International Institute for
Applied Systems Analysis
Schlossplatz 1
A-2361 Laxenburg, Austria

Tel: +43 2236 807 342
Fax: +43 2236 71313
E-mail: publications@iiasa.ac.at
Web: www.iiasa.ac.at

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Scaling and Cost Dynamics of Pollution Control Technologies: Some Historical Examples

Stephen Healey (sfh2@sfu.ca)

Approved by

Arnulf Grubler
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Contents

Abstract

The past forty years have seen significant diffusion of end-of-pipe pollution control devices as numerous developed countries have sought to reduce local air pollutants from coal-fired power. The apparent success of these technologies have led to the hope that Carbon Capture and Storage (CCS)- an end-of pipe technology for capturing and sequestering carbon dioxide- could play a similar role in helping humanity achieve its climate targets. Consequently, a scaling analysis of various pollution control technologies, which describes their rates and extents of growth at both the unit and the total market levels, is used as a historical analogue for CCS' potential in contributing to significant emissions reductions. This scaling analysis also provides corroboration of models predictions of CCS diffusion under climate policy, and also situates pollution control technologies within the existing scaling analysis literature for energy technologies. In addition, the cost dynamics of Flue Gas Desulphurization (FGD) is explored using regression analysis. It is hoped that this costing analysis will provide some insight into the likely future drivers of CCS costs, including a provisional learning rate for CCS.

Keywords: learning rate, diffusion, end-of-pipe, flue gas desulphurization, carbon capture and storage, scaling analysis

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About the Author

Stephen Healey is currently a PhD Student from the Resource and Environmental Management Program at Simon Fraser University in Vancouver, British Columbia, Canada, where his research is focused on Energy Policy and Energy Systems Modelling. The research for this Interim Report was begun during the Young Scientists Summer Program (YSSP) in 2012.

Scaling and Cost Dynamics of Pollution Control Technologies: Some Historical Examples

Stephen Healey

1. Introduction

Carbon Capture and Storage (CCS) is frequently touted in energy policy circles as a technology that could play a significant role in achieving climate targets. Synthesizing the energy modeling literature of the time, the IPCC special report on CCS (2005) has it accounting for between 15 and 55 percent of total emission reductions by 2100 in a climate constrained world (IPCC, 2005). Despite the large range of estimates, the impact of CCS on emissions reductions is important in most model scenarios. A key parameter contributing to this range is how models represent technological progress, and how this progress translates into future cost reductions for CCS relative to other low-GHG technologies. This applies whether models try to represent technological progress exogenously or whether they seek to endogenize technological progress through a number of diverse methods[1]. Nemet (2007), for instance, notes how a relatively modest change in the learning rate[2] -a common method of an aggregate representation of endogenous technical progress- for Solar PV from 0.26 to 0.17 results in a large change in the timing of its breakeven point with conventional technologies. Furthermore, the process of technological progress is complex with uncertainties and non-linearities, and it is unclear how well such a complex process is represented in traditional energy systems models which require a great deal of aggregation and generalization (Winskel et al., 2012).

Consequently, alternative approaches to assess the potential of CCS might be useful to corroborate the story generated from climate policy models. One such approach is the scaling dynamics of energy technology framework (as first pioneered in Wilson 2009), which employs a historical approach to analyze scaling for a given technology at both the unit and industry level. Given that CCS has yet to be implemented at a large scale I will use data of historically analogous technologies- end-of-pipe pollution control technologies in coal-powered plants- to explore possible rates and extents of CCS scaling at both the unit and the total market levels, and then see how these situate within

[1] See Loschel, 2002 for an overview of these methods.
[2] The rate of cost decline for a doubling of cumulative capacity (McDonald and Schrattenholzer 2001). In above example the cost reductions assumed range from 26 to 17 percent cost reductions per a doubling of cumulative installed capacity.

the existing modelling literature. Ultimately this work seeks to contribute to an understanding of whether policy can realistically induce the large scale deployment of CCS on the scale, and in the timeframes, necessary to contribute to significant global emissions reductions. Given that CCS is currently operating at only four sites globally, none of which are a power plant, this is a legitimate research question.[3]

In addition, the cost dynamics of these end-of-pipe technologies will be explored using regression analysis. With this, I seek to derive a learning rate for one of these end-of-pipe technologies-Flue Gas Desulphurization (FGD)- using different model specifications than what currently exists in the literature. In addition, I will use this analysis of the trends of FGD costs to discern the interrelationships (if any) between scaling and costs.

The paper is thus organized as follows. Section two provides a description of the technologies in question and describes their diffusion experience in some key markets. Section three explores the existing literature in scaling analysis and learning rate estimation for pollution control technologies, while section four describes the two aforementioned methodological approaches, and the data used in the analysis, in more detail. Sections five and six contain the results from the scaling and regression analysis respectively, while section seven discusses the results. Section eight concludes with some implications for further research and policy.

2. Background

The technologies considered in this paper include:

- Flue Gas Desulphurization (Wet and Dry)
- Selective Catalytic Reaction (SCR)
- Particulate Control Equipment (Electrostatic Precipitators, Baghouse Filters)

A description of these technologies, their diffusion experience in the US, and the diffusion experience of Japan and Germany, are outlined in subsections 2.1, 2.2, and 2.3 below.

2.1 Technology Description

The technologies assessed in this paper either employ chemical reactions or physical processes to remove pollutants from flue gasses. Flue Gas Desulphurization (FGD) technologies are one type of the former, acting to remove Sulfur Dioxide (SO_2) from waste (flue) gas by bringing the gas into contact with a reactive agent (usually lime or limestone). A reaction occurs with the gas in a steel column called an absorber, where the SO_2 and some of the reactive agent, are converted into solid waste (EPA, n.da).

[3] These are the Sleipner and Snohvit projects in Norway, in In-Salah project in Algeria, and the Weyburn project in the US/Canada (CCS Association, n.d).

FGD technologies can be either wet or dry. Wet FGD systems use a scrubbing liquid as the reactive agent, whereas dry FGD technology utilizes a dry/powdered form (EPA, n.da).

Selective Catalytic Reduction (SCR) scrubbers, which covert Nitrogen Oxide (NOx) into nitrogen and water, are another pollution control technology which utilizes a chemical reaction to achieve its end. SCR works by passing the waste gas through a catalyst container[4] where the gas reacts with the catalyst and ammonia to generate water and N_2 from NOx. On the other hand, the two most common forms of particulate control equipment-Electrostatic Precipitators and Baghouse filters- use an electromagnetic force and a filtration system respectively, i.e. physical processes, to remove particles from the flue gas (EPA, n.db).

These pollution control technologies are assumed to be analogous to post-combustion carbon capture, which is the carbon capture system closest to commercial deployment in power plants (IPCC, 2005). Post-combustion capture operates by passing the flue gas through a reactive agent (Monoethanolamine) in an absorber, where the agent removes the CO_2. A regenerator unit then strips the CO_2 from the reactive agent (Gibbins and Chalmers, 2008). In a fully integrated CCS system, the CO_2 is then compressed, transported, and geologically stored, while the solvent is recycled for later use (Gibbins and Chalmers, 2008).

Clearly, some of the aforementioned pollution control technologies prove to be better analogies than others. For instance, post-combustion capture has little in common with the removal mechanisms employed in particulate control equipment, due to their use of magnetism and filters to remove solid particles, however it does display similarities with the chemical based FGD and SCR. These similarities have influenced the latter's use as analogies for CO_2 capture systems in other papers in the literature (see Rubin et al, 2004; Rubin et al, 2007; Van den Broek et al 2009).

However, some significant differences remain. For one, most FGD systems are non-regenerative with respect to the reactive agent, consequently resulting in the generation of substantial amounts of waste (Calcum and Magnesium sulfite in plants using lime and magnesium as the chemical agent respectively, and gypsum in forced-oxidization plants). For instance, a 500MW coal-fired plant burning 3.5% sulfur coal that contains a forced-oxidation FGD system with 95% removal efficiency can generate about 47 tons of gypsum per hour (Chou, 1995). Assuming a capacity factor of 75% (or 6570 annual hours of operation), the above plant can generate about 308,790 tons of gypsum per year. While regenerative FGD technologies exist, they made up only 3% of the US market in 1998 (Srivastava and Jozewicz, 2001). The second major issue is that the capture stage is only one process of CCS, which also requires compression, transport, and storage of the captured CO_2. Thirdly, CCS costs are generally lower than FGD and

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[4] A container constructed from reactive metals and which changes the speed of the reaction.

SCR costs (per kg removed) due to greater concentration of CO_2 in the flue gas relative to SO_2 and NOx, as costs are generally an inverse relationship to concentration (See pg 230 in Grubler 1998 for a graphic illustration). Table 1 below compares some key engineering parameters for relating to FGD, SCR, and CCS systems from a new pulverized 500 MW (with 75% capacity factor) coal-fired power plant burning eastern bituminous coal with 3.25% sulfur content and 47.85% carbon content.

TABLE 1. SELECT ENGINEERING PARAMETERS FOR POST-COMBUSTION TECHNOLOGIES

	NOx (SCR System)	$S0_2$ (FGD System-Limestone based forced oxydation)	CO_2 (Anime Post-Combustion system
Cost of control device ($/ton removed)	$1200-$3200 (2008 $/ton)	$250-$600 (2008 $/ton)	$23-$35 (Assumed 2005 $/ton)
Pollutant flow (annual tonnes-my estimate)	1463	13,916	3,059,426
Emission Rate (no control)	0.45g NOx/kWh	2.45g SO_2/kWh	941g CO_2/kWh

Data From: (Rao & Rubin, 2002). Cost for NOx and FGD systems from Cichanowicz, 2010 and CCS cost from IPCC, 2005.

