capacity (+) Age of Plant (-) Coal (-) Natural Gas and Other Gases (-) Petroleum (-)	Installed Capacity (+) Age of Plant (-) Coal (-) Natural Gas and Other Gases (-) Petroleum (-)	Installed Capacity (+) Age of Plant (-) Coal (-) Petroleum (-) Non-emitting Inputs (-)
	Scale Efficiency		
	Installed Capacity (+) Age of Plant (-) Coal (-) Natural Gas and Other Gases (+)	Installed Capacity (+) Age of Plant (-) Coal (-) Natural Gas and Other Gases (+) Petroleum (+)	Installed Capacity (+) Age of Plant (-) Coal (-) Petroleum (+) Non-emitting Inputs (-)

Chapter 4 - Effects of Renewable Energy Policy on Changes in Productivity of U.S. Electric Generation Plants from 2003 - 2012

4.1 Introduction

Over the last few decades there has been a shift in electricity production in the U.S. Renewable energy sources other than hydroelectric[1] are becoming more widely used. In addition, electric generation plants that use coal inputs are more heavily regulated now than a couple decades ago due to coal's tendency to emit a number of harmful pollutants. This shift in electricity production was brought on by changes in consumer sentiment – wanting clean electricity produced in the U.S. that led to adoption of policies encouraging the use of renewable energy.

There are four main renewable energy policies implemented on a state by state basis that encourage the deployment of renewable energies. The state level policies are: renewable portfolio standards (RPS), net metering, public benefit funds, and mandatory green power options. At the state level, the main policy is RPS. The RPS requires utilities within a state to generate a certain percent or quantity of electricity from renewable energy sources. The percent or quantity that the utility is required to produce, the attainment year, and whether or not the utility faces a penalty for noncompliance, varies greatly across states. Net metering has been adopted in more states than any other renewable energy policy. Net metering allows customers to produce their own electricity from a renewable resource (most commonly solar) and sell it to the utility company. Under net metering if the customer is not able to produce enough electricity

[1] Hydroelectric power was already widely used during this time period.

they can purchase what they need from the utility. Public benefit funds charge utility consumers a small surcharge on their electricity bill to help support the development of renewable energy in the state. The least used policy is the mandatory green power option. Under the mandatory green power option the state requires utility companies to give their customers the option to purchase electricity generated by renewable energy sources even if the customers' utility does not produce it.

Two of the four state policies – RPS and mandatory green power option – require power plants to make long term decisions about whether they should build new renewable energy plants to meet their requirements or if they should purchase renewable power from the grid. While the public benefit fund is designed to ensure that renewable energy is developed by the power plant from money collected by a surcharge charged to consumers. Net metering is the least likely to affect the deployment of renewable energy by the power plants since the power plants cannot offset how much renewable energy they must purchase under net metering by producing electricity from their own renewable energy sources. Numerous studies have been conducted that show renewable energy policies have at least partially led to the deployment of renewable energy within the states (Chen, et al. 2009, Shrimali and Kniefel 2011, Shrimali, Lynes and Indvik 2015, Yin and Powers 2010, O. Bespalova 2014, O. G. Bespalova 2011, Carley 2009, Kneifel 2008). In most studies, net metering was not found to affect renewable energy deployment, however it is likely that increasing the quantity of electricity the power plant receives from net metering will affect overall production decisions and emissions by the plant.

It can take years of planning and construction to build a new electric generation plant and once the plant is built making drastic changes to the operation of the plant can take a lot of time and money. So when new policies are passed that affect electric generation plants, the changes take place over time. Often the policies give electric power plants several years to become compliant and/or incorporate a tiered system to help the electric generation plants achieve the final goal of policy. The long run plans of the electric generation plant need to account for the policy specifications to ensure productivity growth can be achieved. Where productivity growth is the outward shift of the total factor productivity (TFP). Changes in technical efficiency and technological change lead to shifts in the TFP.

Many of these renewable energy policies place an emphasis on the use of intermittent renewable energies (i.e. wind and solar) either through large scale production at the plant level (i.e. RPS) or through small scale production at the consumer level (i.e. net metering). Due to the increased use of these intermittent renewable energies, non-renewable energies (i.e. natural gas and petroleum) must be used to produce electricity to meet load requirements more now than in the past. Electric generation plants cannot control when the wind blows or sun shines so non-intermittent electric power plants must remain on standby operating below capacity to compensate for when the intermittent fuel sources are not available. This increase in production variability of renewable energy inputs is believed to decrease the efficiencies of power plants. The objectives of this study are twofold. The first is to determine if policies developed to encourage the deployment of renewable energy have had effects on the overall productivity growth of electric generation plants. The second is to determine if the use of intermittent fuel sources affects the overall productivity growth of electric generation plants. A two-stage analysis is used to determine if these renewable energy policies and fuel input used affect the productivity growth of electric generation plants. In the first stage a Malmquist index is used to determine the change in technical efficiency, technological change, the total factor productivity (TFP) of electric generation plants in the U.S between 2003 and 2012. These results will show if there was a clear trend in productivity growth for electric generation plants during the timeframe of the study. By decomposing the Malmquist index into the change in technical efficiency and the technological change, it will show which has led to changes in productivity. The second stage uses the estimated scores from the Malmquist index as the dependent variables to determine if renewable energy policies and fuel input affect productivity growth.

4.2 Literature Review

The Malmquist index was first introduced in a theoretical setting by Caves, Christensen, and Diewert (1982). They aptly named it the Malmquist index after Malmquist who was the first to introduce the concept of constructing input quantity indices as ratios of the distance function. Färe et al. (1990) was one of the first to apply the Malmquist index. They develop an input based Malmquist index that does not rely on input or output prices. They then decompose the index into technical efficiency and changes in the frontier technology – technological change. The distance function used by Färe et al. (1990) is based on the constant returns to scale overall technical production efficiency developed by Charnes, Cooper, and Rhodes (1978). Färe et al. applies the Malmquist index to steam electric generating plants in Illinois. The output used in the study is the total net generation (kWh) while the three inputs were labor, fuel (BTUs) and capital (MW).

Several studies have compared electric generation plants in one country to electric generation plants in other countries. To see if the National Electricity Board in Malaysia is operating as efficiently as electric generation plants in Thailand and the U.K., Yunos and Hawdon (1997) used the Malmquist index. They used one output and four inputs. The one input used was electricity generated (GWh) and the four outputs were installed capacity (MW), labor, electricity losses, and thermal efficiency. Comparing the efficiencies of Japanese and U.S.

investor owned utilities Goto and Tsutsui (1998) used two outputs and four inputs. The two outputs were quantity sold to residential customers (GWh) and quantity sold to non-residential customers (GWh). The four inputs used were nameplate generation capacity (MW), quantity of fuel (kcal), total number of employees, and quantity of power purchase (GWh). An intertemporal efficiency index was used to determine the technical efficiency score.

Arocena and Waddams Price (2002) determine the efficiency change, technological change, scale index, and graphyperbolic Malmquist index of electricity producers in Spain from 1984-1997. Five outputs and three inputs were used in the analysis. The five outputs included annual net power produced (MWh), availability, SO_2 (tons), NO_X (tons), and particulates (tons). The three inputs were capital (MW), labor, and fuel (therms).

Wang et al. (2007) determine the technical efficiency change, technological change, pure technical efficiency change, scale efficiency change, and total factor productivity change for two power utilities in Hong Kong. Customer density and sales of electricity (kWh) were used as the output variables. Capital ($) and labor were used for the input variables.

Fallahi, Ebrahimi, and Ghaderi (2011) use the Malmquist index to find the technical efficiency change, the technological change, changes in the scale efficiency and the change in TFP of 32 power electric generation management companies in Iran from 2005-2009. The one output considered was net electricity produced (MWh) and the five inputs considered were labor – number of employees by company, capital – install capacity (MW), fuel (10^6 calories), electricity (MWh), and average operational time (h).

4.2.1 Policy Analysis Studies

Several studies have used the Malmquist index to determine how regulatory reform in the electricity generation industry affects the efficiency of electric generation plants over time.

Yaisawarng and Klein (1994) considered how sulfur dioxide controls affect the efficiency of power plants in the U.S. They used the Malmquist index to determine the change in productivity efficiency, scale efficiency, and technology of 60 coal-fired plants from 1985-1989. They found that productivity decreased during the first years of the study but grew between 1985 and 1989.

Abbott (2006) determines how reform in the electricity supply industry affected the productivity and efficiency in Australia. Using 30 years of data, one output and three inputs were considered. The one output was the electricity consumed in each jurisdiction, while the inputs were capital stock, energy used (TJ), and labor employed. From the Malmquist index the technical efficiency, pure efficiency, scale efficiency, and total factor productivity changes were determined. Based on the Malmquist index scores they found that the reform in the electricity supply industry lead to substantial improvements in the industry.

In order to capture the effects of regulatory reform in Japan, Nakano, and Managi (2008) used a generalized form of the Malmquist productivity index to determine the efficiency of steam power-generation facilities. One output and three inputs were used in the analysis. The one output was the production of electricity (kWh) and the three inputs were the quantity of fuel used (MJ), number of employees, and the real capital stock (yen). The quantity of fuel used was an aggregation of various types of fuel. They found that the regulatory reform had a positive impact on productivity growth of the steam power-generation industry in Japan.

4.2.2 Two-Stage Studies

A couple studies have tried to determine what led to productivity growth and declines by using a two-stage analysis. Lam and Shiu (2004) determined the technical change and technical efficiency of thermal plants in 30 provinces in China. One output and three inputs were included in the analysis. The one output was the electric power generated by the thermal power plant

(GWh). The three inputs were capital – installed capacity (MW), fuel consumption (kg), and labor. Since the fuel used in different regions varies, the fuel consumption was in terms of standard coal equivalent. In the second-stage analysis, the estimated technical efficiency scores were used as the dependent variable in a tobit regression, instead of the change in technical efficiency scores. The independent variables in the second stage analysis were capacity utilization rate, fuel efficiency, and a dummy variable signifying if the power plant is under the control of the State Power Corporation. Utilization was found to have a positive impact on the technical efficiency score while fuel and State Power Corporation were found to have a negative impact.

Barros (2008) used a two-stage analysis to determine what drives the technically efficient change and technological change of hydroelectric plants in Portugal. He found that the number of years the plant had been operational had a negative and statistically significant effect on the Malmquist score (TFP) using a tobit model.

Only a few of these studies have tried to determine if a policy has affected the productivity growth of electric generation plants (Yaisawarng and Klein 1994, Abbott 2006, Nakano and Managi 2008) and only one study has used a second stage analysis to try to determine what effects productivity growth in electric generation plants (C. P. Barros 2008). This study incorporates the two concepts by using a second-stage analysis to determine if renewable energy policies effect the change in technical efficiency, technological change, and change in TFP. In addition, this study disaggregates the fuel variables to determine if the type of fuel an electric generation plant uses consistently leads to increases or declines in technical efficiency, technology, and productivity.

4.3 Methods

It can take years of planning and construction to build a new electric generation plant and once the plant is built making drastic changes to the operation of the plant can take a significant amount of time and money. So when policies are passed that affect electric generation plants, the changes take place over time. Often the policies give electric generation plants several years to become compliant and/or incorporate a tiered system to help the electric generation plants achieve the final goal of policy. This implies power plants effected by these policies will need to incorporate the requirements of the policy in their long run production decisions. To determine if these renewable energy policies affect the productivity growth of electric generation plants a two-stage approach should be taken. The first stage uses the Malmquist index which shows how the overall productivity of an electric generation plant changes from one period to the next, to account for the nature of electric generation plant decision making. The second stage uses a tobit model to determine how the renewable energy policies and fuel choice affect the productivity of electric generation plants.

The Malmquist index was first introduced by Caves, Christensen, and Diewert (1982) building on the idea of Malmquist by constructing input quantity indices as ratios of the distance function. Färe et al. (1990) develop an input-oriented Malmquist index that does not rely on input or output prices. The Malmquist index relies on Data Envelopment Analysis (DEA) which is a nonparametric linear-programming approach used to determine the best practice of firms in an industry to develop the distance function. The nonparametric aspect of the model ensures that no functional form needs to be established for the production function. By using the ratios of the distance function, shifts in the production function can be determined.

The total factor productivity (TFP) which represents a growth in productivity over time is calculated directly from the Malmquist productivity index:

4.1 $$M_k^{t+1}(y^{t+1}, x^{t+1}, y^t, x^t) = \left[\frac{D_k^t(y^{t+1}, x^{t+1})}{D_k^t(y^t, x^t)} \frac{D_k^{t+1}(y^{t+1}, x^{t+1})}{D_k^{t+1}(y^t, x^t)}\right]^{\frac{1}{2}}$$

where M_k^{t+1} is the Malmquist index in period $t+1$ for firm k; y^{t+1} is the outputs in period $t+1$; x^{t+1} is the inputs in period $t+1$; y^t is the outputs in period t; x^t is the inputs in period t; and $D_k^t(y^t, x^t)$, $D_k^t(y^{t+1}, x^{t+1})$, $D_k^{t+1}(y^t, x^t)$, and $D_k^{t+1}(y^{t+1}, x^{t+1})$ are the distance functions. The distance functions are the inverse of the overall technical efficiency DEA that was first introduced by Charnes, Cooper, and Rhodes (1978). The overall technical efficiency (CCR) is used since it assumes constant returns to scale. The modified overall technical efficiencies for the Malmquist index are:

4.2 $$[D^t(y_k^t, x_{mk}^t)]^{-1} = \min_{\theta_i, z_i} \theta_i$$

Subject to:

$$\sum_{k=1}^{K} z_k^t x_{mk}^t \leq \theta_i x_{mi}^t \quad \text{for } m = 1, \dots, M$$

$$\sum_{k=1}^{K} y_k^t z_k^t \geq y_i^t$$

$$(z_1^t, \dots, z_K^t) \geq 0$$

4.3 $$[D^t(y_k^{t+1}, x_{mk}^{t+1})]^{-1} = \min_{\theta_i, z_i} \theta_i$$

Subject to:

$$\sum_{k=1}^{K} z_k^t x_{mk}^t \leq \theta_i x_{mi}^{t+1} \quad \text{for } m = 1, \dots, M$$

$$\sum_{k=1}^{K} y_k^t z_k^t \geq y_i^{t+1}$$

$$(z_1^t, \dots, z_K^t) \geq 0$$

4.4 $$[D^{t+1}(y_k^t, x_{mk}^t)]^{-1} = \min_{\theta_i, z_i} \theta_i$$

Subject to:

$$\sum_{k=1}^{K} z_k^{t+1} x_{mk}^{t+1} \leq \theta_i x_{mi}^t \quad \text{for } m = 1, \dots, M$$

$$\sum_{k=1}^{K} y_k^{t+1} z_k^{t+1} \geq y_i^t$$

$$(z_1^{t+1}, \dots, z_K^{t+1}) \geq 0$$

4.5 $$[D^{t+1}(y_k^{t+1}, x_{mk}^{t+1})]^{-1} = \min_{\theta_i, z_i} \theta_i$$

Subject to:

$$\sum_{k=1}^{K} z_k^{t+1} x_{mk}^{t+1} \leq \theta_i x_{mi}^{t+1} \quad \text{for } m = 1, \dots, M$$

$$\sum_{k=1}^{K} y_k^{t+1} z_k^{t+1} \geq y_i^{t+1}$$

$$(z_1^{t+1}, \dots, z_K^{t+1}) \geq 0$$

where z is an intensity (or weight) of each electric generation plant k, x_{mk} are the inputs, y_k is the output of each electric generation plant k. θ_i is the measure of overall technical efficiency (CCR). If θ_i is equal to one then the power plant is efficient.

Knowing if an electric generation plant is experiencing productivity growth or a decline in productivity is not likely enough information to help the management decide how to move forward. Fortunately, the Malmquist index can be broken into two components – change in technical efficiency and technological change. Technical change is a measure of the change in technical efficiency score from one period to another. This change captures changes in management, investment, and technical experience of electric generation plants that are operating inside the best-practice frontier (implying they are not on the frontier of the production function). Technological change occurs through innovation (adoption of new technology) by the best-practice firms (the firms on the frontier of the production function). The change in technical efficiency and technological change are calculated by decomposing the change in TFP:

4.6 $$M_k^{t+1}(y^{t+1}, x^{t+1}, y^t, x^t) = \frac{D_k^{t+1}(y^{t+1}, x^{t+1})}{D_k^t(y^t, x^t)} \left[\frac{D_k^t(y^{t+1}, x^{t+1})}{D_k^{t+1}(y^{t+1}, x^{t+1})} \frac{D_k^t(y^t, x^t)}{D_k^{t+1}(y^t, x^t)} \right]^{\frac{1}{2}}$$

$$= E_k^{t+1} T^{t+1}$$

where E_k^{t+1} represents the term outside the bracket and is the change in technical efficiency between periods t and $t+1$; T^{t+1} represents the term inside the brackets which is the technological change, or the shift in technology between periods.

The change in TFP will be less than ‘1’ (TFP < 1) if productivity growth has taken place between periods t and $t+1$, greater than ‘1’ (TFP > 1) if there has been a decline in productivity between periods t and $t+1$, and equals ‘1’ (TFP = 1) if there is no change in productivity between t and $t+1$ (Fare, Grosskopf and Yaisawarng, et al. 1990). Productivity growth will cause the best-practice frontier to shift out while a decline in productivity will cause the best-practice frontier to shift in. Similarly, an electric generation plant whose technical efficiency is less than ‘1’ (TE < 1) experiences increases in technical efficiency, while an electric generation plant whose technical efficiency is greater than ‘1’ (TE > 1) experiences a decline in technical efficiency. If the technical efficiency of the plant equals one (TE = 1), the plant experiences no change in technical efficiency. An increase in technical efficiency implies that the firm is improving their overall technical efficiency from one period to the next but does not imply the firm is technically efficient. An electric generation plant with a very low technical efficiency may experience an increase in technical efficiency from one period to the next and still have a very low technical efficiency score. If the change in technical efficiency is equal to one, this does not imply they are technically efficient, it implies that their technical efficiency did not change from one period to the next. Technological progress occurs when technological change is less than ‘1’ (TC < 1), technological regress occurs when technological change is greater than ‘1’ (TC > 1), and no change in technology occurs when technological change equals ‘1’ (TC = 1). An improvement in technology (TC < 1) occurs when electric generation plants on the frontier improve their technology between periods t and t+1. This implies that the technology they used in period t+1 was not feasible in period t. The opposite is true when there is a regress in technology. A regress (or decline) in technology implies that the technology used in period t is no longer feasible in period t+1. This could occur in the electricity industry when new pollution standards are passed and firms are no longer able to use the same technology as before the standards were passed.