The adverse impact of these differences on the use of FGD as an analogy, however, are lessened by the fact that the regenerative/non-regenerative aspect is one difference out of many similarities, as well as by the fact that the other CCS components- transport and storage- are estimated to make up only 9-18%[5] of total CCS costs. Thus, the capture stage will rightfully be the driving force of future CCS dynamics provided that the underlying geology is suitable to long-term storage of CO_2. Finally, while the initial costs of CCS and FGD systems may differ due to the concentration differences discussed above, this does not mean that their internal dynamics, reflecting their growth and cost decline rates that will be explored here in this report, cannot be analogues.

2.2 Regulations (US)

a) <u>Particulates:</u> While particulate matter has a long history of regulation in the US at the state and municipal level[6], prior to the 1970 Clean Air Act Federal standards did not exist. While there was some strengthening of the Federal role through the Air Quality Act of 1967, it took the Clean Air Act Amendments (CAA) and the formation of the EPA in 1970 to establish widespread Federal regulation of particulates. In 1971, National Ambient Air Quality Standards (NAAQS) applied to Total Particulate Matter, setting 24 hour and annual average standards. Standards were expanded to target PM10

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[5] IPCC 2005, see Table TS9 on page 79.

[6] Prior to 1970, 53 cities has imposed limits on PM emissions from combustion and 10 states within their air quality standards (Bachmann, 2007).

in 1987 and PM2.5 in 1997.[7] Figure 1 below demonstrates the diffusion of particulate control units in the US between 1937 and 2010. Identified on the figure are the major regulations as discussed above. Evident is the pronounced growth in particulate controls installed just after the 1971 NAAQS, although diffusion of this technology begins to saturate by the time the later regulations are introduced. Note that the y-axis in Figure 1 has number of FGP units, while the corresponding figures for FGD (Figure 2) and SCR units (Figure 3) encountered later in this section are in GW. Unfortunately, unit capacity data was unavailable for FGP systems in the EIA source cited below figure 1. Also note that since retirement data was not available for any of the pollution control systems, the following graphs represent capacity installations but not retirement. This differs from some of the data used in the scaling analysis which employed cumulative capacity data (that of Rubin et al., 2004) and thus implicitly incorporated retirements. Furthermore, these figures, while representing installed capacity of these technologies over time, differ somewhat from the scaling analysis which follows in the later sections.

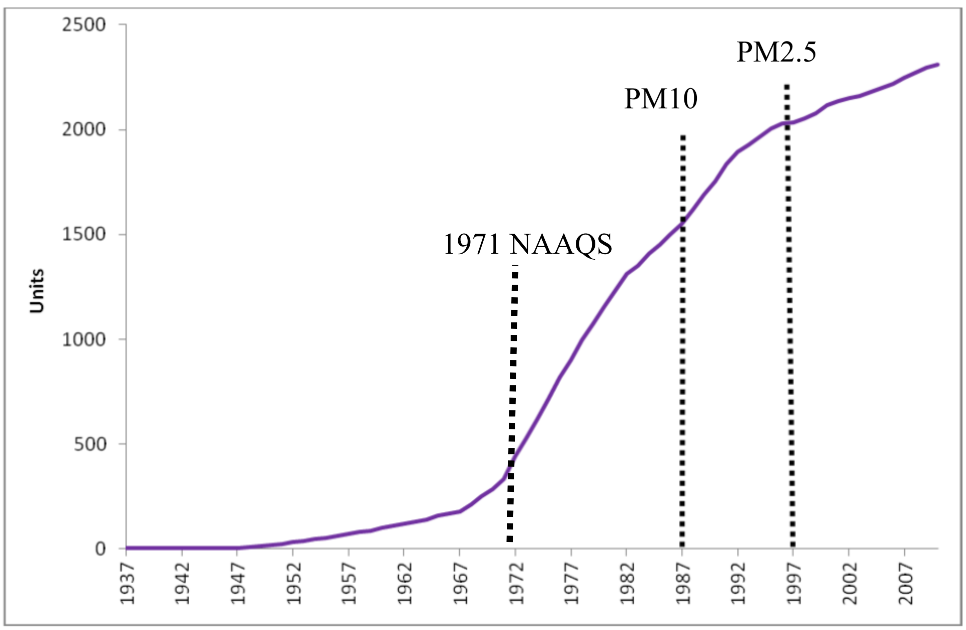

FIGURE 1. US FLUE GAS PARTICULATE (FGP) CONTROL CUMULATIVE UNITS INSTALLED 1937-201

Raw Data From: (EIA, 2011). Assembled by author (see supplementary materials 1 and 2).

b) <u>SO$_2$</u>: SO_2 was fist regulated at the Federal level under the 1970 CAA and the 1971 NAAQS (Popp, 2005). Part of NAAQS were the 1971 New Source Performance Standards (NSPS) which applied to new combustion plants, and which effectively spurred the beginning of the US Flue Gas Desulphurization (FGD) market (Markusson, 2012). In 1979, amendments to the NSPS resulted in the creation of differentiating emission standards for coals with different sulphur content, and in strict standards which

[7] Summarized from Bachmann, 2007.

effectively required that all new coal-fired power plants have FGD (Popp, 2004). This was an intensity target, which regulated the amount of pollutant at 1.2 pounds of SO_2 per million Btu of heat input (Popp, 2004). Figure 2 below illustrates the diffusion of US FGD units in relation to the major US regulations governing SO_2 control. Evident from the graph is how much the 1979 NSPS drove the diffusion of FGD in the US, growing by 44 GW between 1978 and 1990.

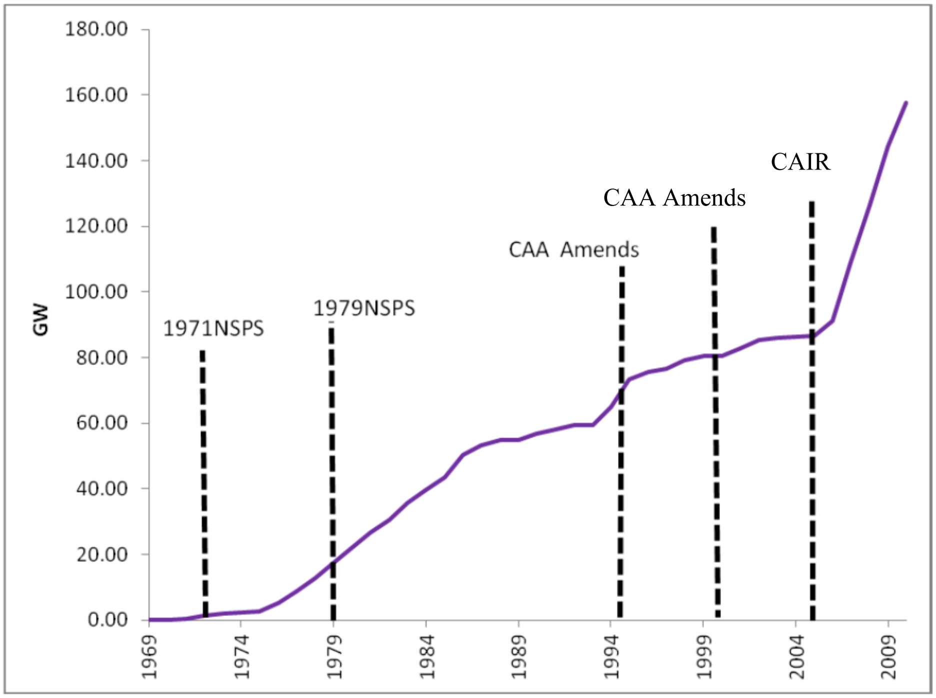

FIGURE 2. US INSTALLED FGD CAPACITY 1969-2010

Raw Data From**: (**EPA, n.dc). Assembled by author (see supplementary materials 1 and 2).

The 1990 Clean Air Act Amendments were the next major US regulation to impact FGD. It established an SO_2 emission permit trading scheme, in which plants are required to hold permits for each ton of SO_2 emitted (Popp, 2004). This occurred in two phases, one from 1995-1999 for one subset of plants and 2000-2009 for the other. This regulation changed the incentives facing utilities to adopt FGD, for unlike the NSPS, the 1990 CAA amendments applied to both new and old plants. At the same time, however, the regulation was no longer an intensity standard and instead created an aggregate emission limit for the power industry (Markusson, 2012). This allowed utilities a choice of methods to reduce emissions, ranging from low-sulfur coal with no post-combustion controls to FGD. While we see a build-up of FGD in Figure 2 immediately prior to the regulation, the growth in installations was nowhere near as pronounced as it was around the introduction of the 1979 NSPS.