Once the change in TFP, technical efficiency, and technological change scores are determined, a second stage regression model is used to determine how policies designed to encourage the adoption of renewable energy affect the productivity growth of power plants. A censored tobit model is used rather than an OLS model since the dependent variable cannot be less than 0. Building on the censored tobit model from Greene (2007) the model used in the analysis is:

4.7 $$\delta_i^* = \alpha + \beta X_i + \gamma Z_s + \varepsilon_i \qquad \varepsilon_i \sim N[0, \sigma^2]$$

$$\delta_i = \delta_i^* \qquad \text{if } \delta_i^* > 0$$

$$\delta_i = 0 \qquad \text{if } \delta_i^* \leq 0$$

where $\delta_i = M_k^{t+1}, E_k^{t+1},$ and T^{t+1} are the observed changes in TFP, changes in technical efficiency, and technological change scores and δ_i^* is the latent variable for plant i; α is the intercept; X_i is made up of fuel inputs and other plant specific variables. Z_s is a vector of state specific policies for state s. The error term, ε_i, is distributed normally with mean 0 and variance σ^2.

4.4 Data

A two-stage analysis is used to determine if policies that encourage renewable energy deployment and if the type of fuel input affects the change in technical efficiency, technological change, and change in TFP. The first stage uses firm level input and output data to determine the change in technical efficiency, technological change, and change in TFP. The second stage uses the results from the first stage as the dependent variable of a tobit regression.

4.4.1 DEA Data

Plant level data is used to determine the change in technical efficiency, technological change, and change in TFP of electric generation plants from 2003 to 2012 in the U.S (EIA 2015). The inputs used in the analysis are fuel and capital. There are up to 31 different types of fuel included in the analysis (Table 4-2). The fuel sources are measured by total fuel consumption MMBTU (million British Thermal Units) annually. Capital is represented by net capacity in megawatts (MW) at a power plant. One output is included in the analysis – net generation in megawatt hours (MWh) (Table 4-2). 2,478 plants are considered in the analysis. The analysis is conducted using cross-sectional data for ten years. Two different sets of analyses are conducted. The first compares two consecutive years (i.e. 2003 to 2004). The second analyzes the change across multiple years in the study (i.e. 2003 – 2012).

When deciding the variables to include in the DEA, it is important to consider three factors: 1) availability of data; 2) the body of literature; and 3) professional opinion of relevant individuals. A key variable that is missing from this analysis is labor. However, due to a lack of availability of a labor variable for the entire data set, it was not included in the analysis. Despite not including labor in the analysis, the results may not be significantly affected. A study conducted by Fallahi, Ebrahimi, and Ghaderi (2011) found the most important inputs are the installed capacity and fuel that described 91% of the full model. In addition, Welch and Barnum (2009) did not include labor for a number of reasons. First their study, like this study, was not focused on labor decisions, instead it was focused on fuel choice decisions. Second, labor makes up a very small portion of the input resources. Lastly, fuel and labor are not substitutes for one another in the electric generation industry, instead they are compliments so only one complimentary variable needs to be included. According to the EIA for the duration of this study, expenditures related to labor make up approximately 10% or less of total expenditures for the utility (EIA 2015). It is important to make sure there are enough degrees of freedom to estimate the DEA model. In general, there are enough degrees of freedom if the number of DMUs is greater than or equal to three times the number of inputs plus the number of outputs (C. P. Barros 2008). Given that the number of observations for every year is 2,478, degrees of freedom is not an issue (2,478> 3(32+1)).

4.4.2 Econometric Data

For the econometric analysis, the estimated results obtained in the first stage analysis are used as the dependent variables. To determine if the type of fuel used affects the productivity growth, dummy variables are created for each category of the fuel inputs. Categories of fuel inputs are used instead of individual fuel inputs due to a lack of variation in some of the fuel inputs. The categories are coal, petroleum, natural gas and other gases, nuclear, solid renewable fuels, liquid renewable fuels, gaseous renewable fuels, other renewable sources, and other energy sources. This implies that if a power plant used natural gas during a given year then natural gas and other gases is equal to '1' and '0' otherwise. Two other plant specific variables are included in the analysis. The first additional plant specific variable is plant capital – installed capacity (in GW); and the second is the average age of the plant (in decades). The average age of the plant is used since some plants are made up of multiple units that began operating at different times. In this case, the average age of all the units is used as the average age of the plant.

To determine how renewable energy policies affect the overall productivity growth of power plants four renewable energies are included in the tobit model. Since there is a large variation in RPS policies across states, three different dummy variables are included in the analysis. The first dummy variable is equal to '1' if the policy was enacted in time t and '0' otherwise. The second variable is equal to '1' if there was a voluntary RPS in place in time t and '0' otherwise. The third variables is equal to '1' if there was a noncompliance penalty associated with the RPS in time t and '0' otherwise. The other three policies – net metering, public benefits funds, and mandatory green power option – are equal to '1' if the policy was in place in time t and '0' otherwise (DSIRE 2013).

Two different tobit models are used in the analysis. The first tobit model is used to determine what effects the change in technical efficiency, technological change, and change in TFP between consecutive year (i.e. 2003 to 2004):

4.8 $$\delta = \alpha + \beta_1 Coal + \beta_2 Petroleum + \beta_3 Natural\ Gas\ and\ Other\ Gases + \beta_4 Nuclear + \beta_5 Solid\ Renewable\ Fuel + \beta_6 Liquid\ Renewable\ Fuel + \beta_7 Gaseous\ Renewable\ Fuel + \beta_8 Other\ Renewabls\ Sources + \beta_9 Other\ Energy\ Sources + \gamma_1 RPS\ in\ Effect + \gamma_2 Voluntary\ RPS +$$

$$\gamma_3 NonCompliance\ Penalty + \ \gamma_4 Mandatory\ Green\ Power\ Option + \gamma_5 Public\ Benefits\ Fund + \gamma_6 Net\ Metering$$

The second tobit model builds on the first tobit and is used to determine what effects the change in technical efficiency, technological change, and change in TFP across multiple years in the study – 2003 to 2007, 2008 to 2012, and 2003 to 2012. The policy variables discussed above equal '1' if the policy was in place in 2003 or 2008. However since numerous states adopted policies between 2003 or 2008 and 2007 or 2012 another set of policy variables is added to account for policy adoption after 2003 or 2008. These policies equal '1' if there was a change in the policy between the first and last year of the analysis. For example, RPS came into effect in California in 2004. This implies that *RPS in Effect* equals '0' in 2003 and Change in *RPS in Effect* equals '1' when analyzing the data between 2003 and 2007 or between 2003 and 2012. The estimated model is:

4.9 $$\delta = \alpha + \beta_1 Coal + \ \beta_2 Petroleum + \beta_3 Natural\ Gas\ and\ Other\ Gases + \beta_4 Nuclear + \ \beta_5 Solid\ Renewable\ Fuel + \beta_6 Liquid\ Renewable\ Fuel + \beta_7 Gaseous\ Renewable\ Fuel + \ \beta_8 Other\ Renewabls\ Sources + \beta_9 Other\ Energy\ Sources + \gamma_1 RPS\ in\ Effect + \ \gamma_2 Voluntary\ RPS + \gamma_3 NonCompliance\ Penalty + \ \gamma_4 Mandatory\ Green\ Power\ Option + \gamma_5 Public\ Benefits\ Fund + \gamma_6 Net\ Metering + \ \gamma_7 Change\ in\ RPS\ in\ Effect + \gamma_8 Change\ in\ Voluntary\ RPS + \ \gamma_9 Change\ in\ NonCompliance\ Penalty + \gamma_{10} Change\ in\ Mandatory\ Green\ Power\ Option + \gamma_{11} Change\ in\ Public\ Benefits\ Fund + \gamma_{12} Change\ in\ Net\ Metering$$

Table 4-3 contains variable means and standard deviations for the variables included in the second stage analysis that are not included in the first stage.

4.4.2.a Hypothesis Concerning Econometric Analysis

Electric Generation Plant Characteristics

Two non-fuel plant characteristics are considered in the analysis – *Installed Capacity* and *Average Age of Plant*. A variation of both of these variables have been considered in previous studies. Lam and Shiu (2004) found capacity to have a positive and statistically significant effect on the efficiency scores. However, the dependent variable used in Lam and Shui's analysis was technical efficiency instead of the change in technical efficiency they found using the Malmquist index. Barros (2008) found that older power plants experience a decline in productivity using change in TFP as the dependent variable.

Fuel Source

There has been an increase in research and development on renewable energy sources over the last decade – namely wind and solar energy. This research and development has led to drastically improved wind and solar technology used by electric generation plants. It is likely that solar and wind will have a positive impact on the change in technical efficiency, technology, and TFP of these power plants. However, if new renewable energy sources are not used during the duration of the study, then renewable energy may have no effect. At the other end of the spectrum, coal is continuously penalized for emitting harmful pollutants resulting in a curtailment of production. This will likely result in a negative impact on the change in technical efficiency, technology, and TFP of electric generation plants that use coal. Nuclear and hydroelectric power plants are typically efficient power producers, however there has not been substantial advancements made in these types of plants over the last decade so this could result in a negative effect or no change in technical efficiency, technology, and TFP.

Policy

When states adopt a RPS policy, utilities within the state are given time to develop renewable energy to meet the requirements of the policy. In addition, many renewable energies are equally if not more efficient than traditional energy sources from a production standpoint. For these reasons, it is likely the RPS policies will have a positive impact on the efficiency scores. Public benefits funds provide funding for utilities to develop renewable energy. Since this is a process that takes place over time and encourages technological change, it is likely that public benefits fund will have a positive impact on the change in technical efficiency, technology, and TFP. Since electric generation plants cannot control for the amount of electricity they receive from net metering, and net metering is becoming more popular over time, it is likely that net metering will have a negative impact on the change in technical efficiency, technology, and TFP.

4.5 Results

The results of the Malmquist index and econometric analysis are reported in Table 4-4 - Table 4-10. The estimated change in technical efficiency, technological change, and change in TFP scores from the first stage analysis are used in the second stage regression analysis.

4.5.1 Malmquist Index Results

Mean change in technical efficiency, technological change, and TFP scores are reported in Table 4-4, Table 4-5, and Table 4-6, respectively. The mean scores are for electric generation plants that use a particular fuel input during a given year. The mean efficiency scores are reported for nine periods covering the change that takes place between consecutive years between 2003 and 2012. In addition, the mean efficiency scores are reported for the change in productivity between 2003 and 2007, 2008 and 2012, 2003 and 2012.

Changes in Technical Efficiency

Changes in technical efficiency are reported in Table 4-4. Across all fuel types there is not a clear trend in the change in technical efficiency. However, there is a decline in technical efficiency across all fuel inputs between 2010 and 2011. This is likely due to the fact that in 2011 there was a large transition in the electric generation sector from coal to natural gas and petroleum inputs due to the increase production of natural gas and oil in the United States. The decline in technical efficiency between 2010 and 2011 also likely led to a decline in technical efficiency for every fuel input between 2008 and 2012. With the exception of nuclear and geothermal (that experienced no change in technical efficiency) and waste/other oil and wind (that experienced an increase in technical efficiency) all inputs experienced a decline in technical efficiency between 2003 and 2007. Wind and waste/other oil were the only inputs to experience an increase in technical efficiency between 2003 and 2012. Despite the decrease in technical efficiency across most inputs between 2003 and 2012, sub-bituminous coal is the only input to experience a decline in technical efficiency during every period of the study. All other inputs experience periods of no change in technical efficiency or increases in technical efficiency.

Technological Change

Technological change scores are reported in Table 4-5. Across all fuel types there is not a clear trend in the technological change. Technological improvement is experienced, at the mean by all inputs, except waste/other oil, between 2010 and 2011. This is likely because many electric utilities switched from using coal, to using natural gas and petroleum. The change might have encouraged technological progress throughout the industry. This likely is the driving factor in all but two inputs (blast furnace gas and other gas) experiencing increases in technology between 2008 and 2012 as well as increases in technology between 2003 and 2012 for all fuel inputs except waste/other oil. There are no inputs that experience increase or decreases in technology across all years of the study. Geothermal and hydroelectric inputs experience increases in technology in all but one period of the study (2009 – 2010).

Changes in Total Factor Productivity

Changes in TFP scores are reported in Table 4-6. Across all fuel types there is not a clear trend in the change in TFP. However, bituminous coal experience a decline in productivity during every period of the study. While wind experiences productivity growth during every period of the study. All other renewable sources experience TFP growth between 2003 and 2007. Only four inputs experience productivity growth between 2003 and 2012 – sub-bituminous coal, other biomass gas, hydroelectric, and wind.

The mean percent change of the change in technical efficiency, technological change, and change in total factor productivity are reported in Figure 4-1 - Figure 4-9, by fuel category. The percent change is the negative of the natural log of the efficiency scores. These figures are helpful in showing if the change in TFP is driven by a change in technical efficiency or a technological change. If the percent change is positive this implies growth or improvement has occurred, if the percent change is negative this implies that a decline or regress has occurred for technical efficiency, technology, and TFP.

The mean scores for coal are reported in Figure 4-1. The percent change in the technical efficiency, technology, and TFP are small and similar to one another for the first five periods. Beginning with 2007/2008 technological change and change in technical efficiency begin to experience opposing changes. As the percent change in technology decreases, the percent change in technical efficiency increases. The change in TFP follows the technological change. This implies that in the years that the change in TFP follows the technological change, the management of the electric generation plant should focus on improving its technology more than its technical efficiency to achieve productivity growth.

The mean percent change of the efficiency scores for petroleum are in Figure 4-2. The mean percent change in technology and technical efficiency move opposite each other in every year of the study. The opposing changes of these two efficiency scores cause the change in TFP to be very small for most periods. The one exception is between 2010 and 2011 the mean change in TFP follows the increase in technological change. Similar results can be seen for natural gas and other gases (Figure 4-3). Nuclear power plants experience very little change in technical efficiency, technological change, or change in TFP (Figure 4-4). This is not surprising since nuclear power plants are already technically efficient (Lynes and Featherstone 2015) and no new nuclear power plants have come online during the duration of the study. The mean percent changes in solid renewable fuels (Figure 4-5) and gaseous renewable fuels (Figure 4-7) show similar results as petroleum and natural gas and other gases. However, the percent change for all the efficiency scores are smaller in magnitude for the renewable fuels. Liquid renewable fuels is the only fuel input that the mean percent change in TFP follows the percent change in technical efficiency or remains flat (Figure 4-6). The mean rate of change of other renewable fuels is very small in all periods (Figure 4-8) for the change in technical efficiency, technological change, and change in TFP. This small change is also not surprising since the other renewable fuel category is very efficient to begin with. The change in TFP follows the change in technical efficiency for the mean percent change in other energy sources (Figure 4-9).

In general, technological change is the driver of changes in TFP. This implies that electric generation plants that want to experience productivity growth should focus more on improving technology thereby shifting the frontier instead of focusing on their technical efficiency. It is likely that the decrease in technical efficiency and increase in technological change for almost all categories of inputs between 2010 and 2011, was due to the reduction of coal inputs to other fuel inputs. This could imply that if a major shift in fuel usage happens over the course of one year in the future, technical efficiency regress and technological progress is likely to occur during that year.

4.5.2 Econometric Results

The tobit regression results for consecutive year changes in technical efficiency, technological change, and change in TFP are reported in Table 4-7, Table 4-8, and Table 4-9, respectively. The change in technical efficiency, technological change, and change in TFP from 2003 to 2007, 2008 to 2012, and 2003 to 2012 are reported in Table 4-10. Recall that a tobit model is used instead of an OLS model because the scores cannot be less than zero. However, none of the results are censored so an OLS model could have been used instead. To keep with convention, tobit model results are reported.

Change in Technical Efficiency

The tobit model regression results for consecutive year changes in technical efficiency are reported in Table 4-7. Overall, the renewable energy policies do not have a large sustaining effect on the change in technical efficiencies of U.S. electric generation plants, during the timespan of the study. *RPS in Effect* is negative and statistically significant between 2005 and 2006 which implies that electric generation plants in states with a RPS policy imposed experienced an improvement in technical efficiency during those time periods. However, between 2006 and 2007 the effect is positive and statistically significant. This implies that electric generation plants in states that had an RPS policy imposed experienced a decline in technical efficiency between 2006 and 2007. *Voluntary RPS* is negative and statistically significant between 2008 and 2009. This implies that electric generation plants in states with a voluntary RPS policy experienced an improvement in technical efficiency between 2008 and 2009. Electric generation plants in states with a *Non-compliance Penalty* experience a decline in their technical efficiency between 2005 and 2006, 2009 and 2010 and again between 2011 and 2012 and an improvement in their technical efficiency between 2006 and 2007 and again between 2010 and 2011. *Mandatory Green Power Option* is negative and statistically significant between 2004 and 2005 and again between 2011 and 2012 then is positive and statistically significant between 2006 and 2007. This implies that electric generation plants in states with a mandatory green power option policy experience an improvement in their technical efficiency between 2004 and 2005 followed by a decline in their technical efficiency between 2006 and 2007. *Public Benefits Fund* is negative and statistically significant between 2010 and 2011 and again between 2011 and 2012. This implies that states that had a public benefits fund in place during these periods experienced improvements in technical efficiency. *Net Metering* is negative and statistically significant between 2006 and 2007 and again between 2009 and 2010 implying that electric generation plants in states with a net metering policy between 2006 and 2007 experienced an improvement in their technical efficiency during this time. However, net metering was positive and statistically significant between 2008 and 2009, 2010 and 2011, and again between 2011 and 2012.

Due to the lack of statistical significance and variation in direction of significance, the policy results imply that having renewable energy policies did not cause electric generation plants to experience increases or declines in technical efficiency over time. This could be because the obligation of compliance falls to the utility rather than the individual electric generation plant, so the management of each electric generation plant may not have to make large (or any) changes from year to year to be in compliance with the policy. Instead other factors are leading to changes in technical efficiency scores of the electric generation plants.

The category of fuel used at the plant has a larger effect on the change in technical efficiency than the policies in terms of significance and magnitude of the effect. *Natural Gas and Other Gases* is statistically significant in eight of the nine periods, however whether the statistical significance is positive or negative varies by period. *Coal, Gaseous Renewable Fuels,* and *Other Renewable Sources* are statistically significant in six periods. Like with *Natural Gas and Other Gases,* whether statistical significance is positive or negative varies by period. *Coal* is positive and statistically significant in three periods and negative and statistically significant in three periods. *Gaseous Renewable Fuels* and *Other Renewable Sources* are negative and statistically significant in four periods. That implies that electric generation plants that used a gaseous renewable fuel and/or an other renewable source input during these periods experienced improvements in technical efficiency.

Overall, these results imply that fuel usage effects the change in technical efficiency, however whether the change is an increase or decrease in technical efficiency varies by period and fuel. This could be caused by the fact that electric generation plants are likely faced with different events every year that have not been taken into account by the model. These events could be changes in prices of inputs, weather events, or other policies that make the plant managers react and decrease an electric generation plants technical efficiency, even if improvements had been made.

The other plant characteristics – *Installed Capacity* and *Average Age of Plant* – did not have a consistent positive or negative statistically significant effect on the technical efficiency of the electric generation plant. Lam and Shiu (2004) found capacity utilization to have a positive and statistically significant effect on the technical efficiency score in their study. The results of this study do not contradict their findings since the dependent variable in their study is technical efficiency, not the change in technical efficiency which is dependent variable in this study.

Technological Change

The tobit model regression results for consecutive year technological change are reported in Table 4-8. The effects the renewable energy policies have on the technological change are not consistent across periods. *RPS in Effect* has a positive and statistically significant effect in four periods and a negative and statistically significant effect in two periods. This implies that during four periods electric generation plants in states that have a RPS policy imposed experienced technological regress while in two periods they experienced technological progress. *Voluntary RPS* has a negative and statistically significant effect between 2007 and 2008. This implies that electric generation plants in states with a voluntary RPS policy experienced improvements in technology between 2007 and 2008. *Non-compliance Penalty* is statistically significant in six of the nine periods – three years it has a positive effect and three years it has a negative effect. The positive effect implies that electric generation plants in states with a non-compliance RPS penalty experienced a regress in technology in those periods whereas the negative effect implies that electric generation plants in states with a non-compliance RPS penalty experienced an improvement in technology. *Mandatory Green Power Option* is positive and statistically significant in three periods. This implies that during these three periods electric generation plants in states with a mandatory green power option policy experienced a regress in technology. However in one period electric generation plants in states that have a mandatory green power option experienced an improvement in technology since the coefficient estimate is negative and statistically significant. *Public Benefits Fund* is positive and statistically significant in three periods. This implies that during these three periods electric generation plants in states with a public benefits fund policy experienced a regress in technology. *Net Metering* has a negative and statistically significant effect in three periods and a positive and statistically significant effect in one period. This implies that in three periods electric generation plants in states with a net metering policy experience technological improvements while in one period electric generation plants in states with a net metering policy experience regress in technology. Despite that renewable energy policies are statistically significant in multiple periods, there is no consistency in the sign of the effect. This implies that these renewable energy policies do not have an overall effect on the technological change of electric generation plants in the U.S.

Plant characteristics have more of an impact on the technological change than the change in technical efficiency in terms of statistical significance. *Installed Capacity* is negative and statistically significant in five periods and positive and statistically significant in two periods. This implies that larger electric generation plants experienced an improvement in technology during five periods and a regress in technology in two periods. *Average Age of Plant* is positive and statistically significant in three periods and negative and statistically significant in two periods. This implies that older plants experienced regress in technology during three periods and improvements in technology in two. The magnitude of these effects are relatively small for all periods.

Natural Gas and Other Gases is statistically significant in every period of the study, however whether the statistical significance is positive or negative varies by period. In six periods natural gas is negative and statistically significant implying that electric generation plants that used natural gas during those periods experienced improvements in technology. Several fuel inputs have a statistically significant effect during eight periods – *Coal, Petroleum, Gaseous*

Renewable Fuels, and *Other Renewable Sources*. However, there is no consistency on whether the effect is positive or negative across all periods. All fuel inputs experience technological improvement and technological regress in approximately half the periods.

Change in Total Factor Productivity

The tobit model regression results for consecutive year changes in TFP are reported in Table 4-9. The renewable energy policies have little effect on the change in TFP. *RPS in Effect* is positive and statistically significant between 2006 and 2007. This implies that between 2006 and 2007 electric generation plants in states that had a RPS policy in effect experience a decline in productivity. However, between 2010 and 2011 there is a negative and statistically significant effect implying electric generation plants in states with a RPS policy in effect experienced a productivity growth during this period. *Voluntary RPS* is negative and statistically significant between 2007 and 2008. This implies that electric generation plants in states that have a voluntary RPS policy in place experienced production growth during this period. *Mandatory Green Power Option* is negative and statistically significant between 2004 and 2005 and between 2011 and 2012 implying that electric generation plants in states that have a mandatory green power option experience productivity growth during these periods. However, *Mandatory Green Power Option* is positive and statistically significant between 2006 and 2007. This implies that states that had a mandatory green power option during this period experienced a decline in productivity. *Public Benefits Fund* is negative and statistically significant between 2003 and 2004. This implies that states that had a public benefits fund in place between 2003 and 2004 experienced productivity growth. *Net Metering* is positive and statistically significant between 2011 and 2012 implying that electric generation plants in states that have a net metering policy experienced a decline in productivity during this period. Due to the lack of statistical significance and variation in direction of significance, renewable energy policies are not the cause of productivity growth or decline on a yearly basis during the period of study. This could be due to the fact that utility companies rather than individual electric generation plants are required to comply with the policies. In order to be in compliance with a given policy a utility company could spread the burden across multiple electric generation plants so no one plant is largely affected or the utility company could build a new plant altogether.

There is little consistency of significance in the effect the power plant characteristics – *Installed Capacity* and *Average Age of Plant* have on the change in TFP. *Installed Capacity* is negative and statistically significant in four periods. This implies that larger electric generation plants experience more productivity growth than smaller electric generation plants during these periods. *Average Age of Plants* is positive and statistically significant between 2007 and 2008 and again between 2010 and 2011. This implies that older electric generation plants experienced a larger decline in productivity than newer electric generation plants. However the magnitude of the effects on *Average Age of Plant* is small.

The fuel source has little impact on productivity growth. *Other Renewable Sources* and *Coal* have a statistically significant effect on the change in TFP in four periods (the highest number of periods for all fuel sources). *Coal* is positive and statistically significant in four periods implying that plants that used coal experienced a decline in productivity during these periods. *Other Renewable Sources* is negative and significant in four periods implying that during these periods, electric generation plants that rely on one of these fuel sources experience productivity growth. *Natural Gas and Other Gases* is positive and statistically significant in one period and negative and statistically significant in two periods. *Gaseous Renewable Fuel* is negative and statistically significant in two periods. A number of inputs are only statistically significant in one period – *Petroleum, Solid Renewable Fuels, Liquid Renewable Fuels,* and *Other Energy Sources*. *Nuclear* is never statistically significant.

Multiple Year Results

The tobit model regression results between 2003 and 2007, 2008 and 2012, and between 2003 and 2012 for the change in technical efficiency, technological change, and change in TFP are reported in Table 4-10. Since these analyses compare the productivity changes to electric generation plants over 5 or 10 years, change in policy variables are added to the model. One variable for each policy is added and is equal to '1' if the policy was not in effect in 2003 or 2008 but was in effect by 2007 or 2012, depending on the model. Similar to the consecutive year change models above, the renewable energy policies have little consistent effect on the changes in productivity. *RPS in Effect* is statistically significant between 2008 and 2012 leading to a decrease in technical efficiency; between 2003 and 2007 leading to a decline in technology; and between 2003 and 2012 leading to an improvement in technology and productivity growth. *Voluntary RPS* is positive and statistically significant between 2008 and 2012 leading to a decrease in technical efficiency. *Mandatory Green Power Option* is statistically significant between 2003 and 2007 leading to an increase in technical efficiency and a decline in technology. *Public Benefits Fund* is statistically significant between 2008 and 2012 and between 2003 and 2012 leading to an increase in technical efficiency. *Public Benefits Fund* is also statistically significant during every period when considering technological change, leading to a decrease in technology. However, *Public Benefits Fund* is negative and statistically significant between 2008 and 2012 when considering TFP leading to productivity growth. *Net Metering* is only statistically significant between 2003 and 2007 leading to an improvement in technology.

The change in policy variables give similar results. Between 2003 and 2007 *Change in RPS*, *Change in Voluntary RPS*, and *Change in Non-compliance Penalty* are all negative and statistically significant. This implies that states that did not have an RPS policy in 2003 but did in 2007 experience an increase in technical efficiency. However, none of these results hold for the entire time period of the study, 2003 to 2012. The only variable that is statistically significant when considering technical efficiency for the entire time period of the study is *Change in Public Benefits Fund*. Due to the magnitude of the variable, electric generation plants in states that did not have a public benefits fund policy in 2003 but did in 2012 experienced large gains in technical efficiency. *Change in RPS in Effect* had a negative and statistically significant effect on technological change between 2008 and 2012 which likely influenced the results between 2003 and 2012. This implies that electric generation plants in states that did not have a RPS policy in effect in 2003 but did in 2012 experience an increase in technology between 2003 and 2012. *Change in Non-compliance Penalty* is positive and statistically significant in every period when considering the in technology. This implies that these electric generation plants experienced a decrease in technology during the time period of the study. There are no change variables that are statistically significant between 2003 and 2012 when TFP is considered. This implies that over the time period of the study, the growth of electric generation plants were not affected by the adoption of new renewable energy policies.

Installed Capacity is positive and statistically significant in the technical efficiency model between 2003 and 2007 and is negative and statistically significant between 2008 and 2012 and between 2003 and 2012 for the technical efficiency model and the TFP model, as well as between 2003 and 2007 for the technological change model. The negative and statistically significant results imply that larger electric generation plants experienced more improvement/growth during the time span of the study than small electric generation plants. This may have happened due to economies of scale allowing larger electric generation plants to make improvements more easily than smaller electric generation plants. *Average Age of Plant* is positive and statistically significant between 2003 and 2012 when technical efficiency is considered and between 2003 and 2007 when technological change is considered. However it is negative and statistically significant between 2008 and 2012 when technological change is considered. It is insignificant in all periods when TFP is considered. This implies that the age of the plant does not have a statistically significant effect on productivity growth.

Every fuel has a statistically significant effect on the change in technical efficiency between 2003 and 2007, however only two fuel inputs – *Coal* and *Solid Renewable Fuels* are statistically significant between 2003 and 2007. This implies that the momentum (positive or negative) experienced in the early years of the study for technical change did not last through the entire time span of the study. This is not surprising since when considering the change across one year, there was not a clear trend in increasing or decreasing technical efficiency across all periods. The opposite is true for change in technology. Every fuel input results in a positive or negative effect on change in technology between 2003 and 2012. This change is driven by the change in technology that occurred between 2008 and 2012. There were no statistically significant results between 2008 and 2012 for the change in TFP. However *Natural Gas and Other Gases, Solid Renewable Fuels, Liquid Renewable Fuels, Gaseous Renewable Fuels,* and *Other Renewable Fuels* were all statistically significant between 2003 and 2012 in the TFP model. All but *Liquid Renewable Fuels* experienced productivity growth between 2003 and 2012. Since a majority of firms use *Natural Gas and Other Gases* or *Other Renewable Sources* this implies that a majority of firms experienced productivity growth during the time period of the study.

4.6 Discussion and Conclusions

Over the last decade renewable energy has contributed to a larger percentage of electricity production than in years past. This is not likely to change as renewable energy policies continue to be adopted by states. Once these policies are adopted, electric power plants are given a specified period of time (up to several years) to be in compliance with the policy. This is necessary since it can take a significant amount of time and money to reconfigure an existing electric generation plant or to build a new electric generation plant to be in compliance. Some of these renewable energy policies encourage the adoption of intermittent renewable energy. When these energy inputs are used to produce electricity, non-intermittent energy sources must be available to meet demand when the intermittent sources are not available. As more intermittent renewable energy sources are adopted, this could lead to a decline in productivity of non-intermittent energy sources.

This study aimed to determine if renewable energy policies have an effect on the change in technical efficiency, technological change, and change in total factor productivity of U.S. electric generation plants in the U.S. between 2003 and 2012. In addition, this study determined if the type of fuel used effects the overall productivity growth of electric generation plants. The Malmquist index was used to determine the change in technical efficiency, technological change, and change in TFP. A second-stage analysis was then conducted to determine if renewable energy policies affect productivity growth and if the type of fuel used affects overall productivity growth.

For a majority of the fuel types, there was no clear trend in technological change or change in TFP across years when considering change in consecutive years. There were also no clear trends across all inputs during a given year. There was one trend evident in the change in technical efficiency analysis – between 2010 and 2011 all inputs, at the mean, experienced a decline in technical efficiency. However, this trend is not carried over to changes in TFP. The study found that renewable energy inputs – wind, geothermal, and hydroelectric – and nuclear power experienced the least variability in technical efficiency change, technological change, or change in TFP. This is likely because these inputs are typically the most technically efficient inputs to begin with. The study also found that bituminous coal and sub-bituminous coal experience decreases in technical efficiency and TFP in almost every period of the study. This is not entirely surprising since coal is very heavily regulated and electric generation plant managers may not feel they can make large improvements in productivity by focusing on improving the technology used to be in compliance with the policy instead of technical efficiency. There was no clear trend in the change in technical efficiency and technological change in natural gas which is often used when intermittent fuel production is unavailable. This implies that using intermittent fuel inputs is not having a noticeable impact on non-intermittent fuel inputs from a production efficiency standpoint. This may be the case because regardless of if intermittent fuel is used the non-intermittent fuels will be used to meet changes in demand throughout the day.

The regression results were as variable as the first stage analysis, which is not surprising. Renewable energy policies did not have much effect on the change in technical efficiency, technological change, and change in TFP regression results. While most of the renewable energy policies were statistically significant during at least one period, whether they had a positive or negative impact depended on the period of study. This implies that the policies do not overwhelmingly lead to productivity growth or decline. As more policies are adopted and the requirements for compliance increase utilities will have to continue adjusting. However, the adjustments are likely coming at the utility level rather than the plant level, because it is the utility, rather than an electric generation plant in the utility that has to be in compliance. At the utility level trends in changes in productivity in relation to renewable energy policies may be evident or become evident in coming years.

Similar to the renewable energy policies, there were not clear trends between the fuel inputs used and the change in technical efficiency, technological change, or change in TFP. Again, this is not surprising since there were no trends evident in the first stage of the analysis. However, a majority of electric generation plants experienced productivity growth from 2003 – 2012 including intermittent and non-intermittent fuel inputs. Therefore, productivity growth that is taking place in the industry likely comes from the development of new electric generation plants.

The fact that there are limited trends in the analysis gives a few insights. First, since renewable energy policies do not have a clear effect on productivity growth this implies that electric generation plants are not taking these policies directly into account when making input and usage decisions. Further analysis needs to be conducted to see if and how these policies effect the utilities. Second, neither intermittent nor non-intermittent energy sources experience a clear trend in the change in technical efficiency, productivity change, or change in TFP over time. This implies that the non-intermittent energy sources that are used when the intermittent sources are unavailable, are not clearly effected by this from a production standpoint. Third, since the mean change in TFP scores implied that a majority of electric generation plants experienced productivity growth between 2003 and 2012 it is likely that electric generation plants will find a way to improve their production even in light of renewable energy policies that might dictate some of their production practices.