In 2005, the US passed the Clean Air Interstate Rule (CAIR) whose goal is to reduce PM2.5 arising from SO_2 and NOx emissions through additional trading schemes for eastern states, and with deadlines for SO_2 reductions in 2010 and 2015 (Markusson, 2012). As seen in Figure 2, CAIR has resulted in a rapid build of FGD units since 2006.

c) ***NOx:*** While NOx emissions were covered by the 1971 NAAQS, standards were less stringent and, consequently, most utilities were able to meet the requirements of the regulations at the pre-combustion stage. As seen in Figure 3 below, widespread diffusion of SCR systems in the US did not occur until the 1990s, when NOx regulations were strengthened in California and in the Eastern US, beginning in 1999. Nationally, the 1990 CAA tightened emission standards by 2000, applying a differentiated emissions standard to both new and existing plants.[8]

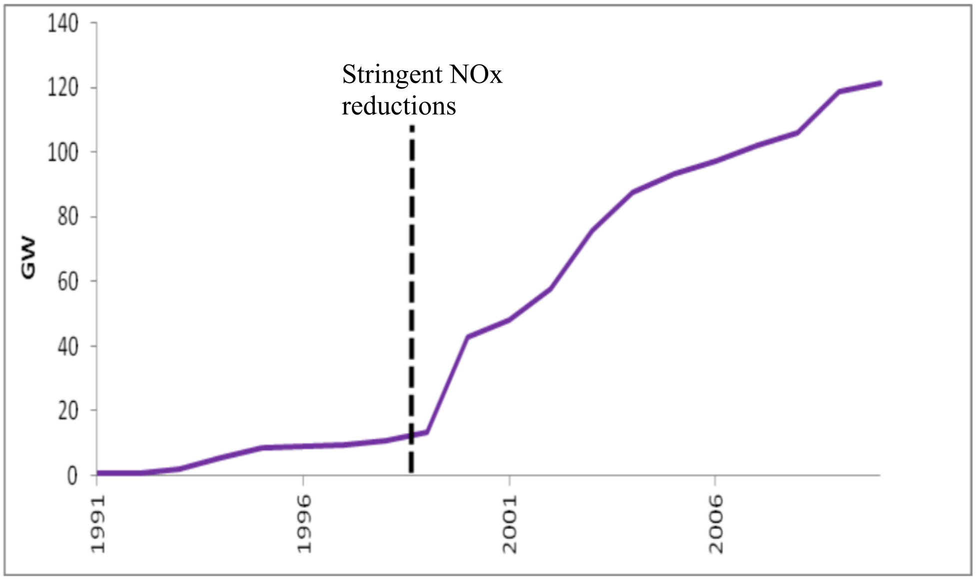

FIGURE 3. US INSTALLED CAPACITY OF SCR 1991-2010

Raw Data From: (EPA, n.dc). Assembled by author (see supplementary materials 1 and 2).

2.3 International Diffusion

This section broadly situates the US diffusion experience, described above, in an international context. Evident from figure 4 below is how both the US and Japan were relative leaders in FGD diffusion with Germany and the Rest of the World (ROW) as laggards. However, the scale of the graph in figure 4 masks some important differences between the two countries in the earlier years of FGD's introduction. Figure 5 below contains capacity data for Japanese Wet FGD units between 1960 and 2004. Comparing this graph to total US data in Figure 1, we see Japan had a considerable lead around 1970 relative to the US. This Japanese head start can be explained by her 1968 Air Pollution Control Law, which set emissions standards in Japan for NOx and SO_2, and which were further strengthened by amendments in 1970 and 1974 (Popp, 2004). These regulations were quite strict relative to the US (Popp 2004). Similarly, Figure 6

[8] The above paragraph was summarized from Popp, 2004

illustrates how Japan was the undisputed leader in SCR diffusion, corresponding to the stringency of its NOx regulations, relative to the US (Markusson, 2012). Evident also from both graphs was how Germany, while initially a laggard in the diffusion of both technologies, saw a subsequent rate of diffusion that was clearly quite rapid. This is due to Germany implementing strict air pollution standards considerably later than the US or Japan. For large (> 50 MW[thermal]) plants, the Ordinance on Large Combustion plants established emissions standards on June 1, 1983. Smaller plants (1-50 MWth) are covered by the Technical Instruction for Air Pollution Control, amended in 1986.[9]

Although international data is not available for comparison, it is assumed that the US is a leading country with respect to diffusion of flue gas particulate control devices.

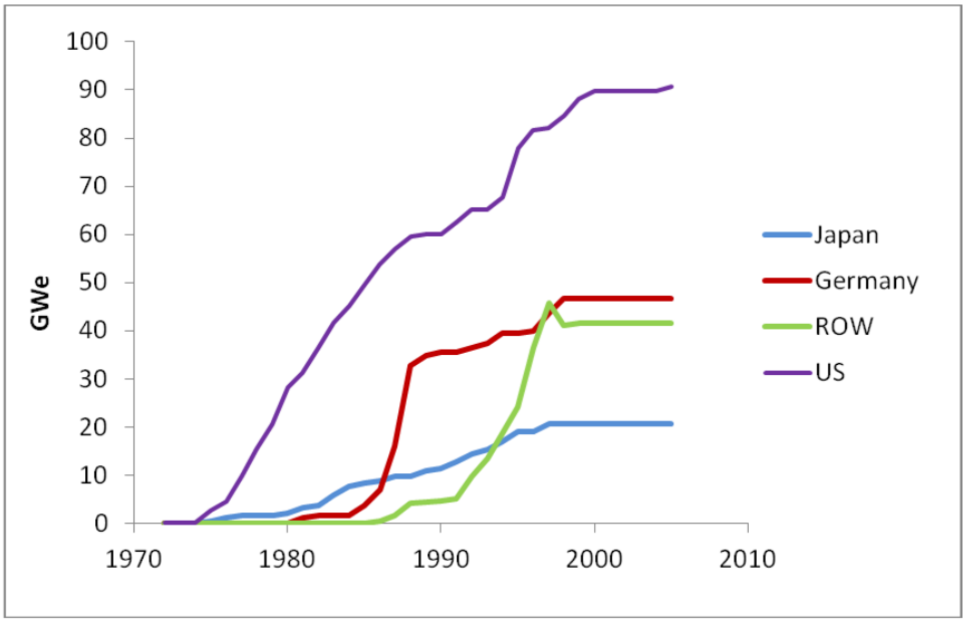

FIGURE 4. WET FGD CUMULATIVE CAPACITY

Data From: (Rubin et al., 2004)

[9] The above was summarized from Popp, 2004.

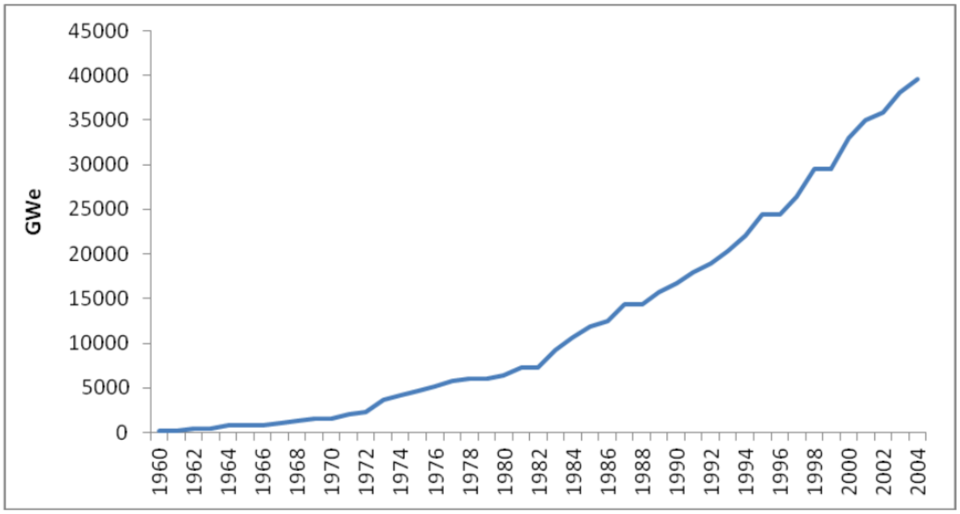

FIGURE 5. WET FGD INSTALLED CAPACITY (JAPAN 1960-2004)

Raw Data From: (CRIEPI, n.d). Assembled by author (see supplementary materials 1).

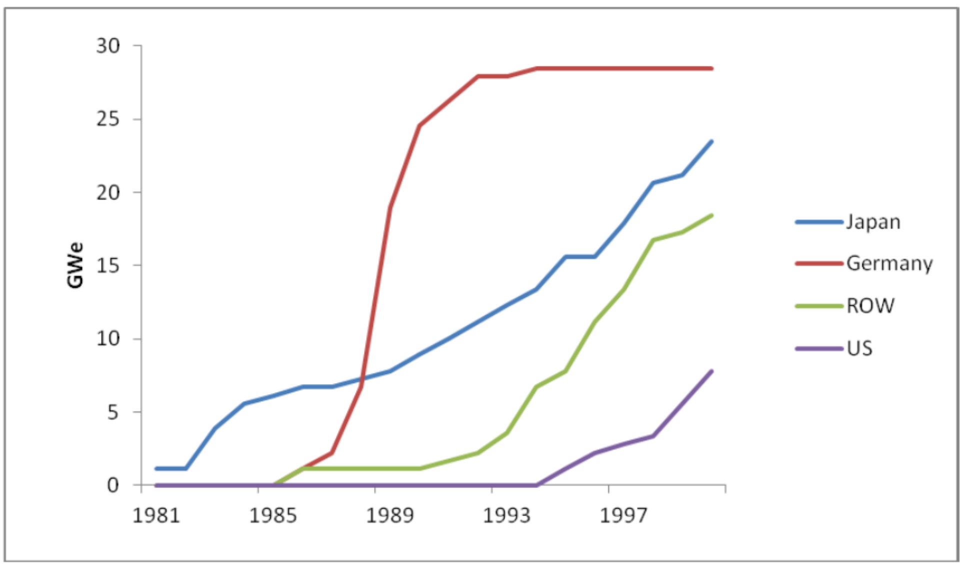

FIGURE 6. SCR CUMULATIVE CAPACITY

Data From: (Rubin et al., 2004)