Table 4-1– Literature Review for Change in Productivity Studies of Electric Generation Plants

Study	Model	Output	Inputs
Färe et al. (1990)	- Technical efficiency - Technological efficiency	- Net generation (kWh)	- Labor - Fuel (BTUs) - Capital (MW)
Yunos and Hawdon, (1997)	- Malmquist Index - Change in productivity - Technological change	- Electricity generated (GWh)	- Installed capital (MW) - Labor - Electricity loses - Thermal efficiency
Goto and Tsutsui (1998)	- Intertemporal efficiency index - Technical Efficiency	- Quantity sold to residential customers (GWh) - Quantity sold to non-residential customers (GWh)	- Nameplate generation capacity (MW) - Quantity of fuel (Kcal), - Number of employees - Quantity of power purchased (GWh)
Arocena and Waddams Price (2002)	- Graphyperbolic Malmquist Efficiency change - Technological change - Scale index	- Net power produced (MWh) - Availability - SO_2 (tons) - NO_x (tons) - Particulates (tons)	- Capital (MW) - Labor - Fuel (therms)
Wang, Ngan, Engriwan, and Lo, (2007)	- Malmquist Index - Technical efficiency change - Pure technology efficiency change - Scale efficiency change - Total factor productivity change	- Sales of electricity (kWh) - Customer density	- Capital ($) - Labor
Fallahi, Abrahimi, and Shaderi (2011)	- Malmquist Index - Technical efficiency change - Technological change	- Net electricity produced (MWh)	- Installed capacity (MW) - Fuel (calories) - Labor - Electricity used (MWh) - Average operational time (h)

Table 4-1– Literature Review for Change in Productivity Studies of Electric Generation Plants

Study	Model	Output	Inputs
Policy Analysis Studies			
Yaisawarng and Klein (1994)	- Malmquist Index - Change in productivity efficiency - Changes in scale efficiency - Technological change	- Net generation (kWh) - SO2 (tons)	- Fuel (BTUs) - Labor - Capital ($) - Sulfur (%)
Abbott (2006)	- Malmquist Index - Efficiency change - Technical change - Pure efficiency change - Scale efficiency change - Total factor productivity change	- Electricity consumed	- Capital stock - Energy used (TJ) - Labor employed
Nakano and Managi (2008)	- Luenberger productivity indicator - Total factor productivity - Decrease in inefficiency - Shift of frontier outward	- Production of electricity (kWh)	- Quantity of fuel (MJ) - Number of employees - Real capital stock (yen)
Two-Stage Studies			
Lam and Shiu (2004)	- Malmquist Index - Technological change - Technical Efficiency change - Pure efficiency change - Scale efficiency change - Total factor productivity change	- Electric power (GWh)	- Capital (MW) - Fuel consumption (kg) - Labor
Barros (2008)	- Technical efficiency change - Technical change	- Energy production (MWh) - Capital utilization	- Labor - Capital (€) - Operational cost (€) - Investment (€)

Table 4-2 – Input and Output Summary Statistics of Electric Generation Plants from 2003 – 2012 for the Malmquist Index

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
					N = 2,498					
					Coal					
Bituminous Coal	3,258,188	3,186,352	3,251,308	3,267,064	3,261,593	3,267,015	2,709,553	2,934,135	2,008,953	1,762,623
	(16,828,475)	(16,601,688)	(16,927,222)	(17,098,852)	(17,230,142)	(17,181,759)	(15,026,284)	(16,089,981)	(13,287,007)	(12,440,661)
Sub-Bituminous Coal	2,104,566	2,254,542	2,260,617	2,276,368	2,300,009	2,408,974	2,368,272	2,388,164	357,615	288,348
	(13,559,419)	(14,003,969)	(14,020,883)	(13,911,422)	(13,999,689)	(14,284,524)	(14,167,062)	(14,254,327)	(5,417,722)	(5,266,797)
Lignite Coal	299,148	287,160	292,845	285,935	278,638	267,587	239,739	230,057	54,169	51,024
	(5,210,651)	(5,021,203)	(5,088,375)	(4,912,775)	(4,826,421)	(4,594,828)	(4,048,325)	(3,976,405)	(1,608,812)	(1,495,121)
Refined Coal	131,581	130,831	146,946	116,838	168,371	1,184	-	-	-	-
	(3,028,301)	(2,668,854)	(2,985,318)	(2,500,785)	(3,580,197)	(41,818)				
Waste/Other Coal	6,706	5,781	3,555	3,942	3,766	3,585	3,486	3,598	4	5
	(237,240)	(206,299)	(160,403)	(180,082)	(178,805)	(175,963)	(174,226)	(179,805)	(206)	(227)
					Petroleum					
Distillate Fuel Oil	29,735	22,919	23,107	16,490	18,808	15,934	15,065	17,008	1,822,913	1,598,600
	(152,976)	(115,570)	(105,211)	(63,621)	(73,809)	(62,677)	(57,069)	(79,000)	(12,897,429)	(12,130,952)
Jet Fuel	154	255	315	133	209	149	55	189	109	155
	(6,459)	(7,897)	(10,996)	(5,964)	(9,660)	(7,062)	(2,095)	(8,772)	(5,167)	(7,470)
Kerosene	284	245	436	236	166	149	89	159	89	81
	(8,067)	(5,307)	(10,534)	(6,006)	(5,462)	(4,275)	(2,544)	(4,816)	(2,480)	(1,985)
Petroleum Coke	7,814	5,148	10,333	7,732	7,686	5,610	7,879	8,851	30,394	14,919
	(149,810)	(111,184)	(238,976)	(156,361)	(158,877)	(135,264)	(177,101)	(199,658)	(905,963)	(543,116)
Residual Fuel Oil	99,482	95,529	105,257	49,573	53,866	32,774	30,090	24,182	59,742	51,135
	(1,263,084)	(1,294,324)	(1,282,132)	(746,520)	(792,545)	(532,521)	(458,437)	(395,588)	(794,965)	(720,737)
Waste/Other Oil	1,289	592	561	552	390	628	725	605	45,698	34,075
	(40,529)	(19,073)	(16,465)	(15,631)	(10,732)	(10,914)	(15,716)	(11,955)	(1,177,956)	(731,022)

Table 4-2 – Input and Output Summary Statistics of Electric Generation Plants from 2003 – 2012 for the Malmquist Index

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
					N = 2,498					
Natural Gas and Other Gases										
Natural Gas	365,701	365,097	380,319	379,426	406,165	349,658	340,218	378,648	674,402	641,328
	(1,839,560)	(1,780,584)	(1,695,834)	(1,692,902)	(1,772,999)	(1,669,729)	(1,670,100)	(1,769,445)	(4,751,177)	(4,341,872)
Blast Furnace Gas	10,281	19,975	23,657	19,761	18,807	18,899	14,407	17,979	21,287	22,478
	(268,398)	(480,238)	(585,560)	(505,755)	(477,567)	(476,505)	(376,376)	(434,237)	(523,588)	(541,113)
Other Gas	33,687	30,169	28,219	27,502	25,442	21,218	21,510	20,124	66,650	67,995
	(682,289)	(530,742)	(499,248)	(456,032)	(425,063)	(279,742)	(307,137)	(253,727)	(1,215,645)	(1,198,439)
Gaseous Propane	45	15	133	27	33	20	22	14	12,243	11,046
	(1,356)	(471)	(5,121)	(914)	(1,154)	(838)	(944)	(587)	(560,185)	(525,711)
Nuclear										
Nuclear	1,104,842	1,136,213	1,142,337	1,151,461	1,175,688	1,147,182	1,166,459	1,176,556	1,159,856	1,122,005
	(14,039,614)	(14,414,298)	(14,452,562)	(14,623,992)	(14,837,017)	(14,561,463)	(14,822,952)	(14,874,511)	(14,737,073)	(14,252,834)
Solid Renewable Fuel										
Agricultural Feedstock	3,915	3,968	3,420	3,232	3,876	4,104	4,731	3,850	2,955	3,555
	(139,970)	(145,840)	(122,151)	(115,261)	(140,746)	(139,119)	(172,130)	(151,155)	(107,782)	(137,430)
Municipal Solid Waste	-	-	-	10,919	10,784	10,768	10,797	10,631	6,090	5,985
				(210,022)	(207,858)	(211,431)	(213,871)	(209,806)	(173,668)	(170,748)
Other Biomass Solids	42	41	1,728	1,676	1,637	2,484	2,092	2,333	2,474	2,646
	(2,118)	(2,026)	(85,361)	(82,050)	(80,135)	(86,391)	(80,985)	(87,612)	(86,992)	(81,641)
Wood/Wood Waste Solids	98,293	110,863	115,633	122,829	121,499	111,422	111,495	113,938	120,812	110,071
	(615,737)	(677,470)	(689,647)	(754,551)	(739,491)	(696,857)	(702,016)	(714,555)	(1,093,944)	(1,018,129)
Liquid Renewable Fuels										
Other Biomass Liquids	27	66	41	73	48	35	28	27	157	5,924
	(1,334)	(2,317)	(1,470)	(2,655)	(2,063)	(1,226)	(1,419)	(1,288)	(7,195)	(289,614)

Table 4-2 – Input and Output Summary Statistics of Electric Generation Plants from 2003 – 2012 for the Malmquist Index

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
					N = 2,498					
Black Liquor	124,905	157,496	144,188	150,160	148,646	133,664	129,822	137,825	83,443	79,682
	(1,115,835)	(1,386,453)	(1,232,848)	(1,296,502)	(1,284,794)	(1,182,431)	(1,160,731)	(1,220,150)	(991,693)	(969,010)
Sludge Waste	2,985	2,290	2,489	1,783	1,939	1,115	964	1,025	30,301	30,244
	(84,178)	(45,081)	(50,845)	(30,800)	(33,485)	(21,552)	(17,743)	(18,207)	(886,251)	(864,771)
Wood Waste Liquids	827	942	-	-	-	-	-	-	-	-
	(37,094)	(47,102)								
Gaseous Renewable Fuels										
Landfill Gas	16,770	17,672	17,426	18,812	18,505	20,157	20,050	20,276	17,327	17,139
	(119,166)	(131,546)	(135,482)	(140,485)	(139,232)	(146,861)	(141,573)	(148,907)	(102,230)	(102,225)
Other Biomass Gas	1,323	1,453	1,577	1,554	1,589	1,536	1,455	1,456	4,937	5,512
	(32,023)	(36,568)	(36,210)	(36,343)	(38,164)	(37,063)	(34,806)	(30,596)	(192,981)	(225,931)
Other Renewable Energy Sources										
Geothermal	47,612	47,544	46,757	45,538	45,530	44,663	44,475	44,607	43,357	41,751
	(1,029,644)	(1,014,966)	(1,004,291)	(984,415)	(1,000,971)	(968,570)	(962,542)	(957,141)	(958,011)	(957,406)
Hydroelectric	478,074	433,725	449,289	457,225	373,323	387,662	431,798	416,840	466,662	381,315
	(2,626,257)	(2,521,118)	(2,577,109)	(2,743,765)	(2,643,026)	(2,490,655)	(2,354,806)	(2,195,638)	(2,887,638)	(2,751,194)
Solar	2,188	2,290	2,148	1,964	2,199	2,657	2,405	2,580	1,438	1,385
	(42,655)	(44,321)	(42,129)	(39,518)	(43,519)	(50,226)	(46,278)	(51,549)	(27,718)	(26,449)
Wind	39,891	50,267	49,331	51,360	51,219	52,528	47,228	48,898	49,814	47,772
	(288,528)	(356,900)	(337,072)	(352,734)	(350,140)	(361,549)	(315,851)	(329,357)	(339,606)	(331,182)
Other Energy Sources										
Other Energy Sources	104	48	43	23	23	1,574	5,261	5,261	19,440	17,746
	(3,636)	(2,160)	(1,997)	(1,149)	(1,135)	(57,534)	(252,226)	(250,492)	(834,370)	(806,910)

Table 4-2 – Input and Output Summary Statistics of Electric Generation Plants from 2003 – 2012 for the Malmquist Index

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
					N = 2,498					
					Capacity					
Installed Capacity (MW)	175	176	176	176	176	176	178	178	178	177
	(433)	(434)	(433)	(433)	(434)	(434)	(436)	(437)	(436)	(436)
					Output					
Net Generation (MWh)	197,234	194,644	200,306	200,996	198,243	192,615	197,418	200,267	201,485	197,819
	(1,373,014)	(1,405,574)	(1,409,282)	(1,427,849)	(1,441,470)	(1,411,858)	(1,434,253)	(1,439,893)	(1,414,769)	(1,402,020)

Standard deviations are in parenthesis.

Table 4-3 – Summary Statistics of State Policies and Plant Variables from 2003 – 2012 Used in the Econometric Model

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
N = 50										
Mandatory Green Power Option[a]	0.06	0.08	0.08	0.10	0.14	0.14	0.16	0.16	0.16	0.16
Net Metering[a]	0.54	0.60	0.62	0.64	0.66	0.74	0.82	0.84	0.86	0.86
Public Benefits Funds[a]	0.28	0.28	0.30	0.32	0.34	0.34	0.34	0.34	0.32	0.34
RPS in Effect[a]	0.02	0.06	0.10	0.24	0.30	0.38	0.42	0.46	0.52	0.58
RPS Penalty[a]	-	0.04	0.06	0.12	0.16	0.22	0.26	0.26	0.28	0.30
Voluntary RPS[a]	-	-	0.02	0.02	0.06	0.10	0.10	0.12	0.14	0.14
N = 2,478										
Average Age of Plant (in decades)	3.252	3.333	3.420	3.512	3.602	3.702	3.783	3.872	3.958	4.042
	(2.614)	(2.617)	(2.623)	(2.627)	(2.627)	(2.627)	(2.633)	(2.640)	(2.642)	(2.645)

[a] Policy variables are binary variables, that equal '1' if the policy is in place during a given year and '0' otherwise.

Standard deviations are in parenthesis.

Table 4-4 – Mean Change in Technical Efficiency Scores of Electric Generation Plants in the U.S. between 2003 and 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012	2003 - 2007	2008 - 2012	2003 - 2012
All Fuels												
All Fuel Inputs					N = 2498						N = 2498	
	1.134	0.982	1.098	1.432	1.071	1.312	0.852	7.722	2.135	1.572	10.200	13.630
	(1.441)	(0.306)	(0.427)	(0.955)	(1.015)	(2.636)	(0.355)	(19.841)	(10.536)	(3.187)	(66.940)	(163.706)
Coal Fuel Category												
Bituminous Coal	N = 209	N = 213	N = 211	N = 213	N = 211	N = 211	N = 212	N = 213	N = 208	N = 207	N = 211	N = 207
	1.603	1.107	1.180	1.087	1.233	1.542	0.907	4.303	9.162	1.462	3.354	3.883
	(2.869)	(0.602)	(0.673)	(0.586)	(1.470)	(5.682)	(0.441)	(15.058)	(26.197)	(2.272)	(10.148)	(12.217)
Sub-Bituminous Coal	N = 117	N = 122	N = 123	N = 124	N = 138	N = 137	N = 131	N = 131	N = 127	N = 112	N = 138	N = 112
	2.041	1.023	1.085	1.127	1.311	1.586	1.030	1.983	4.119	1.421	1.394	1.809
	(2.998)	(0.611)	(0.644)	(0.597)	(1.886)	(5.063)	(0.512)	(2.760)	(16.555)	(1.688)	(1.904)	(3.290)
Lignite Coal	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11
	0.945	1.179	0.994	2.221	0.853	1.833	0.951	21.089	1.943	1.779	37.007	45.949
	(0.770)	(0.790)	(0.426)	(1.142)	(0.570)	(0.965)	(0.611)	(33.452)	(0.677)	(1.846)	(33.329)	(123.179)
Petroleum Fuel Category												
Distillate Fuel Oil	N = 648	N = 648	N = 638	N = 630	N = 634	N = 642	N = 634	N = 643	N = 640	N = 632	N = 634	N = 632
	1.159	0.926	1.114	1.938	1.059	1.940	0.688	18.874	4.780	1.461	34.428	32.705
	(1.882)	(0.497)	(0.609)	(1.246)	(1.343)	(3.775)	(0.464)	(30.595)	(19.586)	(1.668)	(129.391)	(234.508)
Kerosene	N = 9	N = 15	N = 13	N = 9	N = 10	N = 10	N = 9	N = 8	N = 10	N = 11	N = 10	N = 11
	1.002	0.913	1.061	2.009	1.060	0.942	0.763	8.491	0.555	2.050	1.129	5.432
	(0.211)	(0.272)	(0.234)	(1.203)	(0.305)	(0.155)	(0.569)	(12.927)	(0.334)	(1.463)	(1.323)	(5.469)
Petroleum Coke	N = 9	N = 12	N = 10	N = 9	N = 8	N = 11	N = 9	N = 8	N = 7	N = 11	N = 8	N = 11
	1.566	0.740	1.570	1.343	0.925	2.377	0.827	3.753	5.456	1.447	2.657	4.213
	(1.969)	(0.365)	(1.093)	(0.863)	(0.337)	(5.194)	(0.615)	(4.531)	(12.197)	(0.976)	(2.941)	(5.858)

Table 4-4 – Mean Change in Technical Efficiency Scores of Electric Generation Plants in the U.S. between 2003 and 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012	2003 - 2007	2008 - 2012	2003 - 2012
Residual Fuel Oil	N = 74	N = 75	N = 76	N = 72	N = 68	N = 68	N = 63	N = 61	N = 58	N = 74	N = 68	N = 74
	1.595	0.983	1.100	1.321	1.020	2.317	0.785	7.376	3.742	1.392	8.242	12.720
	(3.296)	(0.410)	(0.715)	(0.763)	(0.479)	(7.770)	(0.391)	(17.976)	(13.046)	(1.542)	(21.479)	(48.641)
Waste/Other Oil	N = 7	N = 7	N = 7	N = 7	N = 12	N = 12	N = 10	N = 11	N = 10	N = 5	N = 12	N = 5
	0.760	1.054	1.115	1.282	0.903	5.887	0.875	1.482	2.282	0.465	1.062	0.771
	(0.750)	(0.514)	(0.278)	(0.502)	(0.584)	(16.557)	(0.289)	(0.979)	(3.477)	(0.361)	(0.588)	(0.710)
Natural Gas and Other Gases Fuel Category												
Natural Gas	N = 648	N = 647	N = 651	N = 644	N = 646	N = 649	N = 655	N = 660	N = 661	N = 652	N = 646	N = 652
	1.533	0.974	1.315	2.186	1.387	1.434	0.545	18.665	1.348	3.087	9.319	35.750
	(2.491)	(0.405)	(0.653)	(1.268)	(1.785)	(3.801)	(0.437)	(33.837)	(5.972)	(5.846)	(78.117)	(315.671)
Other Gas	N = 23	N = 24	N = 25	N = 25	N = 27	N = 25	N = 25	N = 26	N = 24	N = 21	N = 27	N = 21
	4.035	1.102	1.467	1.382	3.402	1.172	0.733	2.485	1.041	8.165	1.281	3.458
	(6.818)	(0.348)	(0.891)	(1.229)	(5.694)	(0.955)	(0.284)	(3.570)	(0.514)	(26.376)	(2.104)	(3.458)
Nuclear Fuel Category												
Nuclear	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17
	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.095	0.969	1.000	1.060	1.060
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.049)	(0.060)	(0.000)	(0.063)	(0.063)
Solid Renewable Fuels Fuel Category												
Municipal Solid Waste			N = 13	N = 13	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11
	-	-	1.026	0.993	0.996	1.201	1.091	3.186	1.020	3.306	3.306	3.306
			(1.458)	(0.219)	(0.127)	(0.539)	(0.313)	(4.654)	(0.285)	(4.083)	(4.083)	(4.083)
Wood/Wood Waste Solids	N = 101	N = 100	N = 101	N = 100	N = 99	N = 99	N = 100	N = 102	N = 100	N = 96	N = 99	N = 96
	1.504	1.039	1.245	0.990	1.022	1.725	0.944	2.099	1.152	1.495	2.170	2.504
	(3.010)	(0.326)	(0.928)	(0.348)	(0.352)	(6.211)	(0.297)	(6.563)	(0.763)	(2.730)	(7.015)	(7.096)
Liquid Renewable Fuels Fuel Category												

Table 4-4 – Mean Change in Technical Efficiency Scores of Electric Generation Plants in the U.S. between 2003 and 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012	2003 - 2007	2008 - 2012	2003 - 2012
	N = 39	N = 39	N = 39	N = 39	N = 38	N = 37	N = 37	N = 37	N = 37	N = 39	N = 38	N = 39
Black Liquor	1.819	1.146	1.200	1.008	0.898	2.742	0.867	1.390	1.101	2.017	3.113	3.447
	(4.482)	(0.489)	(0.336)	(0.240)	(0.383)	(10.145)	(0.245)	(0.650)	(0.394)	(3.636)	(10.996)	(10.411)
	N = 13	N = 13	N = 13	N = 13	N = 10	N = 11	N = 11	N = 12	N = 12	N = 11	N = 10	N = 11
Sludge Waste	3.791	1.026	1.477	1.148	0.796	7.441	0.745	7.014	1.273	2.739	3.681	6.808
	(7.570)	(0.355)	(0.468)	(0.763)	(0.386)	(18.398)	(0.246)	(18.070)	(0.633)	(2.431)	(4.022)	(10.894)
Gaseous Renewable Fuels Fuel Category												
	N = 106	N = 106	N = 106	N = 107	N = 108	N = 108	N = 108	N = 108	N = 108	N = 106	N = 108	N = 106
Landfill Gas	0.951	1.094	1.070	1.077	0.943	0.865	1.142	1.216	1.188	1.135	1.346	1.256
	(0.189)	(0.427)	(0.253)	(0.200)	(0.236)	(0.142)	(0.274)	(0.963)	(0.337)	(0.530)	(0.908)	(0.752)
	N = 13	N = 13	N = 13	N = 12	N = 12	N = 12	N = 13	N = 13	N = 13	N = 14	N = 12	N = 14
Other Biomass Gas	1.506	0.829	1.577	1.119	1.499	0.862	1.019	8.556	0.701	1.706	2.171	5.754
	(1.988)	(0.260)	(0.791)	(0.518)	(2.215)	(0.361)	(0.421)	(24.862)	(0.293)	(1.975)	(3.835)	(17.424)
Other Renewable Sources Fuel Category												
	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26
Geothermal	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.504	1.077	1.000	1.603	1.603
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.648)	(0.243)	(0.000)	(0.706)	(0.706)
	N = 1090	N = 1089	N = 1089	N = 1090	N = 1090	N = 1090	N = 1091	N = 1090	N = 1090	N = 1089	N = 1090	N = 1089
Hydroelectric	1.012	1.005	0.999	1.007	0.997	0.999	0.997	1.582	1.169	1.010	1.845	1.721
	(0.351)	(0.067)	(0.037)	(0.125)	(0.047)	(0.058)	(0.049)	(4.199)	(1.667)	(0.198)	(6.671)	(5.812)
	N = 10	N = 10	N = 10	N = 9	N = 11	N = 11	N = 11	N = 11	N = 11	N = 10	N = 11	N = 10
Solar	1.036	0.953	1.152	1.728	1.111	2.280	0.443	3.503	1.024	2.004	2.078	3.128
	(0.138)	(0.101)	(0.236)	(1.145)	(0.709)	(1.018)	(0.419)	(1.602)	(0.406)	(1.844)	(1.050)	(0.928)

Table 4-4 – Mean Change in Technical Efficiency Scores of Electric Generation Plants in the U.S. between 2003 and 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012	2003 - 2007	2008 - 2012	2003 - 2012
	N = 138	N = 138	N = 138	N = 138	N = 139	N = 140	N = 141	N = 141	N = 141	N = 139	N = 139	N = 139
Wind	1.000	1.000	1.000	1.000	0.994	0.996	0.988	1.325	0.997	0.994	1.128	0.993
	(0.000)	(0.000)	(0.000)	(0.000)	(0.067)	(0.048)	(0.103)	(2.663)	(0.024)	(0.074)	(1.512)	(0.083)

Standard deviations are in parenthesis. Results for inputs that were used by less than 10 power plants in every period were not included in the table.

Table 4-5 – Mean Technological Change Scores of Electric Generation Plants in the U.S. between 2003 and 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012	2003 - 2007	2008 - 2012	2003 - 2012
All Fuels												
All Fuel Inputs					N = 2498						N = 2498	
	1.115	1.047	0.950	0.857	1.137	0.984	1.554	0.615	1.005	0.922	0.639	0.587
	(0.396)	(0.138)	(0.147)	(0.266)	(0.652)	(0.391)	(1.149)	(0.404)	(0.551)	(0.329)	(0.396)	(0.379)
Coal Fuel Category												
Bituminous Coal	N = 209	N = 213	N = 211	N = 213	N = 211	N = 211	N = 212	N = 213	N = 208	N = 207	N = 211	N = 207
	1.134	0.982	1.003	0.973	1.011	1.279	1.197	0.696	0.824	1.077	0.667	0.673
	(0.187)	(0.073)	(0.062)	(0.126)	(0.072)	(0.193)	(0.450)	(0.603)	(0.463)	(0.199)	(0.470)	(0.484)
Sub-Bituminous Coal	N = 117	N = 122	N = 123	N = 124	N = 138	N = 137	N = 131	N = 131	N = 127	N = 112	N = 138	N = 112
	0.984	1.050	1.035	0.930	1.064	0.983	1.094	0.301	1.095	0.975	0.318	0.274
	(0.089)	(0.022)	(0.036)	(0.089)	(0.052)	(0.139)	(0.264)	(0.366)	(0.935)	(0.105)	(0.344)	(0.269)
Lignite Coal	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11
	1.913	1.213	1.105	0.589	1.922	0.659	1.780	0.187	0.608	1.222	0.190	0.179
	(1.063)	(0.169)	(0.204)	(0.317)	(0.961)	(0.286)	(0.920)	(0.204)	(0.308)	(0.507)	(0.280)	(0.174)
Petroleum Fuel Category												
Distillate Fuel Oil	N = 648	N = 648	N = 638	N = 630	N = 634	N = 642	N = 634	N = 643	N = 640	N = 632	N = 634	N = 632
	1.477	1.161	0.974	0.692	1.483	0.868	1.976	0.268	0.772	1.079	0.245	0.271
	(0.642)	(0.222)	(0.207)	(0.311)	(0.789)	(0.363)	(1.168)	(0.451)	(0.448)	(0.467)	(0.376)	(0.373)
Kerosene	N = 9	N = 15	N = 13	N = 9	N = 10	N = 10	N = 9	N = 8	N = 10	N = 11	N = 10	N = 11
	1.100	1.060	0.909	0.781	0.997	0.985	2.575	0.664	2.069	0.701	0.552	0.470
	(0.252)	(0.147)	(0.171)	(0.359)	(0.246)	(0.026)	(1.900)	(0.562)	(1.782)	(0.360)	(0.506)	(0.529)
Petroleum Coke	N = 9	N = 12	N = 10	N = 9	N = 8	N = 11	N = 9	N = 8	N = 7	N = 11	N = 8	N = 11
	1.094	1.010	1.000	0.997	0.964	1.283	1.281	0.614	0.963	1.002	0.637	0.574
	(0.210)	(0.035)	(0.060)	(0.198)	(0.159)	(0.172)	(0.504)	(0.429)	(0.175)	(0.274)	(0.382)	(0.385)

Table 4-5 – Mean Technological Change Scores of Electric Generation Plants in the U.S. between 2003 and 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012	2003 - 2007	2008 - 2012	2003 - 2012
Residual Fuel Oil	N = 74	N = 75	N = 76	N = 72	N = 68	N = 68	N = 63	N = 61	N = 58	N = 74	N = 68	N = 74
	1.078	1.032	0.939	0.869	1.031	1.057	1.599	0.430	0.990	0.914	0.529	0.462
	(0.120)	(0.097)	(0.130)	(0.256)	(0.224)	(0.191)	(0.968)	(0.422)	(0.307)	(0.311)	(0.480)	(0.445)
Waste/Other Oil	N = 7	N = 7	N = 7	N = 7	N = 12	N = 12	N = 10	N = 11	N = 10	N = 5	N = 12	N = 5
	0.977	0.950	0.949	1.012	0.982	1.161	1.019	1.016	0.830	0.946	0.949	1.333
	(0.029)	(0.236)	(0.081)	(0.068)	(0.130)	(0.307)	(0.101)	(0.756)	(0.301)	(0.064)	(0.394)	(0.766)
Natural Gas and Other Gases Fuel Category												
Natural Gas	N = 648	N = 647	N = 651	N = 644	N = 646	N = 649	N = 655	N = 660	N = 661	N = 652	N = 646	N = 652
	1.078	1.043	0.809	0.613	1.033	1.042	2.816	0.267	1.335	0.568	0.505	0.300
	(0.228)	(0.090)	(0.155)	(0.315)	(0.935)	(0.595)	(1.605)	(0.344)	(0.930)	(0.337)	(0.463)	(0.374)
Other Gas	N = 23	N = 24	N = 25	N = 25	N = 27	N = 25	N = 25	N = 26	N = 24	N = 21	N = 27	N = 21
	0.993	0.992	0.858	0.917	1.054	1.482	1.371	0.607	1.153	0.701	1.138	0.962
	(0.233)	(0.129)	(0.155)	(0.171)	(0.138)	(1.472)	(0.581)	(0.352)	(0.231)	(0.176)	(0.933)	(0.819)
Nuclear Fuel Category												
Nuclear	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17
	1.002	1.000	1.001	1.001	1.003	0.999	0.998	0.931	1.031	1.004	0.941	0.949
	(0.004)	(0.004)	(0.005)	(0.013)	(0.010)	(0.006)	(0.004)	(0.017)	(0.018)	(0.008)	(0.018)	(0.023)
Solid Renewable Fuels Fuel Category												
Municipal Solid Waste			N = 13	N = 13	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11
	-	-	0.319	1.132	0.911	2.335	1.088	0.365	1.173	0.772	0.772	0.772
			(0.292)	(0.288)	(0.290)	(4.485)	(0.164)	(0.250)	(0.650)	(1.211)	(1.211)	(1.211)
Wood/Wood Waste Solids	N = 101	N = 100	N = 101	N = 100	N = 99	N = 99	N = 100	N = 102	N = 100	N = 96	N = 99	N = 96
	1.013	1.045	0.909	1.053	1.020	1.026	1.123	0.694	0.995	0.978	0.771	0.718
	(0.083)	(0.097)	(0.148)	(0.193)	(0.113)	(0.095)	(0.426)	(0.382)	(0.208)	(0.144)	(0.360)	(0.401)

Table 4-5 – Mean Technological Change Scores of Electric Generation Plants in the U.S. between 2003 and 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012	2003 - 2007	2008 - 2012	2003 - 2012
Liquid Renewable Fuels Fuel Category												
Black Liquor	N = 39	N = 39	N = 39	N = 39	N = 38	N = 37	N = 37	N = 37	N = 37	N = 39	N = 38	N = 39
	1.025	0.999	0.873	0.984	1.047	1.052	1.216	0.801	1.012	0.871	0.895	0.815
	(0.069)	(0.138)	(0.105)	(0.127)	(0.178)	(0.167)	(0.366)	(0.272)	(0.143)	(0.161)	(0.300)	(0.344)
Sludge Waste	N = 13	N = 13	N = 13	N = 13	N = 10	N = 11	N = 11	N = 12	N = 12	N = 11	N = 10	N = 11
	1.036	1.041	0.857	0.966	1.036	1.104	1.208	0.665	1.108	0.817	0.874	0.877
	(0.109)	(0.131)	(0.148)	(0.185)	(0.112)	(0.366)	(0.452)	(0.371)	(0.269)	(0.146)	(0.348)	(0.338)
Gaseous Renewable Fuels Fuel Category												
Landfill Gas	N = 106	N = 106	N = 106	N = 107	N = 108	N = 108	N = 108	N = 108	N = 108	N = 106	N = 108	N = 106
	1.039	1.012	0.955	0.956	1.145	1.160	0.935	0.897	0.902	0.956	0.874	0.894
	(0.072)	(0.025)	(0.141)	(0.074)	(0.252)	(0.138)	(0.149)	(0.179)	(0.083)	(0.151)	(0.263)	(0.102)
Other Biomass Gas	N = 13	N = 13	N = 13	N = 12	N = 12	N = 12	N = 13	N = 13	N = 13	N = 14	N = 12	N = 14
	1.050	1.069	0.831	0.951	1.057	1.140	1.455	0.530	1.895	0.907	0.799	0.708
	(0.159)	(0.065)	(0.075)	(0.276)	(0.043)	(0.096)	(0.930)	(0.373)	(1.776)	(0.294)	(0.352)	(0.408)
Other Renewable Sources Fuel Category												
Geothermal	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26
	0.982	0.995	0.995	0.995	0.997	0.990	1.013	0.721	0.999	0.966	0.688	0.691
	(0.009)	(0.007)	(0.010)	(0.006)	(0.000)	(0.002)	(0.037)	(0.200)	(0.007)	(0.003)	(0.206)	(0.202)
Hydroelectric	N = 1090	N = 1089	N = 1089	N = 1090	N = 1090	N = 1090	N = 1091	N = 1090	N = 1090	N = 1089	N = 1090	N = 1089
	0.983	0.999	0.991	0.993	0.999	0.990	1.007	0.814	0.982	0.965	0.755	0.735
	(0.050)	(0.014)	(0.014)	(0.038)	(0.028)	(0.015)	(0.085)	(0.152)	(0.032)	(0.037)	(0.166)	(0.171)
Solar	N = 10	N = 10	N = 10	N = 9	N = 11	N = 11	N = 11	N = 11	N = 11	N = 10	N = 11	N = 10
	0.822	0.967	1.074	0.558	0.876	1.019	2.920	0.328	1.220	0.419	0.987	0.586
	(0.132)	(0.026)	(0.182)	(0.168)	(0.086)	(0.049)	(0.964)	(0.273)	(0.575)	(0.195)	(0.963)	(1.011)

Table 4-5 – Mean Technological Change Scores of Electric Generation Plants in the U.S. between 2003 and 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012	2003 - 2007	2008 - 2012	2003 - 2012
Wind	N = 138	N = 138	N = 138	N = 138	N = 139	N = 140	N = 141	N = 141	N = 141	N = 139	N = 139	N = 139
	0.980	0.996	0.993	0.997	1.003	0.990	1.012	0.977	0.982	0.967	0.960	0.926
	(0.019)	(0.018)	(0.015)	(0.003)	(0.071)	(0.006)	(0.108)	(0.134)	(0.022)	(0.016)	(0.081)	(0.060)

Standard deviations are in parenthesis. Results for inputs that were used by less than 10 power plants in every period were not included in the table.

Table 4-6 – Mean Change in Total Factor Productivity Scores of Electric Generation Plants in the U.S. between 2003 and 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012	2003 - 2007	2008 - 2012	2003 - 2012
All Fuels												
All Fuel Inputs	N = 2498									N = 2498		
	1.219	1.013	1.023	1.012	1.149	1.176	1.010	0.941	1.428	1.146	1.226	1.478
	(1.721)	(0.302)	(0.370)	(0.271)	(1.238)	(2.442)	(0.276)	(0.502)	(6.415)	(2.005)	(4.768)	(6.650)
Coal Fuel Category												
Bituminous Coal	N = 209	N = 213	N = 211	N = 213	N = 211	N = 211	N = 212	N = 213	N = 208	N = 207	N = 211	N = 207
	1.824	1.076	1.183	1.036	1.237	1.886	1.017	1.100	1.827	1.539	1.945	1.950
	(3.363)	(0.573)	(0.692)	(0.523)	(1.495)	(6.623)	(0.467)	(1.128)	(4.142)	(2.512)	(6.458)	(4.630)
Sub-Bituminous Coal	N = 117	N = 122	N = 123	N = 124	N = 138	N = 137	N = 131	N = 131	N = 127	N = 112	N = 138	N = 112
	2.112	1.074	1.123	1.034	1.382	1.495	1.085	0.367	1.177	1.379	0.450	0.477
	(3.726)	(0.644)	(0.668)	(0.498)	(1.939)	(4.560)	(0.505)	(0.574)	(1.200)	(1.700)	(0.854)	(1.347)
Lignite Coal	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11
	1.249	1.361	1.065	1.043	1.240	0.966	1.340	1.139	0.996	1.441	2.346	3.835
	(0.518)	(0.786)	(0.410)	(0.490)	(0.413)	(0.139)	(0.467)	(1.270)	(0.146)	(0.870)	(4.372)	(8.450)
Petroleum Fuel Category												
Distillate Fuel Oil	N = 648	N = 648	N = 638	N = 630	N = 634	N = 642	N = 634	N = 643	N = 640	N = 632	N = 634	N = 632
	1.507	1.032	1.055	1.035	1.319	1.313	1.023	0.833	1.749	1.203	1.415	2.218
	(2.406)	(0.490)	(0.546)	(0.399)	(1.598)	(2.622)	(0.456)	(0.820)	(8.406)	(0.908)	(8.348)	(11.737)
Kerosene	N = 9	N = 15	N = 13	N = 9	N = 10	N = 10	N = 9	N = 8	N = 10	N = 11	N = 10	N = 11
	1.128	0.942	0.936	1.214	1.032	0.928	1.095	0.703	0.720	1.026	0.437	1.193
	(0.516)	(0.253)	(0.144)	(0.470)	(0.306)	(0.155)	(0.330)	(0.459)	(0.298)	(0.250)	(0.404)	(2.143)
Petroleum Coke	N = 9	N = 12	N = 10	N = 9	N = 8	N = 11	N = 9	N = 8	N = 7	N = 11	N = 8	N = 11
	1.727	0.751	1.596	1.260	0.917	3.194	0.958	1.174	3.638	1.424	1.233	3.490
	(2.287)	(0.374)	(1.152)	(0.789)	(0.388)	(7.187)	(0.586)	(0.884)	(7.355)	(1.094)	(1.815)	(5.820)