3. Literature Review on Technology Scaling/Costing Analysis

Scaling, or up-scaling, refers to the increase in size of a technology at both the unit and industry level (Wilson, 2012). The literature on the scaling dynamics of energy technologies was pioneered in Wilson 2009, Wilson and Grubler 2011, and Wilson

2012. With precedents in the extensive work on diffusion theory[10] (see Mansfield 1968 and Grubler 1998 for reviews), the scaling dynamics of energy technologies is unique in both its meta-analytic approach, taking historical examples of scaling for a number of energy supply and demand technologies in order to discern patterns among them, and in its emphasis on both unit and industry scaling and their interrelationships. Some key findings from this research include:

a) Unit level scaling is often preceded by a lengthy formative phase where experimentation and learning can occur from the manufacturing of many smaller units (Wilson, 2012).
b) Unit-level scaling precedes industry-level scaling
c) Specific technology and market characteristics influence unit and industry scaling rates across technologies. For example, Wilson argues that the balancing of benefits from scale economies with the countervailing benefit of meeting demand for heterogeneous markets, is a key driver in understanding unit scaling rates across energy supply technologies (Wilson, 2012). Also, considerably faster industry-level scaling occurred in a later-adopting periphery relative to an early-innovating core.
d) There exists a consistent relationship between the extent and duration of industry scaling for both supply-side and end use technologies (Wilson, 2009).

While the aforementioned work explored scaling for a wide range of energy supply and end use technologies, pollution control technologies were not analyzed. As a starting point of this research I hypothesize the existence of fundamentally different dynamics for end of pipe pollution control technologies relative to energy supply and end use technologies. Firstly, the former's diffusion was almost entirely driven by regulation, while most of the latter diffused primarily according to market dynamics. Secondly, pollution control technologies are so called "add on" technologies, which serve no purpose on their own and need to combine with existing energy supply technologies such as coal power generation. This is an important consideration for, unlike energy supply/demand technologies, pollution control technologies need not be concerned to the same degree with capital stock turnover or missing supporting infrastructure, which would affect their rate of diffusion (Wilson, 2009). This is only partially analogous to CCS, which combines elements of "add on" technologies (in the capture stage) with the requirement of supporting infrastructure and the need to combine with other technologies in the transport and storage stages.

As mentioned previously, this work also seeks to derive a learning rate for Flue Gas Desulphurization technologies. Unlike the scaling dynamics of energy technologies, the learning curve literature is extensive with considerable antecedents (Wright 1936; Arrow 1962, Argote and Epple 1990). Traditional learning curves relate declines in unit costs to a measure of cumulative experience gained with that technology, as for instance

[10] Research seeking to understand the controlling factors determining the rates and extents of technology diffusion, i.e. the spread of technology adoption over time and space.

total cumulative production volumes, or cumulative units built. Learning curves are used to measure the phenomenon known in economics as learning-by-doing, whereby firms get better at producing a given technology by practice and experience manifested through improved plant management, improved worker productivity, and improved design- all of which drive down costs (Grubler et al. 1999). The learning rate, derived from the linear estimation of the aforementioned learning curve, is the rate in which unit costs decline for every doubling of cumulative experience.

In the energy field, almost exclusively cumulative installed capacity (McDonald and Schrattenholzer 2001) is used in learning curve analysis, due to the dominance of electricity generating technologies in the energy learning curve literature. A serious issue with this approach, however, is that unit-level economies of scale and learning are confounded by such an aggregate measure of cumulative experience. Learning curve concepts have seen a resurgence in the energy literature with the emergence of a so-called two-factor learning curve model (Klaassen et al. 2005, Barreto and Kypreos 2003, Miketa and Schrattenholzer 2004) that try to describe the influence of both R&D and cumulative capacity on cost declines, referred to as learning “by searching” and “doing” respectively. Further studies by Soderholm and Sundqvist (2007), Isoard and Soria (2001), and Kalouhi-Brahmi (2010), create simple multi-factor learning curves that also try to control for input cost changes, economies of scale, and exogenous technological change. Criticisms of these models, however, include (but are not limited to) statistical identification issues pertaining to separating learning from exogenous technological progress (Nordhaus, 2009), the assumption of R&D and Cumulative experience being two separate learning processes which are substitutes for one another, rather than complements (Halsnaes et al., 2007), as well as other statistical issues pertaining to omitted variable bias and simultaneity (Soderholm and Sundqvist, 2007).

A more promising approach has been developed by Nemet (2007) who employs a multi-factor decompositional approach for analyzing cost declines in US Solar PV technologies. His use of a bottom-up engineering analysis, rather than industry level regression analysis, allows for consideration of a greater number of factors when explaining cost changes for a relatively new energy technology. Consistent with the findings of the technology scaling analysis literature discussed above, Nemet (2007) found significant economies of scale effects at the industry scale. Similar studies were performed for nuclear reactors by Zimmerman (1982) and for coal-fired power plants by Joskow and Rose (1985).

For pollution control technologies there are few studies assessing their cost dynamics. Rubin et al., (2004) calculated learning rates of 11% and 12% for FGD and SCR technologies respectively; however, this paper based these rates off of five data points, with standardized engineering parameters, and thus statistically problematic and also may not truly reflect the historical reality. Similar work, although with different data, was performed by Lohwasser and Madleiner who estimated a two-factor learning curve for FGD technologies and found a joint learning rate of 12.1%. After decomposing learning into learning-by-doing and learning-by-researching, the learning-by-doing component had a learning rate of 7.1% (Lohwasser and Madlener, 2010).

Lange and Bellas (2005) conducted a large model, in the style of Zimmerman (1982) and Joskow and Rose (1985), to explain capital and operating cost trends for FGD units. Interestingly, they found there to be a positive time trend with respect to capital costs, contradicting the findings of Rubin (2004). In addition, this trend was not statistically significant in explaining cost dynamics.

4. Data and Methodology

4.1 Scaling Analysis

As in Wilson (2009), the scaling analysis seeks to describe the growth of a technology at both the unit and industry levels. Following his method, I fitted a three-parameter logistic function to historical data of cumulative capacity and unit scale for the aforementioned pollution control technologies. The logistic function takes the following form (Wilson, 2009):

$$y = \frac{K}{1+e^{-b(t-t_0)}} \tag{1}$$

and

$$\Delta t = \frac{1}{b} log81 \tag{2}$$

where:

K= the eventual saturation level of a technology

T_m= the inflection point or maximum growth point

b= diffusion rate

Δt= Time, in years, for the technology to go from 10% to 90% of the total extent of scaling. Diffusion time.

Parameters of interest included the Δt, T_m, and K which were calculated for the industry scaling variable cumulative capacity (measured by units and MW's), as well as the unit scaling variables of average unit size and maximum unit size (both in MW). FGD and SCR units had the best data, allowing me to estimate the parameters for all the variables described above for these technologies. For Flue Gas Particulate (FGP) control technologies, data limitations limited the analysis to the industry scale, and for units only. US industry scale data for most technologies was obtained from EIA Form 860, containing detailed information on pollution control equipment. Data for non-US cumulative capacity for SCR and Wet FGD technologies was obtained from figures 1 and 3 in Rubin et al., (2004). Unit capacity data for both US FGD and SCR technologies was obtained from the EPA's preliminary draft estimates of current and announced control technology installation, which is available online[11]. Finally, Japanese FGD unit capacity data was obtained from communications with officials at Japan's Central Research Institute for the Electric Power Industry (CRIEPI, n.d).

Data fitting was performed by the Logistic Substitution Model II (LSM2), a logistic function fitting program freely available online at the International Institute for Applied Systems Analysis (IIASA). Rules of thumb for retaining the fitted logistic curve results for subsequent analysis were taken from Wilson (2009) and included: a) the data series having to cover at least 60% of the full S-curve range and b) the logistic function displaying high goodness of fit to the data (>95%). The use of logistic functions is justified on the basis of a wealth of empirical evidence demonstrating the appropriateness of S-shaped growth function such as the logistic in describing the historical diffusion patterns of most technologies (Geroski, 2000).

Other analytical simplifications used included taking the average of the stock- that is the cumulative average at the end of a given year- to calculate annual average unit scale, and using an envelope approach- where the largest unit produced to date is taken to be the "maximum" for that year- to estimate maximum unit scale. This was done to eliminate the fluctuations that would occur from taking annual averages/maximums that would make the fitting of a logistic function nonsensical for these unit-scale indicators.

Finally, for some data there are multiple logistic curves nested within the same dataset. For instance, due to the nature of US regulations for sulfur reductions, which have been increasing in scope over time, an initial pattern of growth and saturation for cumulative FGD capacity was later followed by a second round of expansion around 2006. For the purpose of fitting logistic curves to the data, it is sufficient to employ only one of these subsequent phases, as it is assumed that the dynamics inherent in the first phase will best represent the initial stages of diffusion of a new pollution control technology (i.e. CCS) under a more or less constant incentive/regulatory environment. A similar approach was applied to maximum and average unit scale for FGD.

Once the above parameters were obtained for pollution control technologies, they were then compared to the results in Wilson (2009) for conventional and renewable energy technologies in order to ascertain if pollution control technologies are characterized by fundamentally different dynamics than other energy technologies. In addition, the estimated parameters for pollution control technologies were used to see whether or not the diffusion experience for pollution control technologies is consistent with some of the key tenants of diffusion theory, explained in further detail in section 5.