Table 4-6 – Mean Change in Total Factor Productivity Scores of Electric Generation Plants in the U.S. between 2003 and 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012	2003 - 2007	2008 - 2012	2003 - 2012
Residual Fuel Oil	N = 74	N = 75	N = 76	N = 72	N = 68	N = 68	N = 63	N = 61	N = 58	N = 74	N = 68	N = 74
	1.679	0.997	1.027	0.995	1.094	2.170	1.000	0.947	1.816	1.130	2.325	2.722
	(3.271)	(0.394)	(0.717)	(0.346)	(1.000)	(7.400)	(0.417)	(1.204)	(4.109)	(1.120)	(9.432)	(7.585)
Waste/Other Oil	N = 7	N = 7	N = 7	N = 7	N = 12	N = 12	N = 10	N = 11	N = 10	N = 5	N = 12	N = 5
	0.742	0.897	1.053	1.294	0.879	5.563	0.881	1.255	1.306	0.431	1.089	1.341
	(0.730)	(0.091)	(0.272)	(0.522)	(0.564)	(14.837)	(0.268)	(0.785)	(0.982)	(0.310)	(0.763)	(2.021)
Natural Gas and Other Gases Fuel Category												
Natural Gas	N = 648	N = 647	N = 651	N = 644	N = 646	N = 649	N = 655	N = 660	N = 661	N = 652	N = 646	N = 652
	1.672	1.006	1.047	1.009	1.432	1.490	1.006	0.788	1.722	1.343	1.463	1.488
	(3.057)	(0.413)	(0.580)	(0.389)	(2.222)	(4.188)	(0.389)	(0.644)	(9.191)	(3.630)	(8.618)	(5.749)
Other Gas	N = 23	N = 24	N = 25	N = 25	N = 27	N = 25	N = 25	N = 26	N = 24	N = 21	N = 27	N = 21
	4.473	1.088	1.234	1.198	3.706	1.834	0.888	1.082	1.217	5.004	1.651	2.751
	(8.517)	(0.347)	(0.745)	(0.913)	(6.213)	(2.567)	(0.252)	(0.883)	(0.780)	(15.343)	(3.217)	(2.752)
Nuclear Fuel Category												
Nuclear	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17	N = 17
	1.002	1.000	1.001	1.001	1.003	0.999	0.998	1.019	0.999	1.004	0.997	1.005
	(0.004)	(0.004)	(0.005)	(0.013)	(0.010)	(0.006)	(0.004)	(0.045)	(0.063)	(0.008)	(0.061)	(0.058)
Solid Renewable Fuels Fuel Category												
Municipal Solid Waste			N = 13	N = 13	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11	N = 11
	-	-	0.345	1.086	0.911	2.634	1.224	0.850	1.113	2.130	2.130	2.130
			(0.511)	(0.226)	(0.305)	(4.835)	(0.604)	(0.851)	(0.410)	(3.816)	(3.816)	(3.816)
Wood/Wood Waste Solids	N = 101	N = 100	N = 101	N = 100	N = 99	N = 99	N = 100	N = 102	N = 100	N = 96	N = 99	N = 96
	1.519	1.076	1.085	1.018	1.036	1.742	1.003	0.836	1.070	1.453	1.771	1.626
	(2.984)	(0.317)	(0.812)	(0.315)	(0.356)	(6.108)	(0.271)	(0.535)	(0.363)	(2.889)	(7.624)	(5.230)

Table 4-6 – Mean Change in Total Factor Productivity Scores of Electric Generation Plants in the U.S. between 2003 and 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012	2003 - 2007	2008 - 2012	2003 - 2012
Liquid Renewable Fuels Fuel Category												
Black Liquor	N = 39	N = 39	N = 39	N = 39	N = 38	N = 37	N = 37	N = 37	N = 37	N = 39	N = 38	N = 39
	1.840	1.103	1.033	0.976	0.935	2.771	1.002	1.037	1.082	1.830	3.146	2.590
	(4.443)	(0.362)	(0.265)	(0.198)	(0.411)	(9.972)	(0.251)	(0.450)	(0.295)	(3.906)	(12.215)	(8.022)
Sludge Waste	N = 13	N = 13	N = 13	N = 13	N = 10	N = 11	N = 11	N = 12	N = 12	N = 11	N = 10	N = 11
	3.850	1.066	1.246	1.059	0.841	7.906	0.893	1.240	1.395	2.125	3.861	5.419
	(7.489)	(0.387)	(0.403)	(0.625)	(0.490)	(18.131)	(0.383)	(0.828)	(0.679)	(1.796)	(5.283)	(7.180)
Gaseous Renewable Fuels Fuel Category												
Landfill Gas	N = 106	N = 106	N = 106	N = 107	N = 108	N = 108	N = 108	N = 108	N = 108	N = 106	N = 108	N = 106
	0.982	1.109	1.003	1.023	1.051	0.993	1.053	0.971	1.067	1.065	1.034	1.130
	(0.192)	(0.449)	(0.216)	(0.167)	(0.257)	(0.153)	(0.283)	(0.240)	(0.314)	(0.464)	(0.401)	(0.674)
Other Biomass Gas	N = 13	N = 13	N = 13	N = 12	N = 12	N = 12	N = 13	N = 13	N = 13	N = 14	N = 12	N = 14
	1.793	0.884	1.287	0.942	1.574	0.971	1.251	0.895	1.058	1.257	0.974	0.905
	(2.924)	(0.273)	(0.612)	(0.174)	(2.311)	(0.385)	(0.562)	(0.457)	(0.629)	(1.248)	(0.801)	(0.754)
Other Renewable Sources Fuel Category												
Geothermal	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26	N = 26
	0.982	0.995	0.995	0.995	0.997	0.990	1.013	0.990	1.076	0.966	1.002	1.013
	(0.009)	(0.007)	(0.010)	(0.006)	(0.000)	(0.002)	(0.037)	(0.130)	(0.243)	(0.003)	(0.183)	(0.211)
Hydroelectric	N = 1090	N = 1089	N = 1089	N = 1090	N = 1090	N = 1090	N = 1091	N = 1090	N = 1090	N = 1089	N = 1090	N = 1089
	0.993	1.004	0.990	0.997	0.995	0.989	1.000	1.001	1.147	0.971	1.006	0.985
	(0.343)	(0.075)	(0.031)	(0.057)	(0.042)	(0.055)	(0.038)	(0.160)	(1.610)	(0.115)	(0.407)	(0.425)
Solar	N = 10	N = 10	N = 10	N = 9	N = 11	N = 11	N = 11	N = 11	N = 11	N = 10	N = 11	N = 10
	0.846	0.922	1.207	0.869	1.015	2.327	0.948	0.921	1.169	0.723	1.819	1.156
	(0.133)	(0.107)	(0.133)	(0.329)	(0.804)	(1.051)	(0.201)	(0.317)	(0.555)	(0.441)	(0.936)	(0.832)

Table 4-6 – Mean Change in Total Factor Productivity Scores of Electric Generation Plants in the U.S. between 2003 and 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012	2003 - 2007	2008 - 2012	2003 - 2012
Wind	N = 138	N = 138	N = 138	N = 138	N = 139	N = 140	N = 141	N = 141	N = 141	N = 139	N = 139	N = 139
	0.980	0.996	0.993	0.997	0.992	0.987	0.989	0.984	0.979	0.960	0.962	0.924
	(0.019)	(0.018)	(0.015)	(0.003)	(0.052)	(0.049)	(0.089)	(0.086)	(0.011)	(0.072)	(0.054)	(0.081)

Standard deviations are in parenthesis. Results for inputs that were used by less than 10 power plants in every period were not included in the table.

Table 4-7 – Tobit Model Change in Technical Efficiency Regression Results between 2003 – 2004 to 2011 – 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012
Intercept	1.071***	0.938***	1.195***	1.960***	0.917***	1.833***	0.816***	2.604	1.391***
	(0.186)	(0.037)	(0.044)	(0.089)	(0.106)	(0.336)	(0.034)	(2.239)	(0.620)
Policies									
RPS in Effect	-0.174	-0.045	-0.180***	0.084**	0.026	0.268	-0.025	-0.232	1.215
	(0.115)	(0.051)	(0.045)	(0.040)	(0.059)	(0.184)	(0.018)	(1.107)	(0.781)
Voluntary RPS	-	-	-0.026	-0.002	-0.046	-0.340***	0.017	-1.290	0.444
			(0.018)	(0.035)	(0.039)	(0.121)	(0.023)	(0.983)	(0.726)
Non-compliance Penalty	-	0.066	0.172***	-0.256***	-0.042	-0.140	0.050***	-1.949**	1.490**
		(0.054)	(0.052)	(0.045)	(0.071)	(0.114)	(0.015)	(0.814)	(0.722)
Mandatory Green Power Option	-0.018	-0.026*	-0.012	0.156***	-0.081	0.244	0.001	0.477	-1.721***
	(0.046)	(0.014)	(0.017)	(0.048)	(0.054)	(0.191)	(0.016)	(0.792)	(0.564)
Public Benefits Fund	-0.105	-0.018	0.016	-0.008	-0.034	-0.216	0.010	-1.441*	-1.861*
	(0.065)	(0.017)	(0.023)	(0.034)	(0.057)	(0.155)	(0.016)	(0.793)	(1.113)
Net Metering	0.045	-0.004	0.019	-0.088**	0.094	0.302**	-0.069***	2.755***	1.646***
	(0.065)	(0.018)	(0.023)	(0.039)	(0.059)	(0.150)	(0.018)	(0.970)	(0.641)
Power Plant Characteristics									
Installed Capacity	-0.100	0.006	0.030	0.088*	0.041	-0.673***	-0.045*	-3.108***	3.929
	(0.114)	(0.037)	(0.036)	(0.047)	(0.054)	(0.225)	(0.023)	(1.068)	(2.669)
Average Age of Plant	0.005	-0.001	0.002	-0.013***	0.009	-0.013	0.004***	0.256**	0.070*
	(0.007)	(0.001)	(0.003)	(0.004)	(0.006)	(0.012)	(0.001)	(0.106)	(0.042)
Fuel									
Coal	0.633***	0.187***	-0.085*	-1.136***	0.124	0.151	0.385***	-14.011***	1.016
	(0.200)	(0.048)	(0.052)	(0.071)	(0.116)	(0.437)	(0.039)	(1.746)	(1.495)

Table 4-7 – Tobit Model Change in Technical Efficiency Regression Results between 2003 – 2004 to 2011 – 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012
Petroleum	-0.258	-0.071**	-0.126***	0.258***	-0.106	0.367	-0.106***	14.988***	0.698
	(0.199)	(0.029)	(0.040)	(0.071)	(0.105)	(0.287)	(0.026)	(2.321)	(0.558)
Natural Gas & Other Gases	0.440**	0.014	0.161***	0.547***	0.383***	-0.660**	-0.290***	14.016***	-3.610***
	(0.183)	(0.034)	(0.041)	(0.067)	(0.086)	(0.275)	(0.028)	(2.042)	(0.855)
Nuclear	0.190	0.068	-0.272***	-1.036***	-0.062	0.392	0.307***	3.500	-11.026**
	(0.314)	(0.082)	(0.078)	(0.125)	(0.148)	(0.466)	(0.060)	(3.281)	(5.520)
Solid Renewable Fuel	-0.007	-0.012	0.036	-0.894***	-0.058	-0.568**	0.264***	-6.319***	-0.561
	(0.188)	(0.050)	(0.130)	(0.078)	(0.077)	(0.248)	(0.043)	(2.159)	(0.698)
Liquid Renewable Fuel	0.164	0.221**	0.015	0.106	-0.282***	1.393	-0.088	-9.277***	-0.143
	(0.674)	(0.113)	(0.127)	(0.151)	(0.110)	(1.287)	(0.065)	(3.068)	(1.080)
Gaseous Renewable Fuel	-0.096	0.134***	-0.104*	-0.783***	0.014	-1.129***	0.360***	-2.772	-2.030***
	(0.204)	(0.049)	(0.055)	(0.084)	(0.129)	(0.314)	(0.041)	(2.088)	(0.699)
Other Renewable Sources	-0.064	0.082**	-0.224***	-0.803***	-0.008	-0.968***	0.210***	-3.164	-2.219***
	(0.197)	(0.036)	(0.039)	(0.081)	(0.107)	(0.340)	(0.031)	(2.027)	(0.649)
Other Energy Sources	-0.209	-0.326	-0.227	-0.475***	-0.993***	0.571	-0.103	-10.059*	9.158
	(0.919)	(0.339)	(0.687)	(0.165)	(0.156)	(1.033)	(0.261)	(5.230)	(6.593)
Sigma	1.409***	0.296***	0.402***	0.711***	0.999***	2.572***	0.266***	17.077***	10.168***
	(0.208)	(0.013)	(0.036)	(0.021)	(0.154)	(0.469)	(0.011)	(1.105)	(2.082)
Observations					2498				
Log Likelihood	-4402	-504	-1268	-2691	-3542	-5904	-234	-10,633	-9338

Standard errors are in parenthesis. *** implies significance at the 1% level, ** implies significance at the 5% level, and * implies significance at the 10% level.

Table 4-8 – Tobit Model Technological Change Regression Results between 2003 – 2004 to 2011 – 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 – 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012
Intercept	1.345***	1.149***	0.923***	0.735***	1.624***	0.826***	1.711***	0.643***	0.928***
	(0.033)	(0.013)	(0.014)	(0.022)	(0.055)	(0.030)	(0.094)	(0.032)	(0.050)
Policies									
RPS in Effect	0.442***	0.105***	0.132***	-0.009	0.049**	-0.050***	0.000	-0.057***	-0.013
	(0.073)	(0.023)	(0.022)	(0.009)	(0.021)	(0.011)	(0.039)	(0.018)	(0.029)
Voluntary RPS	-	-	0.009*	0.005	-0.106**	0.120	0.046	-0.024	0.010
			(0.005)	(0.012)	(0.042)	(0.096)	(0.049)	(0.024)	(0.054)
Non-compliance Penalty	-	-0.121***	-0.118***	0.071***	0.007	0.024**	-0.164***	0.027**	-0.029
		(0.024)	(0.023)	(0.011)	(0.030)	(0.011)	(0.039)	(0.014)	(0.021)
Mandatory Green Power Option	0.023**	0.000	0.019***	-0.034***	0.106***	0.001	-0.046	-0.020	0.029
	(0.011)	(0.005)	(0.007)	(0.010)	(0.023)	(0.042)	(0.030)	(0.014)	(0.023)
Public Benefits Fund	0.041***	0.009	-0.006	-0.006	-0.003	0.034***	-0.045	0.052***	0.029
	(0.014)	(0.005)	(0.005)	(0.008)	(0.021)	(0.011)	(0.035)	(0.015)	(0.025)
Net Metering	-0.046***	-0.003	-0.013**	0.007	-0.002	-0.023*	0.272***	0.011	-0.016
	(0.016)	(0.005)	(0.006)	(0.009)	(0.021)	(0.013)	(0.051)	(0.021)	(0.027)
Power Plant Characteristics									
Installed Capacity	-0.137***	-0.028***	-0.021***	-0.022**	-0.206***	0.092***	0.282***	0.039	0.007
	(0.021)	(0.007)	(0.006)	(0.010)	(0.022)	(0.022)	(0.050)	(0.035)	(0.032)
Average Age of Plant	0.002	0.001*	0.001**	0.003***	0.000	0.000	-0.018***	-0.004**	0.003
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)	(0.002)	(0.003)
Fuel									
Coal	-0.230***	-0.139***	0.139***	0.350***	-0.279***	0.257***	-1.409***	0.227***	0.029
	(0.034)	(0.011)	(0.010)	(0.016)	(0.037)	(0.031)	(0.068)	(0.034)	(0.052)

Table 4-8 – Tobit Model Technological Change Regression Results between 2003 – 2004 to 2011 – 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 – 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012
Petroleum	0.326***	0.091***	0.055***	-0.101***	0.182***	-0.134***	0.123	-0.334***	-0.325***
	(0.021)	(0.008)	(0.009)	(0.017)	(0.026)	(0.020)	(0.079)	(0.021)	(0.051)
Natural Gas & Other Gases	-0.282***	-0.097***	-0.160***	-0.209***	-0.548***	0.191***	1.298***	-0.350***	0.537***
	(0.029)	(0.011)	(0.011)	(0.016)	(0.054)	(0.035)	(0.062)	(0.022)	(0.034)
Nuclear	-0.093*	-0.101***	0.122***	0.295***	-0.225***	0.005	-1.341***	0.217***	0.123
	(0.051)	(0.018)	(0.015)	(0.028)	(0.060)	(0.041)	(0.131)	(0.078)	(0.083)
Solid Renewable Fuel	-0.204***	-0.034**	0.025	0.328***	-0.099	0.243	-0.994***	0.123***	-0.081
	(0.035)	(0.017)	(0.022)	(0.034)	(0.295)	(0.183)	(0.102)	(0.042)	(0.051)
Liquid Renewable Fuel	0.039	-0.029	-0.065**	-0.039	-0.018	-0.178	0.100	0.346***	-0.032
	(0.056)	(0.032)	(0.028)	(0.048)	(0.262)	(0.164)	(0.166)	(0.073)	(0.065)
Gaseous Renewable Fuel	-0.266***	-0.119***	0.037*	0.206***	-0.455***	0.314***	-0.910***	0.244***	0.003
	(0.034)	(0.013)	(0.019)	(0.024)	(0.048)	(0.032)	(0.094)	(0.031)	(0.068)
Other Renewable Sources	-0.361***	-0.153***	0.070***	0.229***	-0.649***	0.169***	-0.761***	0.197***	0.049
	(0.031)	(0.013)	(0.013)	(0.021)	(0.043)	(0.025)	(0.083)	(0.026)	(0.055)
Other Energy Sources	-0.177	-0.059*	-0.030	0.250***	0.270	0.551**	-1.087***	0.615	-0.097
	(0.111)	(0.035)	(0.064)	(0.051)	(0.265)	(0.263)	(0.401)	(0.453)	(0.174)
Sigma	0.295***	0.104***	0.109***	0.168***	0.583***	0.364***	0.722***	0.282***	0.489***
	(0.010)	(0.003)	(0.006)	(0.004)	(0.186)	(0.119)	(0.015)	(0.008)	(0.098)
Observations					2498				
Log Likelihood	-494	2115	1989	906	-2195	-1017	-2732	-378	-1757

Standard errors are in parenthesis. *** implies significance at the 1% level, ** implies significance at the 5% level, and * implies significance at the 10% level.