[11]See EPA(n.dc) in references

4.2 Regression (Costing Analysis)

In addition to the scaling analysis described above, regression analysis was performed to understand the cost dynamics for FGD. Here I estimated as a base model an equation relating unit costs (normalized by MW's) to a number of key engineering and economic variables. All cost data was obtained from EIA Form 860 which contained cost data for over 600 FGD units.[12] This number was reduced to 303 observations after removing all sites below 25MW to ensure an apples-to-apples comparison of similar units[13] and after taking into account considerations of data availability for capacity and other variables (see supplementary materials 2 for the final dataset used in the regression). The theoretical model is described in equation 1 below:

$$COST/MW_i = (EXP_i, UNSIZE_i, PLCON_i, RETROFITi, COALSO_2i, TRAINSi, INDCONi, REMEFF_i, STEEL_i, AVGUNI_i, ENER_i, WETi) \quad (3)$$

The rationale for these variables, an explanation of their construction, and a documentation of their data sources, are all found in Table 2 below. Justification for this model was based on the consultation of a number of technical and economic studies of FGD systems[14]-where the aforementioned variables re-appeared regularly. In addition to this base model, a number of alternative specifications (with additional variables that were mentioned in the literature, albeit less frequently), were included in the sensitivity analysis in section 6. A description of the sensitivity analysis is located in Appendix F.

TABLE 2. VARIABLE EXPLANATIONS

Variable	Explanation and Rationale	Construction	Data
COST/MW	Dependent variable ($/MW).	Total installation cost (structure cost, disposal cost, and other) and divided by the corresponding MW size of the boiler. Being an "installation cost", the value reflects markup/profits on the part of FGD unit manufacturers.	EIA 2011. EPA n.dc
EXP	Cumulative units built as measure of experience and a proxy for learning-by-doing. As more units are built, FGD manufacturers and utilities are expected to learn from experience, translating into lower costs	Count of all previous FGD units constructed preceding the construction of the FGD unit in question.	EIA 2011
UNSIZE	Size of the unit in MW. Captures (dis)economies of	Given in EPA's preliminary draft estimates of current and	EPA n.dc

[12] Disaggregated originally as structure, disposal, and other costs. My dependent variable was the sum of these three.

[13] Many smaller sites involve FGD units installed in paper mills and other applications. Since the emphasis of the costing analysis is on the cost trends of FGD units as an analogy to CCS is coal-fired power plants, these observations were removed.

[14] Srivastava & Jozewicz (2001), Cichanowicz (2010), Devitt et al., (1976), EPA (2002)

	scale where larger(smaller) units result in lower(higher) costs per unit	announced control technology installation	
PLCON	Sulfur concentration in the flue gas. The higher the concentration, the easier to remove from the flue stack and thus the lower the costs	Given pounds of sulfur emitted per hour (after pollution control) and efficiency of the removal unit, one can calculate how much SO_2 is emitted per hour. Dividing this by flow rate in ft^3 per hour provides the SO_2 concentration of the plant's flue gas.	EIA 2011
RETROFIT	FGD units built simultaneously with a new plant can be incorporated into its design, reducing costs. Retrofit applications require the system be adapted to the existing plant design (Hoskins, 2012).	Binary variable. If the date the FGD unit was built is <2 years[15] after the date of construction of its associated boiler, one can conclude that it was not a retrofit.	Platts (2011) for date of boiler. EIA 2011 for date of FGD unit.
$COALSO_2$	Sulfur concentration of the coal (see PLCON for rationale)	% of SO_2 in the coal. Given in Form 860.	EIA 2011
TRAINS	The number of absorber trains associated with a given FGD unit. Multiple (spare) trains were often built in order to ensure higher reliability. More equipment/unit = Higher costs	Divided the number of trains associated with a given FGD unit by the MW size of the unit.	EIA 2011
INDCON	Index of market concentration of FGD suppliers for the year the specific FGD unit was built. More concentrated market implies the ability to engage in oligopolistic pricing by FGD manufacturers and hence higher costs	Created a Herfindahl-Hirschman index of unit manufacturers from data provided in EIA form 860. Took a five year moving average to remove data perturbations from economic business cycles. See Appendix A for further details on its construction.	EIA 2011
REMEFF	Pollutant removal efficiency. Increased performance targets and associated design changes are expected to result in higher costs	Removal efficiency of the scrubber in %. Given in Form 860	EIA 2011
MAT	Index measuring the cost of key input materials specific	See Appendix B for details. Took the average of the two years	My construction. See Appendix B

[15] It takes on average 3 years from design to completed installation for an FGD System with most construction work occurring in the latter 2 years (Cichanowicz, 2010)

	to FGD units for a given FGD unit in the sample.	preceding the unit's start date as it takes an average of three years to build and install and FGD system with most of the construction work occurring in the latter two years (Cichanowicz, 2010.)	
AVGUNI	A measure of economies of scale at the firm level. The greater the output per firm, the greater the opportunity for manufacturing-scale economies, i.e. economizing by reducing overlap/redundancy, and thus lowering costs.	Annual output divided by the number of firms producing output for the year a given FGD unit was built. Took a five year moving average to remove data perturbations from economic business cycles.	EIA 2011
ENER	Index of energy prices. Since FGD units employ energy in their construction, higher energy prices correspond to higher unit costs.	Weighted consumer energy price across energy sources which I then converted to an index with 1982 as the base year. Took the average of the two years preceding the unit's start date as it takes an average of three years to build and install and FGD system with most of the construction work occurring in the latter two years.	EIA 2012
WET	Type of FGD unit (wet or dry) which impacts the cost structure with wet units tending to have higher capital costs than dry FGD units	1 if wet FGD and 0 otherwise. Compared relative to the reference group of dry FGD units.	EPA n.dc

The functional form for this analysis was similar to that used in Lange and Bellas (2005) and results in a log-log specification. Evidently, the model above is quite similar to that of Lange and Bellas (2005), who employed a similar approach in explaining FGD capital cost trends, including use of a very similar datatset (basically employing the same dataset as me until 2005). However, there are some important differences as discussed below:

1) I normalize the dependent variable by MW to determine trends in the cost per MW rather than the absolute cost trends. This is important as MW's are the ultimate products delivered by utilities, and so the relative advantage of a given technology depends on its trend in costs normalized to this unit.
2) Similarly, by normalizing the dependent variable to unit size, I capture unit economies of scale through an independent variable that tests if larger units result in lower costs *per unit*. Unit economies of scale cannot be captured by

simply regressing size against un-normalized cost. Obviously larger units in absolute size will result in larger absolute costs.

3) My model specification includes an explicit consideration of technological learning and documents alternative formulations of the experience variable used in learning curve analysis.
4) My base model, combined with the numerous specifications in my sensitivity analysis, contains several additional variables identified in the literature as important in understanding FGD cost trends.
5) I update the analysis to include years after 2005, where there was a substantial increase in the build of new FGD units with potential implications for cost dynamics.

5. Scaling Analysis Results

5.1 Market Scaling

The results from the market scaling analysis are illustrated in Table 3 below. The data comes from a number of sources and, in some instances I estimated scaling parameters for the same technology from more than one data source to corroborate my findings.

TABLE 3. MARKET SCALING ANALYSIS PARAMETERS

Technology	Juris-diction	Time	Data Source	Unit	K	Tm	Δt	R^2
Wet FGD Scrubbers	US	1972-2005	Rubin et al., 2004	GW	91	1985	22	0.98
Wet FGD Scrubbers	Japan	1972-2005	Rubin et al., 2004	GW	22	1989	20	0.99
SCR	Japan	1981-2000	Rubin et al., 2004	GW	46	1999	31	0.98
FGD Scrubbers	US	1969-2006	EPA n.dc	GW	80	1985	23	0.98
FGD Scrubbers	US	1969-2006	EPA n.dc	Units	220	1986	23	0.99
FGD Scrubbers	Japan	1960-2004	CRIEPI n.d	GW	59	1989	38	0.98
FGD Scrubbers	Japan	1960-2004	CRIEPI n.d	Units	118	1979	23	0.97
Wet FGD Scrubbers	US	1969-2006	EPA 2011	GW	72	1984	21	0.98
Wet FGD Scrubbers	US	1969-2006	EPA n.dc	Units	155	1982	19	0.98
Dry FGD Scrubbers	US	1981-2010	EPA n.dc	GW	23.5	2001	40	0.97
Dry FGD Scrubbers	US	1981-2010	EPA n.dc	Units	69	1994	24	0.99
All FGP Units (Particulate Removal)	US	1937-2010	EIA 2011	Units	2249	1980	29	0.99
Electrostatic Precipitator (Particulate Removal)	US	1937-2010	EIA 2011	Units	1338	1977	22	0.99
Baghouse (Particulate Removal)	US	1962-2010	EIA 2011	Units	507	1990	21	0.99
FGP- Wet Scrubber (Particulate Removal)	US	1956-2010	EIA 2011	Units	90	1979	29	0.99
Wet FGD Scrubbers	Germany	1972-2005	Rubin et al., 2004	GW	44	1988	7	0.98
Wet FGD Scrubbers	Rest of World	1972-2005	Rubin et al., 2004	GW	43	1994	6	0.99
SCR	Germany	1981-2000	Rubin et al., 2004	GW	28	1988	2.7	0.99
SCR	ROW	1981-2000	Rubin et al., 2004	GW	20	1995	8.7	0.99
SCR	US	1981-2000	Rubin et al., 2004	GW	18	2000	8	0.98
SCR	US	1991-2010	EPA n.dc	GW	118	2001	9.6	0.99
SCR	US	1991-2010	EPA n.dc	Units	240	2002	10.2	0.99

The main parameter of interest is the delta t (Δt), which, as described earlier, measures the number of years for the technology in question to grow from 10% to 90% of its eventual market size. Evident from the table, this varies substantially between the technologies and jurisdictions in question, ranging from 2.7 years for German SCR units to 40 years for US dry FGD units.