Table 4-9 – Tobit Model Total Factor Productivity Regression Results between 2003 – 2004 to 2011 – 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012
Intercept	1.154***	1.028***	1.063***	1.069***	1.269***	1.254***	1.023***	1.254***	1.508***
	(0.220)	(0.037)	(0.039)	(0.031)	(0.130)	(0.390)	(0.036)	(0.060)	(0.337)
Policies									
RPS in Effect	0.014	0.031	-0.062	0.041**	0.049	0.121	-0.016	-0.046*	0.911
	(0.177)	(0.051)	(0.042)	(0.019)	(0.065)	(0.164)	(0.019)	(0.028)	(0.754)
Voluntary RPS	-	-	-0.010	0.004	-0.091*	-0.118	0.042	0.060	0.296
			(0.013)	(0.021)	(0.047)	(0.150)	(0.031)	(0.047)	(0.232)
Non-compliance Penalty	-	-0.026	0.077	-0.019	-0.015	-0.079	0.022	0.014	0.416
		(0.054)	(0.047)	(0.019)	(0.081)	(0.120)	(0.016)	(0.024)	(0.514)
Mandatory Green Power Option	0.034	-0.030**	0.004	0.031*	-0.052	0.140	-0.005	0.028	-0.878**
	(0.084)	(0.014)	(0.013)	(0.018)	(0.058)	(0.192)	(0.017)	(0.026)	(0.416)
Public Benefits Fund	-0.141*	-0.011	0.004	-0.001	-0.039	-0.100	-0.013	0.006	-1.270
	(0.081)	(0.017)	(0.021)	(0.014)	(0.063)	(0.126)	(0.018)	(0.025)	(0.816)
Net Metering	0.051	-0.004	0.011	-0.020	0.088	0.181	0.010	-0.031	0.698*
	(0.087)	(0.018)	(0.021)	(0.016)	(0.069)	(0.136)	(0.020)	(0.039)	(0.373)
Power Plant Characteristics									
Installed Capacity	-0.186	-0.005	0.003	-0.024	-0.074	-0.510**	-0.038*	-0.154***	-0.620***
	(0.131)	(0.036)	(0.035)	(0.030)	(0.059)	(0.260)	(0.023)	(0.045)	(0.235)
Average Age of Plant	0.012	-0.001	0.003	-0.001	0.013*	-0.008	0.000	0.006**	0.010
	(0.009)	(0.001)	(0.002)	(0.001)	(0.007)	(0.009)	(0.001)	(0.003)	(0.034)
Fuel									
Coal	0.519**	0.086*	0.118**	0.027	-0.023	0.851*	0.060	0.020	0.042
	(0.224)	(0.047)	(0.052)	(0.043)	(0.125)	(0.501)	(0.039)	(0.072)	(0.427)

Table 4-9 – Tobit Model Total Factor Productivity Regression Results between 2003 – 2004 to 2011 – 2012

	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012
Petroleum	0.062	-0.007	-0.049	0.002	-0.029	-0.113	0.002	-0.206***	-0.191
	(0.235)	(0.030)	(0.033)	(0.026)	(0.116)	(0.355)	(0.028)	(0.046)	(0.611)
Natural Gas & Other Gases	0.418*	-0.040	-0.042	-0.060**	0.075	-0.032	-0.022	-0.321***	-0.260
	(0.224)	(0.034)	(0.038)	(0.024)	(0.107)	(0.298)	(0.031)	(0.048)	(0.409)
Nuclear	0.274	-0.005	-0.083	-0.010	-0.199	0.727	0.050	0.125	0.000
	(0.374)	(0.081)	(0.074)	(0.068)	(0.163)	(0.456)	(0.058)	(0.110)	(0.571)
Solid Renewable Fuel	-0.122	-0.001	0.030	-0.061	0.004	-0.107	-0.010	-0.242***	-0.548
	(0.188)	(0.044)	(0.115)	(0.043)	(0.296)	(0.335)	(0.041)	(0.085)	(0.420)
Liquid Renewable Fuel	0.093	0.142	-0.033	0.090	-0.378	1.158	-0.027	0.411***	-0.268
	(0.681)	(0.096)	(0.112)	(0.098)	(0.269)	(1.266)	(0.062)	(0.118)	(0.540)
Gaseous Renewable Fuel	-0.105	0.070	-0.043	-0.047	-0.221	-0.424	0.032	-0.209***	-1.121**
	(0.243)	(0.050)	(0.046)	(0.031)	(0.143)	(0.370)	(0.048)	(0.052)	(0.582)
Other Renewable Sources	-0.193	-0.009	-0.097***	-0.066**	-0.388***	-0.341	-0.024	-0.235***	-0.926
	(0.221)	(0.035)	(0.034)	(0.028)	(0.123)	(0.409)	(0.034)	(0.052)	(0.601)
Other Energy Sources	-0.375	-0.371	-0.118	-0.060	-0.786***	2.702	-0.373	0.247	5.475
	(0.902)	(0.326)	(0.589)	(0.102)	(0.295)	(1.909)	(0.239)	(0.465)	(4.009)
Sigma	1.690***	0.299***	0.366***	0.269***	1.224***	2.411***	0.274***	0.482***	6.379***
	(0.253)	(0.015)	(0.039)	(0.019)	(0.176)	(0.536)	(0.016)	(0.026)	(1.936)
Observations					2498				
Log Likelihood	-4856	-527	-1032	-266	-4049	-5743	-313	-1724	-8173

Standard errors are in parenthesis. *** implies significance at the 1% level, ** implies significance at the 5% level, and * implies significance at the 10% level.

Table 4-10 – Tobit Model Regression Results Across Multiple Years

	Change in Technical Efficiency			Technological Change			Change in TFP		
	2003 - 2007	2008 – 2012	2003 – 2012	2003 - 2007	2008 - 2012	2003 - 2012	2003 - 2007	2008 - 2012	2003 - 2012
Intercept	2.771***	27.191**	4.640	1.035***	0.730***	0.677***	1.773***	1.194	2.881***
	(0.333)	(10.973)	(18.587)	(0.026)	(0.035)	(0.035)	(0.239)	(0.783)	(0.496)
Policies									
RPS in Effect	-0.186	15.676*	7.673	0.288***	-0.037	-0.195***	0.393	0.694	-1.366*
	(0.365)	(8.054)	(10.593)	(0.046)	(0.027)	(0.042)	(0.345)	(0.500)	(0.821)
Voluntary RPS	-	11.806*	-	-	0.033	-	-	0.802	-
		(6.335)			(0.036)			(0.524)	
Non-compliancy Penalty	-	2.302	-	-	0.025	-	-	0.269	-
		(3.211)			(0.018)			(0.115)	
Mandatory Green Power Option	-0.405**	-5.004	-3.244	0.026**	-0.010	0.031	-0.174	-0.313	-0.997
	(0.199)	(5.111)	(3.236)	(0.013)	(0.025)	(0.021)	(0.122)	(0.343)	(0.735)
Public Benefits Fund	-0.124	-11.952**	-20.550*	0.028**	0.055***	0.036**	-0.020	-0.468**	-1.654
	(0.260)	(5.528)	(11.127)	(0.014)	(0.018)	(0.018)	(0.164)	(0.242)	(1.252)
Net Metering	0.265	-9.198	4.317	-0.035***	0.014	-0.001	0.133	-0.192	0.972
	(0.344)	(10.550)	(4.730)	(0.014)	(0.026)	(0.026)	(0.203)	(0.417)	(0.792)
Change in RPS in Effect	-0.229*	15.585*	22.440	-0.003	-0.078***	-0.075***	-0.155**	0.924	0.663
	(0.125)	(8.153)	(16.577)	(0.015)	(0.026)	(0.022)	(0.089)	(0.921)	(0.540)
Change in Non-compliance Penalty	-0.247**	2.818	-7.405	0.044***	0.073**	0.032***	0.037	0.283	0.769
	(0.104)	(8.115)	(7.997)	(0.012)	(0.032)	(0.014)	(0.074)	(0.655)	(0.683)
Change in Voluntary RPS	-0.417**	7.126	5.522	-0.004	-0.017	-0.036	-0.319**	0.234	-0.121
	(0.212)	(6.107)	(6.527)	(0.030)	(0.051)	(0.033)	(0.142)	(0.513)	(0.270)
Change in Mandatory Green Power Option	-0.155	-3.055	-11.924	0.011	0.036	-0.006	-0.007	-0.258	-0.270
	(0.171)	(3.163)	(8.355)	(0.029)	(0.034)	(0.022)	(0.106)	(0.170)	(0.440)
Change in Public Benefits Fund	0.098	-	-21.777*	0.039	-	0.028	0.178	-	-1.180
	(0.237)		(12.611)	(0.025)		(0.024)	(0.175)		(0.779)

Table 4-10 – Tobit Model Regression Results Across Multiple Years

	Change in Technical Efficiency			Technological Change			Change in TFP		
	2003 - 2007	2008 – 2012	2003 – 2012	2003 - 2007	2008 - 2012	2003 - 2012	2003 - 2007	2008 - 2012	2003 - 2012
Change in Net Metering	-0.048	-11.898	12.330	-0.002	0.074**	-0.028	-0.110	0.719	0.245
	(0.165)	(11.225)	(7.904)	(0.019)	(0.032)	(0.025)	(0.101)	(0.996)	(0.258)
Power Plant Characteristics									
Installed Capacity	0.663*	-13.043***	-12.314***	-0.115***	0.001	-0.017	0.063	-0.762***	-1.030***
	(0.384)	(2.783)	(5.262)	(0.018)	(0.030)	(0.028)	(0.235)	(0.210)	(0.308)
Average Age of Plant	-0.018	0.304	1.531*	0.006***	-0.006***	0.000	0.004	0.004	-0.003
	(0.015)	(0.276)	(0.908)	(0.001)	(0.002)	(0.002)	(0.010)	(0.016)	(0.034)
Fuel									
Coal	-1.133***	-22.653***	-28.473***	0.205***	0.170***	0.232***	0.206	0.417	-0.429
	(0.413)	(4.176)	(9.382)	(0.025)	(0.035)	(0.033)	(0.286)	(0.437)	(0.460)
Petroleum	-1.419***	26.359***	20.030	0.163***	-0.489***	-0.310***	-0.616**	0.053	0.176
	(0.360)	(6.535)	(20.846)	(0.020)	(0.026)	(0.025)	(0.252)	(0.558)	(0.509)
Natural Gas & Other Gases	1.174***	-16.066**	22.693	-0.566***	-0.113***	-0.288***	-0.236*	-0.039	-1.540**
	(0.171)	(7.081)	(15.456)	(0.022)	(0.023)	(0.023)	(0.142)	(0.587)	(0.603)
Nuclear	-2.816***	-0.189	10.046	0.166***	0.219***	0.353***	-0.798	1.008	-0.230
	(0.991)	(7.148)	(23.629)	(0.046)	(0.072)	(0.067)	(0.594)	(0.650)	(0.605)
Solid Renewable Fuels	-1.482***	-16.811***	-18.204**	0.155***	0.116*	0.155***	-0.387	-0.344	-1.951***
	(0.334)	(3.438)	(8.899)	(0.035)	(0.060)	(0.047)	(0.274)	(0.378)	(0.623)
Liquid Renewable Fuels	1.392**	-1.086	-8.053	-0.089*	0.387***	0.257***	0.924	2.089	2.996**
	(0.653)	(6.034)	(11.679)	(0.050)	(0.081)	(0.075)	(0.617)	(1.628)	(1.221)
Gaseous Renewable Fuels	-1.467***	-22.467***	-15.158	-0.045	0.126***	0.260***	-0.613**	-0.546	-2.077***
	(0.327)	(5.931)	(16.273)	(0.034)	(0.038)	(0.032)	(0.240)	(0.494)	(0.640)
Other Renewable Sources	-1.576***	-24.218***	-15.501	-0.100***	0.057*	0.113***	-0.815***	-0.475	-2.354***
	(0.336)	(5.552)	(16.590)	(0.024)	(0.030)	(0.030)	(0.247)	(0.535)	(0.642)

Table 4-10 – Tobit Model Regression Results Across Multiple Years

	Change in Technical Efficiency			Technological Change			Change in TFP		
	2003 - 2007	2008 – 2012	2003 – 2012	2003 - 2007	2008 - 2012	2003 - 2012	2003 - 2007	2008 - 2012	2003 - 2012
Other Energy Sources	-1.316**	-8.116	-0.150	-0.024	0.462	0.389**	-1.061**	2.994	0.181
	(0.546)	(15.379)	(10.019)	(0.143)	(0.343)	(0.196)	(0.452)	(3.093)	(2.128)
Sigma	3.008***	64.311***	162.075***	0.210***	0.313***	0.283***	1.982***	4.733***	6.566***
	(0.961)	(18.486)	(53.455)	(0.004)	(0.018)	(0.011)	(0.557)	(1.601)	(2.341)
Observations	2498			2498			2498		
Log Likelihood	-6295	-13945	-16254	349	-647	-395	-5254	-7428	-8246

Standard errors are in parenthesis. *** implies significance at the 1% level, ** implies significance at the 5% level, and * implies significance at the 10% level.

Figure 4-1 Mean Rate of Productivity Growth 2003 – 2012 for Coal Inputs

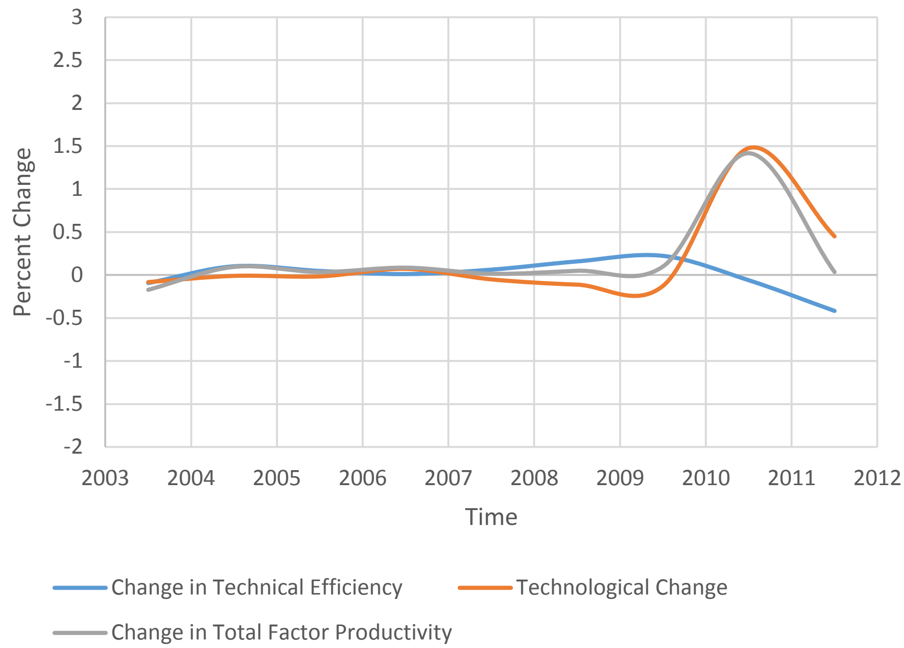


Figure 4-2 Mean Rate of Productivity Growth 2003 – 2012 for Petroleum Inputs

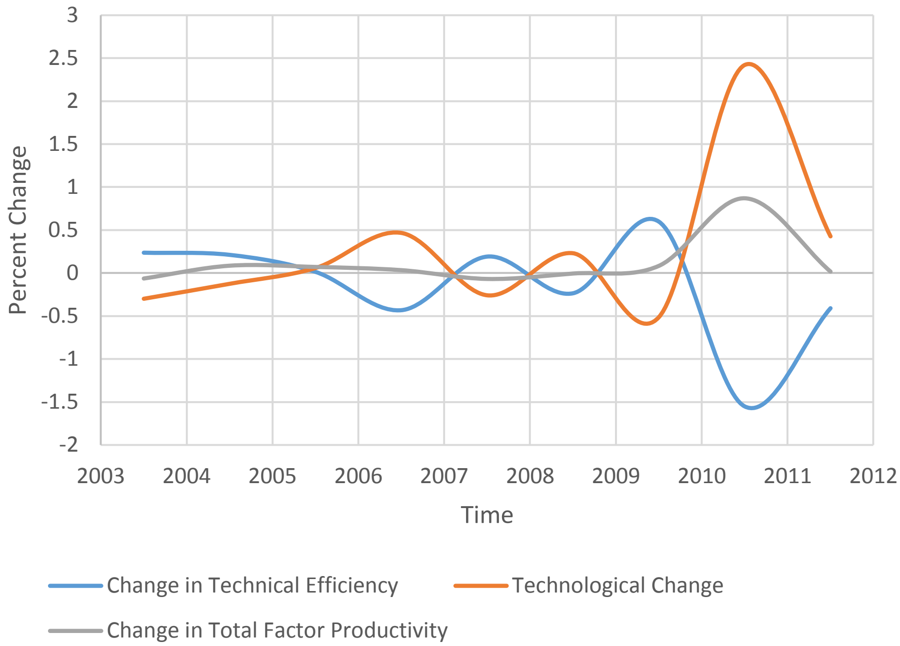


Figure 4-3 Mean Rate of Productivity Growth 2003 – 2012 for Natural Gas and Other Gases Inputs