This aggregation of jurisdictions, however, masks an important distinction- that between core and periphery markets. Core markets are the initial markets where diffusion of a given technology begins, while periphery markets are followers which see diffusion later. One of the key tenants of diffusion theory is that the delta t's exhibited for a technology in its core market tends to be higher- that is, diffusion is slower- than the corresponding delta t in a non-core markets (Grubler, 1996). Non-core markets benefit by learning from the experiences of the core area (Grubler, 1996). The separation of these two types of markets- core and non-core- is thus essential for making meaningful comparisons of rates of diffusion.

Figure 7 below compares my estimated delta t's for pollution control technologies (blue) with those for conventional and renewable energy technologies for core markets as estimated in Wilson (2009).

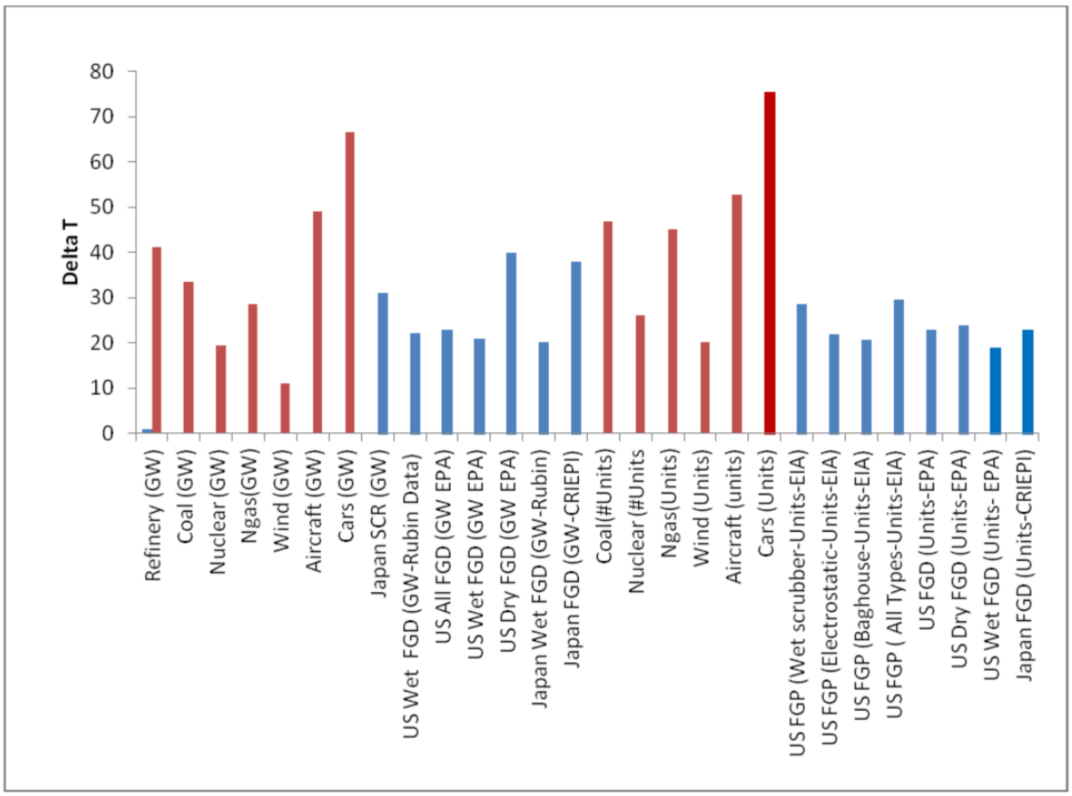

FIGURE 7. INDUSTRY SCALE ACROSS TECHNOLOGIES (CORE MARKETS)

Assembled by Author: See Supplementary Materials 1

We see from Figure 7 that the delta t's for pollution control technologies compare rather well with conventional energy technologies. Thus, even though these technologies were forced into the market through various regulations, their rates of diffusion were no different than energy technologies which were more market driven in nature. The consistency of this observation across technologies, across countries, and thus, across regulatory regime is particularly fascinating. Further exploration of this phenomenon will be elaborated upon in Section 6.

Figure 8 below compares the delta t's for non-core markets for pollution control technologies (green) with the delta t's for non-core markets for other energy technologies (taken from Wilson 2009).

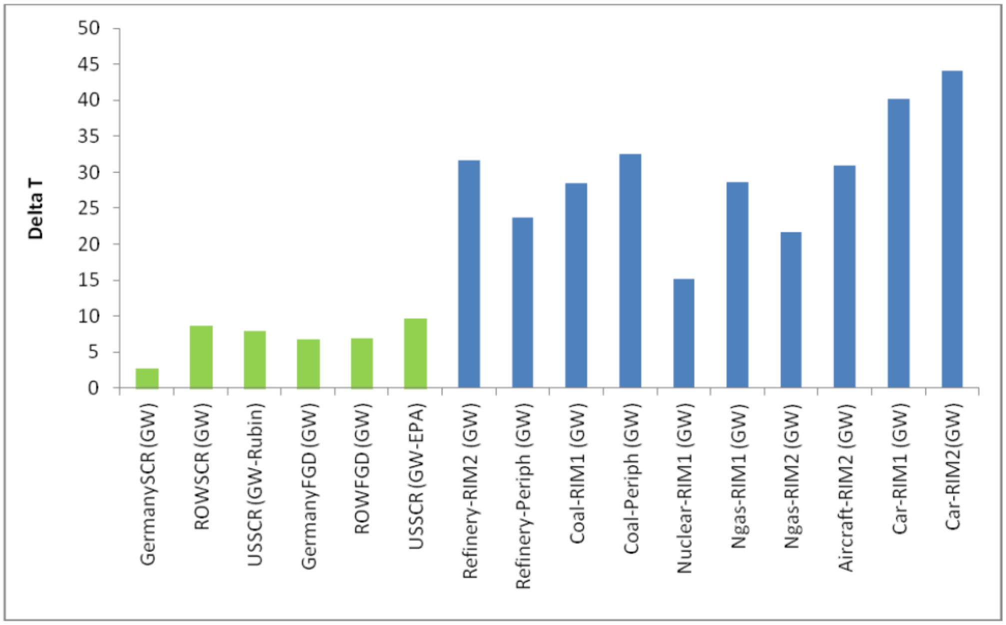

FIGURE 8. INDUSTRY SCALING ACROSS TECHNOLOGIES (NON-CORE)

Assembled by Author: See Supplementary Materials 1

In contrast to the earlier finding surrounding core markets, here we see the delta t's for pollution control technologies to be much lower than that of conventional technologies diffusion in non-core markets. While the reason behind this finding is unclear, its implications are quite positive for the prospects of CCS as it implies that once CCS has seen diffusion in a core market, and if there are policy regimes in the non-core markets supportive of CCS, we could see a rapid diffusion of CCS in these jurisdictions. An important caveat to this last point, however, is that CCS's diffusion is also constrained by the suitability of geological storage, and so we are likely to only see the above rates of diffusion in areas where the geology supports CO_2 storage and where sufficient CO_2 transportation infrastructure is developed.

In addition to the above analysis, it can be also shown that pollution control technologies are consistent with most key aspects of diffusion theory. Three aspects to be tested include:

1) The inverse relationship between delta t and adoption date (where we would expect to see higher Delta T's for core markets relative to non-core).
2) The inverse relationship between intensity of diffusion and adoption date (core markets essentially witness a more thorough extent of diffusion than non-core markets) (Grubler 1996).

3) The positive relationship between the rate of scaling (delta t) and the extent or magnitude of scaling (k) (Wilson, 2009).

Regarding the first point, Figures 9 and 10 below plot the estimated delta t against the adoption date (measured as the date the first unit was installed) for FGD and SCR technologies respectively. As one can see, there are less FGD observations in Figure 9 relative to Table 3 as I only include the calculated diffusion rates for wet and total FGD while excluding dry FGD which I categorize as a separate technology.

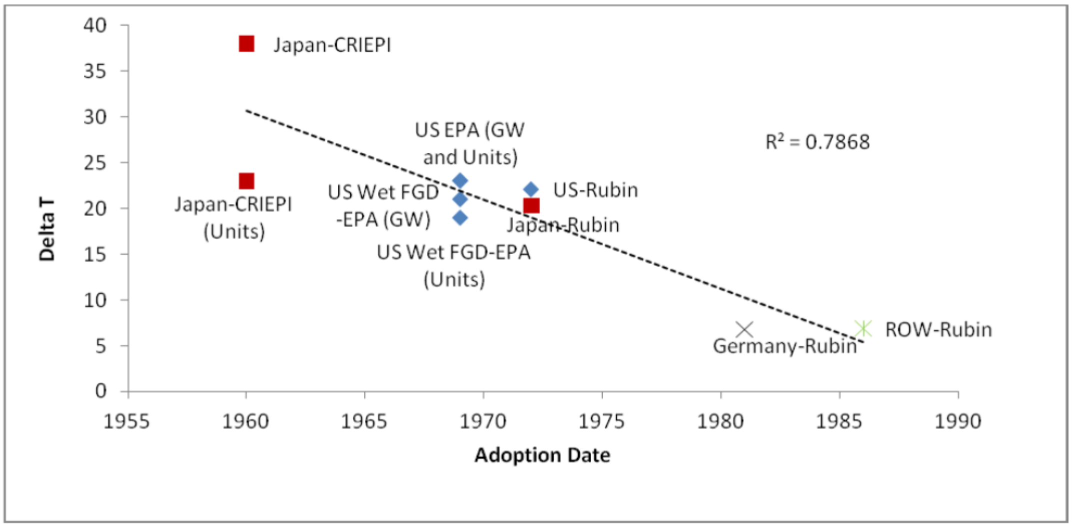

FIGURE 9. FGD DELTA T VS. ADOPTION DATE

Assembled by Author: See Supplementary Materials 1

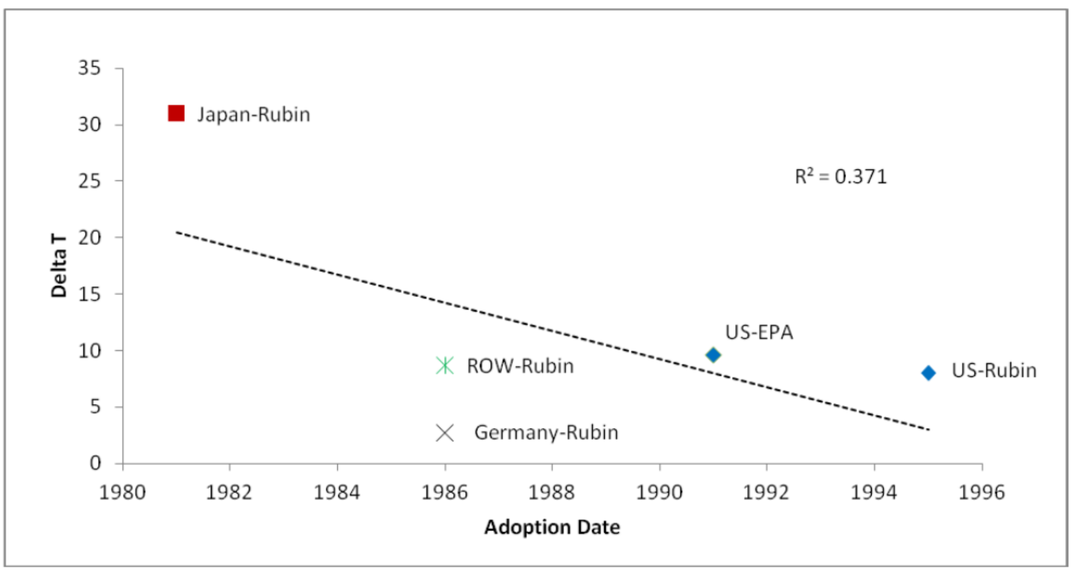

FIGURE 10. SCR DELTA T VS. ADOPTION DATE

Assembled by Author: See Supplementary Materials 1

As expected, for both technologies we see a downward sloping relationship, where jurisdictions who adopt earlier show slower diffusion (higher delta t), albeit a much stronger one for FGD technologies compared to SCR. With so few data points and a major outlier (Germany for SCR), one cannot state any firm conclusions about the above exercise. However, its consistency with a major point in diffusion theory is reassuring.

A second finding in diffusion theory is that although diffusion is slower in core markets relative to non-core, the intensity of adoption tends to be higher, indicating a greater preponderance of that technology in core markets (Grubler, 1996). Although the relationship is not as strong as the adoption date-diffusion rate relationship, the experience with pollution control technologies appears somewhat consistent with this intensity finding for SCR technologies, although barely for FGD units demonstrated in Figures 11 and 12 respectively, which plot intensity (measured by GW pollution control equipment installed per TWh of coal use) against the adoption date. We again witness the expected negative relationship, as adoption intensity is higher among early adopters, consistent with diffusion theory. Part of the reason for the weaker relationship seen here is Germany, who is a major outlier in both cases. Evidently, the number of observations in each figure is much lower than compared to the tables and figures above. This is because here I am measuring intensity as my dependent variable rather than diffusion speed and so, it would not make sense for me to subdivide FGD units into dry and wet FGD systems (as dry FGD systems employ a niche market relative to Wet FGD, they would differ in intensity by definition). Similarly, because intensity was measured as GWe per TWh of coal use, all data points in units were excluded.

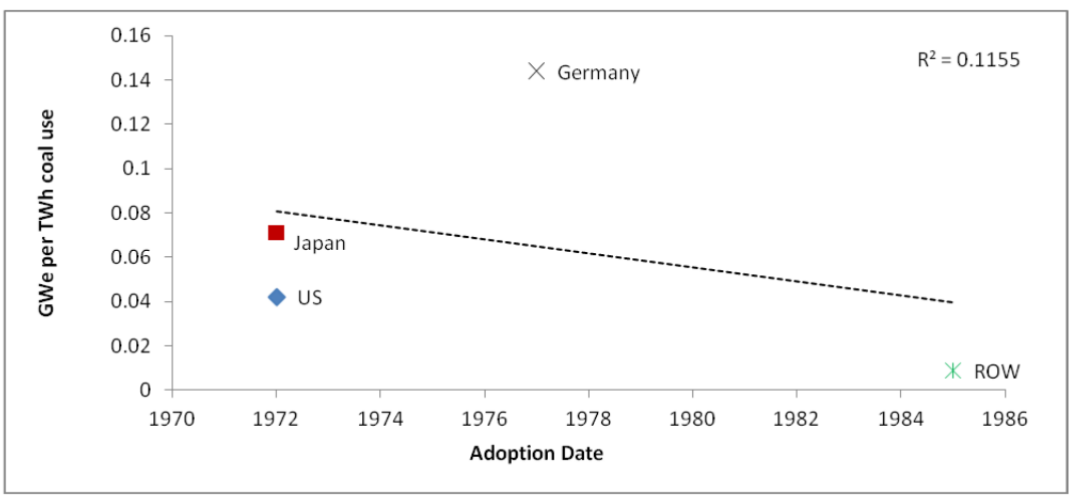

FIGURE 11. INTENSITY VS. ADOPTION DATE FGD

Data from: (Rubin et al., 2004 for GWe, IEA 2007 for TWh of coal use). Assembled by Author: See Supplementary Materials 1

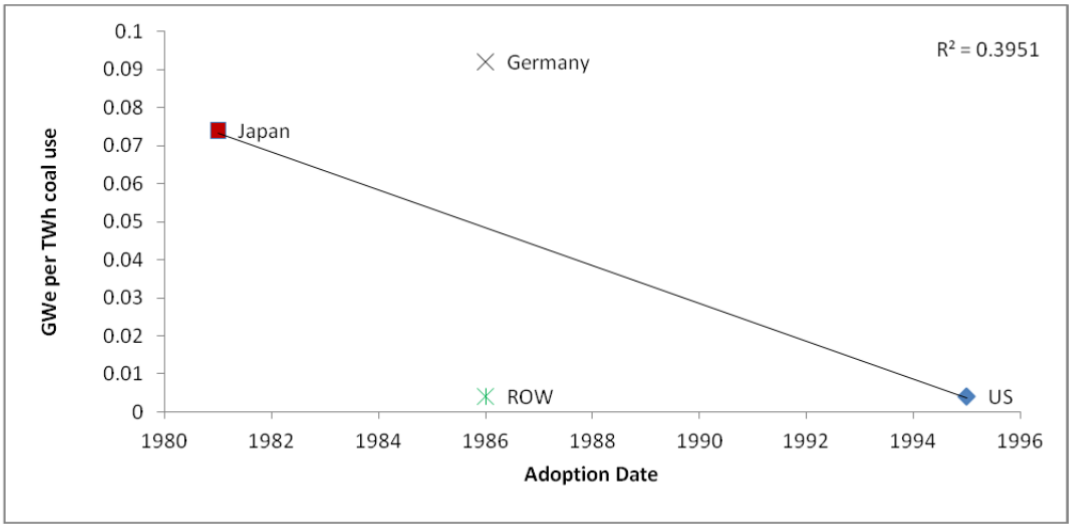

FIGURE 12. INTENSITY VS. ADOPTION DATE SCR

Data from: (Rubin et al., 2004 for GWe, IEA 2007 for TWh of coal use). Assembled by Author: See Supplementary Materials 1

The final point explored was the relationship between the eventual K (saturation point) and delta t. A major finding in Wilson (2009) was that technologies with higher saturation levels (higher K) also took longer to diffuse (higher delta t). While this is partially a simple artifact of the fact that it takes longer to diffuse in larger markets, the consistency and strong fit of this relationship for various technologies, ranging across jurisdictions and policy regimes, and applying equally well to both supply and end-use energy technologies, was definitely noteworthy (Wilson, 2009). Figure 13 below demonstrates this phenomenon with core market data from Wilson (2009) for a number of energy technologies. Since the saturation level will vary depending on the jurisdiction chosen, I chose diffusion rates for one country (the US) to compare to Wilson's OECD data (which I reduced by 65% to reflect that the US is roughly 35% of the total OECD in GDP) to ensure an apples-to-apples comparison. Furthermore, SCR data points for the US were excluded due to the fact that the US was a periphery rather than a core market for these technologies (see Figure 10). Finally, as was mentioned previously, capacity data was not present in EIA Form860 for US particulate removal equipment, hence their exclusion here.