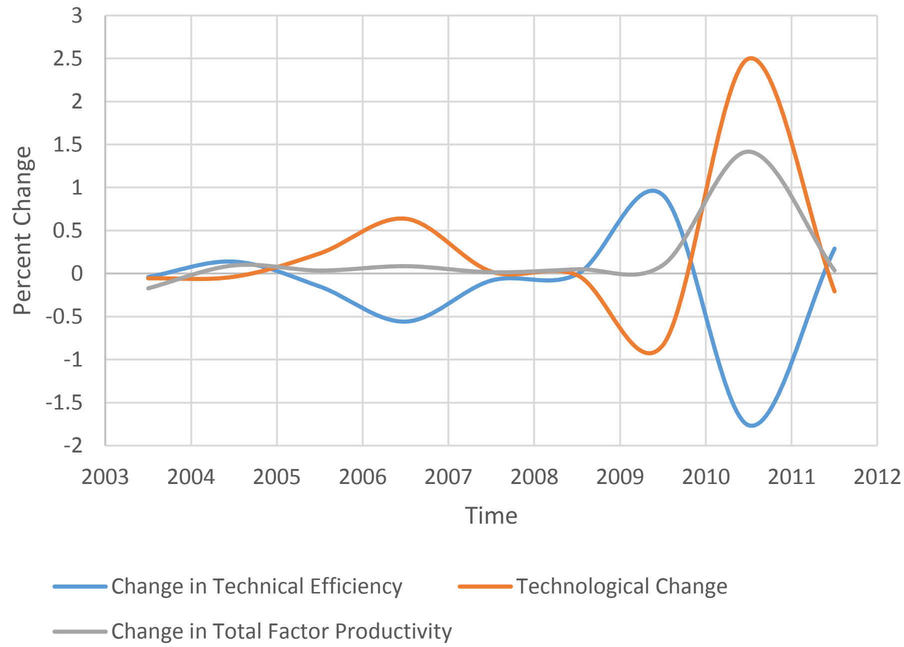


Figure 4-4 Mean Rate of Productivity Growth 2003 – 2012 for Nuclear Inputs

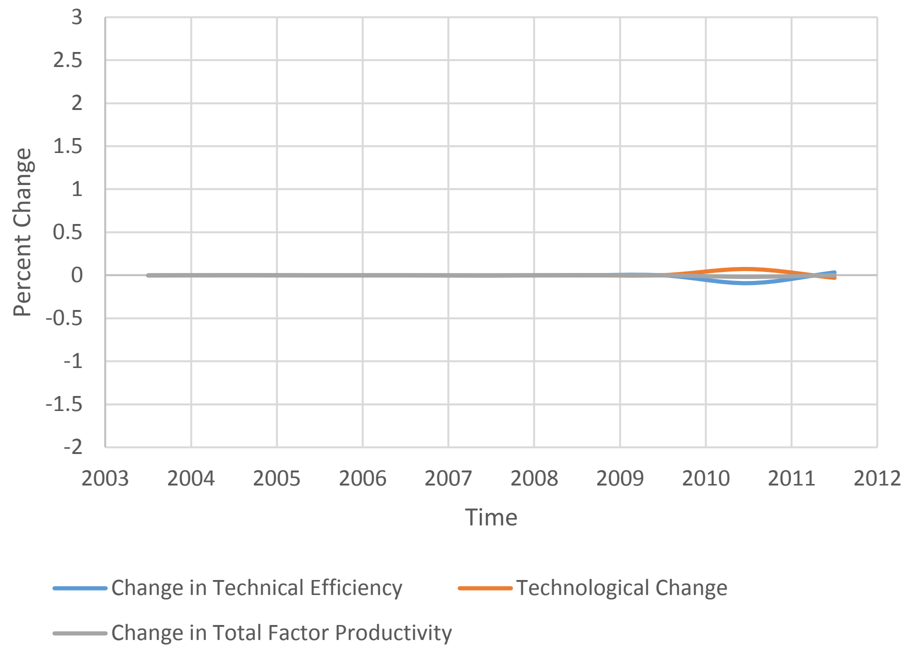


Figure 4-5 Mean Rate of Productivity Growth 2003 – 2012 for Solid Renewable Fuel Inputs

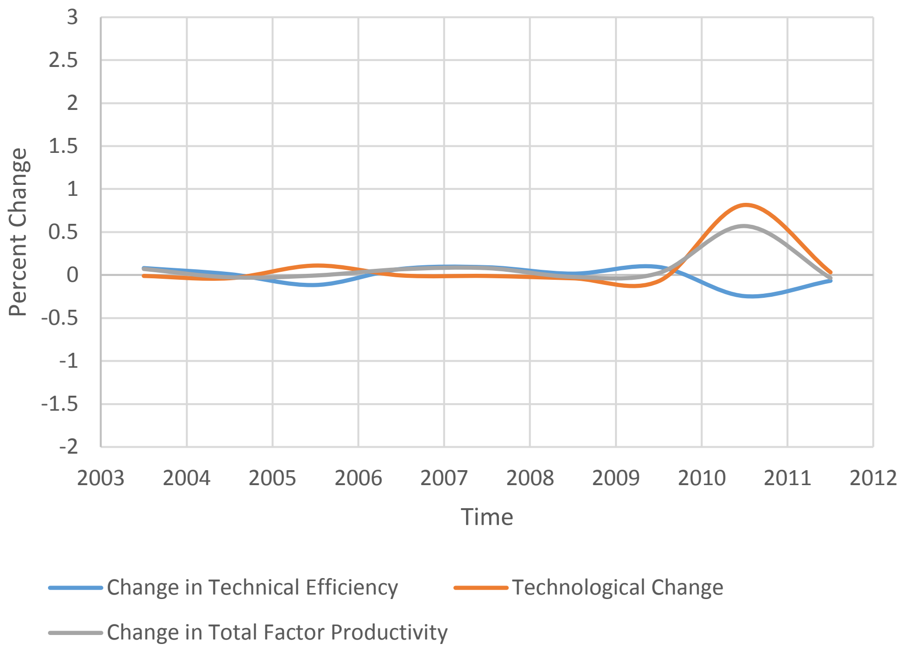


Figure 4-6 Mean Rate of Productivity Growth 2003 – 2012 for Liquid Renewable Fuel Inputs

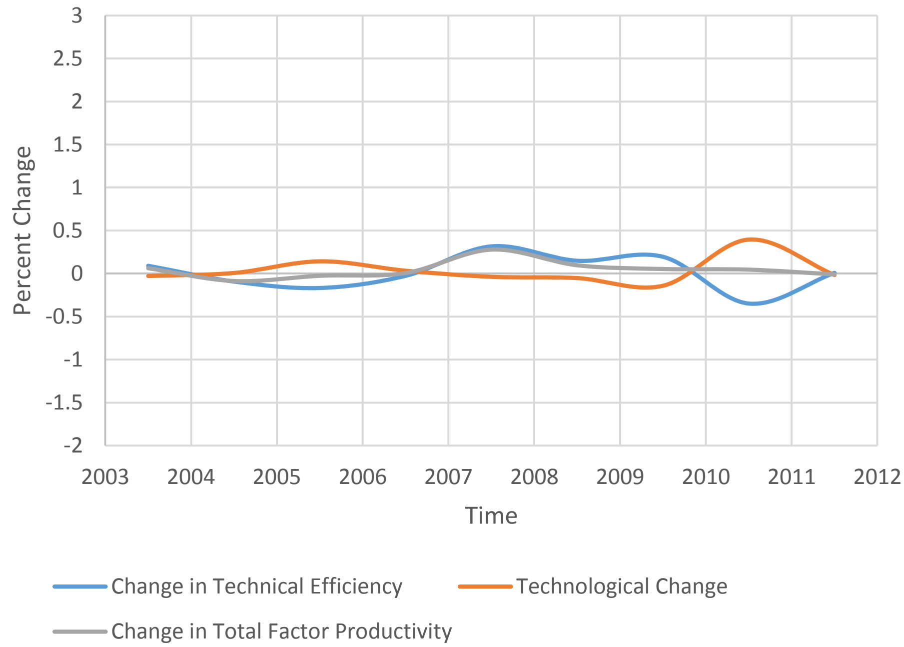


Figure 4-7 Mean Rate of Productivity Growth 2003 – 2012 for Gaseous Renewable Fuel Inputs

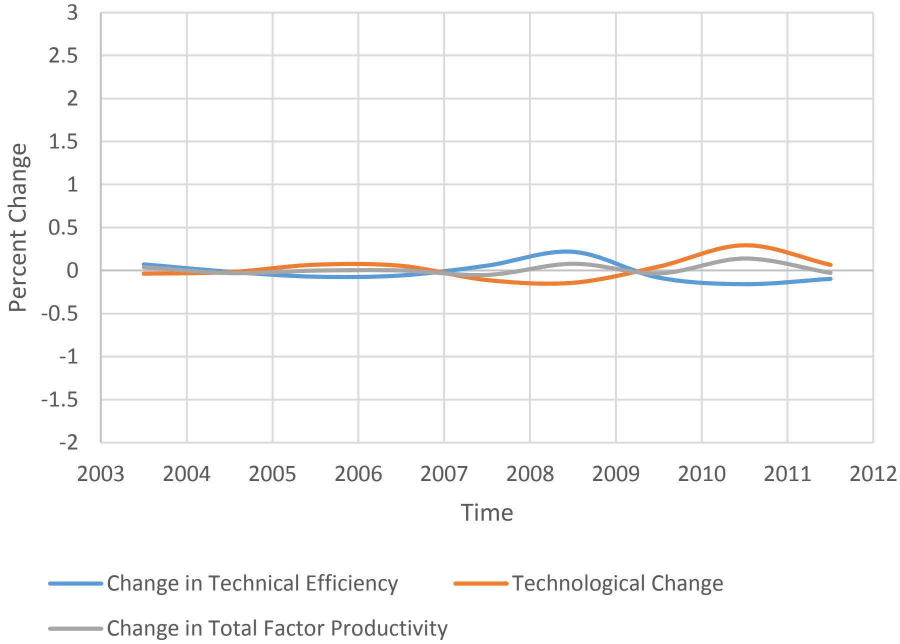


Figure 4-8 Mean Rate of Productivity Growth 2003 – 2012 for Other Renewable Sources

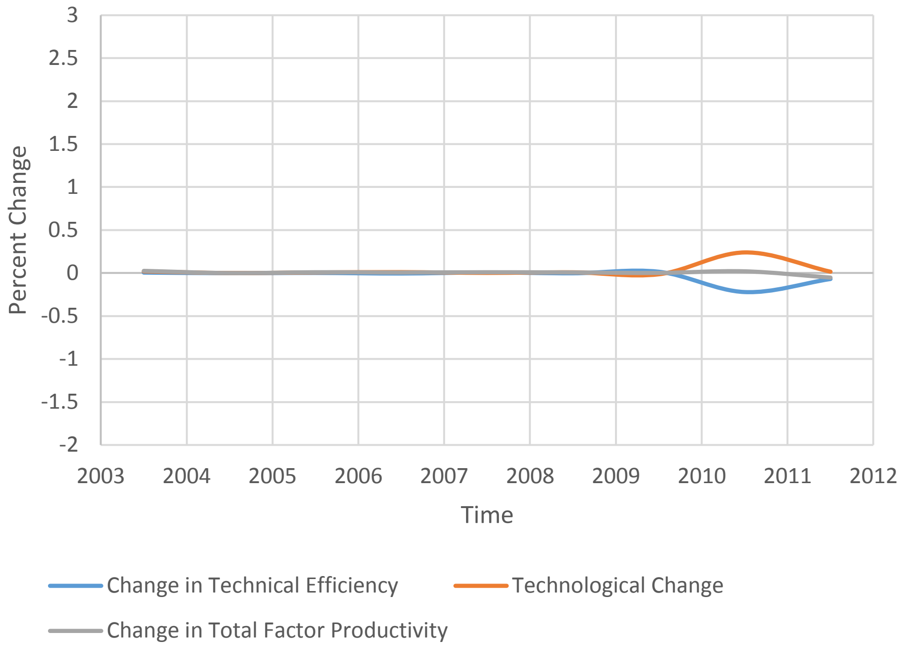
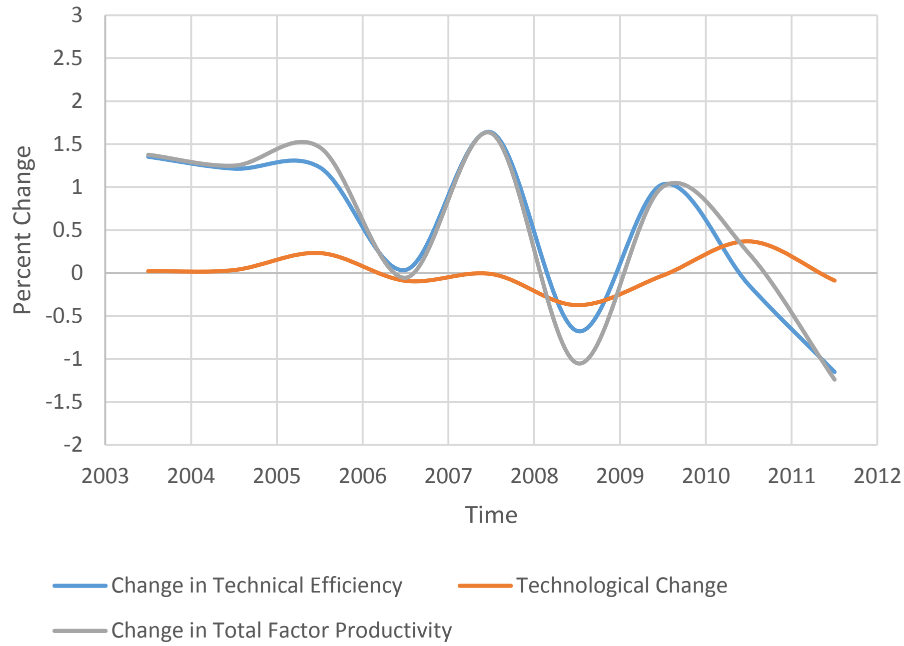


Figure 4-9 Mean Rate of Productivity Growth 2003 – 2012 for Other Energy Sources



Chapter 5 - Conclusions

This study examined the production of electric generation plants in the United States from 2003 to 2012 to answer three questions. 1) Does the level of aggregation of fuel input variables affect the plant efficiency scores and how does the efficiency of renewable energy compare to nonrenewable energy inputs; 2) Are policies geared toward directly or indirectly reducing greenhouse gas emissions affecting the production efficiencies of emitting electric generation plants; and 3) Do renewable energy policies and the use of intermittent energy sources affect the productivity growth of electric generation plants.

The first study used an input-oriented production DEA analysis to see if the level of aggregation of the input variables affect the pure technical, overall technical, and scale efficiencies. An average of 4,750 conventional and/or renewable power plants in the U.S. from 2003 – 2012 were analyzed. In general, the results show that power plants that use nuclear and renewable energy resources including geothermal, hydroelectric, and wind, have the highest mean pure technical, overall technical, and scale efficiencies of all the aggregate fuel groups. This implies that they are efficient from production standpoint but may not be the lowest cost producing plants. Plants that use coal and other energy sources have the lowest mean efficiency scores. The disaggregate and aggregate fuel groups were found to result in similar rankings based on the efficiencies of the electric generation plants. However, caution should be used when aggregating renewable energy sources since this resulted in the largest difference between the disaggregate and aggregate fuel groups. The rankings between the disaggregate and total aggregate fuel groups were not as similar compared to the rankings between the disaggregate and aggregate fuel groups particularly when the scale efficiency scores were determined. This implies that information about the efficiencies of different types of plants is lost in the aggregation of all the fuel inputs.

Using a total aggregate fuel input may make it harder for researchers to suggest how a firm can improve their production practices to become efficient from a production standpoint. In addition, it may artificially punish some power plants by suggesting they are inefficient even though, for the type of plant and type of fuel the plant is using, they are running efficiently. This implies that if a researcher is considering thermal power plants that use different types of coal, oil, and natural gas as inputs and that all these inputs are aggregated together, the plants that use coal are likely to be less efficient. To reduce the inefficiency the power plant may be inclined to decrease their use of coal, since they assume that it is making the plant inefficient. However, if the inputs are disaggregated it might be clear the coal unit is operating efficiently, given it is a coal unit, and that the power plant could improve its efficiency more by adjusting the input levels or scale of the petroleum or natural gas unit instead. In addition, by also considering nuclear and breaking down the types of renewable energy into smaller categories, it is easier to see what the most efficient fuel inputs are – nuclear and other renewable energy sources.

The second study used an input-oriented production DEA to determine if policies focused on reducing greenhouse gas emissions affect the pure technical, overall technical, and scale efficiencies when greenhouse gas emissions were included as an undesirable output. These policies are necessary to reduce greenhouse gas emissions because electric generation plants act myopically, conditional on government policies, focusing on their bottom line rather than what is best for the environment. This assumption implies that electric generation plants make production decisions based on what will generate the highest level of profit or lowest costs with a disregard for the environment unless policies with financial or production burdens dictate otherwise. Five policies were analyzed. One policy, the Regional Greenhouse Gas Initiative (RGGI), was the only policy directly designed to reduce greenhouse gas emissions. The other four policies – renewable portfolio standard, public benefits fund, mandatory green power option, and net metering, were designed to encourage the development of renewable energies.

The study found that these policies have resulted in mixed results on the production efficiencies of electric generating plants. RGGI was the only policy found to have a positive and statistically significant effect on the production efficiencies of the electric generation plants. This is the only current policy that is designed to directly reduce greenhouse gas emissions. This may be the result of the policy or due to electric generation plants in states with RGGI are more efficient from a production standpoint than electric generation plants in states without RGGI. Additional research needs to be done to determine the cause of the statistical significance.

To effectively reduce greenhouse gas emissions it might be beneficial to enact more policies like RGGI. Since the other renewable energy policies do not have a consistent negative effect on the production efficiencies, RGGI like policies (if found to make electric generation plants more efficient when greenhouse gases are considered) should not replace the policies that focus on increasing renewable energy deployment, instead they should be developed alongside these policies like RGGI has been. The renewable energy polices will encourage new energy development to come from clean sources while programs like RGGI directly encourage the reduction of greenhouse gas emissions from power plants that are already established. In addition, not all new power plant development will come from clean energy sources. By creating policies like RGGI, any new coal, natural gas, and petroleum power plants will be developed with lower emission levels than in years past.

The third study determined if renewable energy policies have an effect on the change in technical efficiency, technological change, and change in total factor productivity (TFP) for U.S. electric generation plants in the U.S. between 2003 and 2012. In addition, this study determined if the type of fuel used affects the overall productivity growth of electric generation plants. The Malmquist index was used to determine the change in technical efficiency, technological change, and change in TFP. A second-stage analysis used a tobit model to determine if renewable energy policies affect productivity growth and if the type of fuel used affects overall productivity growth.

Overall the study found that renewable energy policies do not have much, if any, consistent effect on the productivity of electric generation plants. Also, neither intermittent nor non-intermittent energy sources experience a clear consistent effect on the change in technical efficiency, productivity change, or change in TFP over time

The results of this thesis give some insight into the productivity of electricity in the U.S. First, renewable energies (intermittent or otherwise) are some of the most efficient fuel options from a production standpoint. In general, renewable energy policies do not have a consistent effect on the efficiency of power plants. The possible exception is RGGI, which has potentially encouraged the reduction of greenhouse gas emissions, making greenhouse gas emitting electric generation plants more efficient. The remaining renewable energy policies may be effective in encouraging the adoption of renewable energy but likely because renewable energy is an efficient fuel source, they do not affect the overall production efficiency of the firms.

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