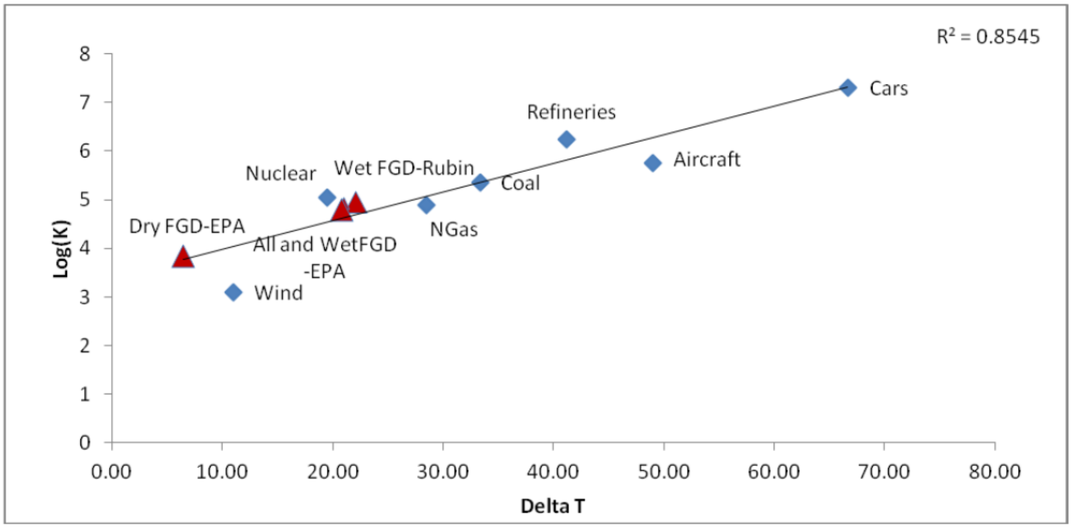

FIGURE 13. LOG K VS. DELTA T (CORE-MARKETS)

Assembled by Author: See Supplementary Materials 1

The resulting pollution control technologies red triangles) when added, fit the line almost perfectly, indicating that pollution control technologies are no different in this respect than the supply and end use technologies reported by Wilson (2009).

5.2 Unit Scaling

Thus far, I have been discussing market diffusion of pollution control technologies. However, another important dimension of scaling analysis, as mentioned previously, is unit scaling, which seeks to understand the dynamics of increases in scale at the unit level. As mentioned in Section 4, this involved taking both the average unit scale and the maximum unit scale for various pollution control technologies subject to data availability. These two variables were measured by taking the average of the stock of the time series, and by taking the largest unit produced to date, respectively. Table 4 contains the key results regarding the estimated scaling parameters.

TABLE 4. UNIT SCALING ANALYSIS PARAMETERS

Type	Juris-diction	Time	Source	Unit	K	Tm	Δt	R^2
FGD	US	1969-1986	EPA, n.d c	Average (MW)	390	1973	10	0.95
FGD	US	1969-1986	EPA, n.d c	Max Scale (MW)	844	1972	5	0.97
Wet FGD	US	1969-1986	EPA, n.d c	Average (MW)	394	1973	11	0.95
Wet FGD	US	1969-1986	EPA n.d c	Max Scale (MW)	844	1972	5	0.97
Dry FGD	US	1978-1988	EPA n.d c	Average (MW)	435	1981	17	0.95
Dry FGD	US	1978-2010	EPA n.d c	Max Scale (MW)	948	1983	11.3	0.94 (no fit)
FGD	Japan	1960-1971	CRIEPI n.d	Max Scale (MW)	383	1961	7.2	0.93 (no fit)
FGD	Japan	1960-1966	CRIEPI n.d	Average (MW)	319	1960	13.9	0.91 (no fit)
SCR	US	1991-2010	EPA n.d c	Average (MW)	7533036	993	-463	0.45 (no fit)
SCR	US	1991-1999	EPA n.d c	Max Scale (MW)	865	1990	6.2	0.88 (no fit)

As was the case with market scaling, only part of the dataset was fitted with logistic curves if it was noticed that a section of the data was one logistic function nested within a series containing multiple logistic functions. Graphs of the data for both industry and unit scaling are located in Appendix C. The dashed lines on some graphs indicate the point where the series was truncated when estimating the above parameters. Even after truncating the data this way, I was unable to meet the 0.95 goodness of fit inclusion criteria for some instances of unit scaling. As a result, these estimates were excluded from later analysis. The strange outlier pertaining to US SCR units can be explained by the US being a non-core market for SCR technologies, where much of the normal scaling evolution would have been seen in the core market. Again, since unit scale data for particulate removal equipment was unavailable in form EIA860, the unit scaling analysis for those technologies was excluded here.

Evident from these estimates are how the delta t's are quite small, indicating rapid upscaling at the unit level. This rapid upscaling is further illustrated in Figure 14 below, which compares unit scaling parameters for core markets calculated in Wilson (2009) to my estimates. Evident is how the Delta T's for both maximum and average unit scale for pollution control technologies (green) is systemically lower than those estimated for other energy technologies (light blue). The implications of this finding are considerable, and will be discussed further in the discussion section.

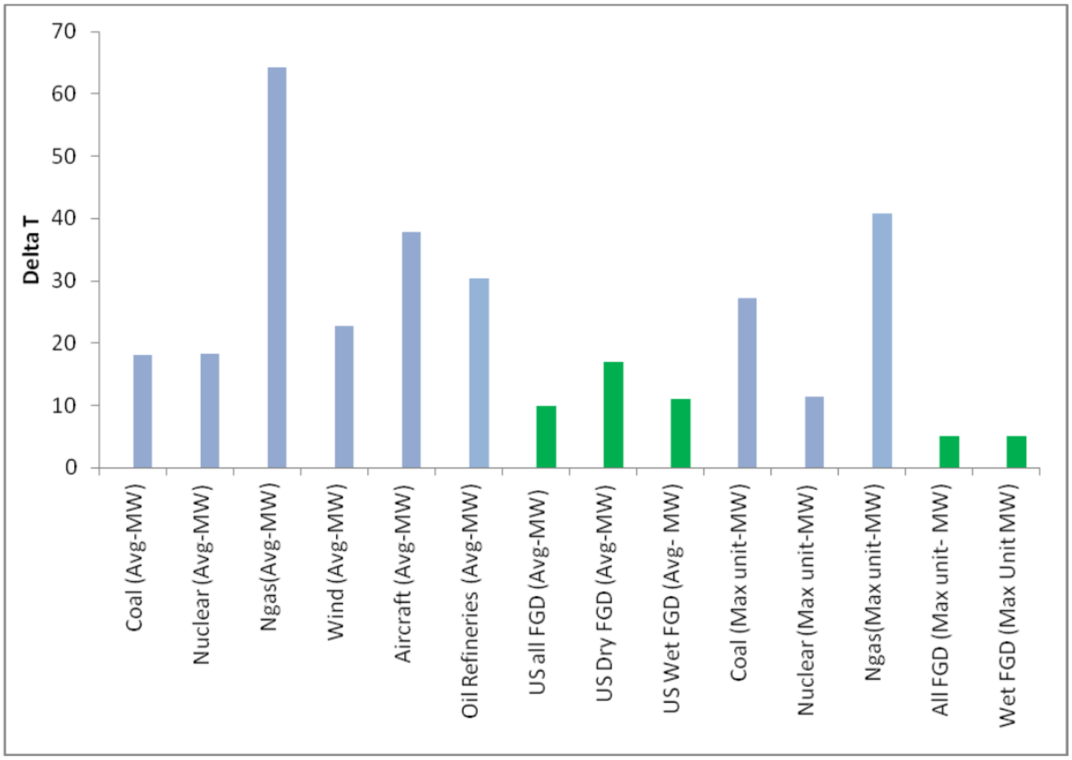

FIGURE 14. UNIT SCALE ACROSS TECHNOLOGIES (CORE MARKETS)

Assembled by Author: See Supplementary Materials 1

5.3 Scenario Corroboration

As mentioned previously, the scaling dynamics of energy technology framework could be a useful metric with which to corroborate the results generated by energy economy-models. Work to this regard was done by Wilson et al (2012), where they compared the extent-duration relationship of a number of technologies that were generated from integrated assessment modeling scenarios and compared them to the historical extent-duration relationship for eight energy technologies. They found that the scenario derived extent-duration relationships were inherently conservative, with longer durations of growth than seen in the historical data (Wilson et al., 2012). However, they also noted how the scenario derived extent-duration relationship for CCS was closer to the historical trend seen by the eight energy technologies (Wilson et al., 2012).

Since my estimates for the delta t's for FGD technologies in core-markets fit well with the extent-duration relationship of these other technologies (See figure 13), then it implies that the existing CCS adoption trajectories seen in models have some semblance to reality. Furthermore, Table 5 below compares the range of my estimated delta t's for core-markets to some which I estimated from several modeling studies. As one can see, the estimated delta t's for the scenarios fall within the range of the historic data. This is true across a range of, relatively stringent, policy targets. Unfortunately, the measures used for diffusion (i.e. the market size variable) across the studies differed from one another and so I was unable to directly compare extent-diffusion relationships to those found in Wilson (2009). For future scenario studies, therefore, it may be beneficial for modellers to report their diffusion findings using several metrics in order to ease comparison with the growing historical scaling literature.

TABLE 5. COMPARISON OF MODEL GENERATED DELTA T'S VS. HISTORIC DATA

Source	Model	Target	Jurisdiction	Delta T
My Estimate	Historical Data	NA	US, Japan	20-40
IEA 2009, CCS Roadmap	MARKAL	50% Reduction relative to 2005 emissions by 2050	North America	31
Odenberger and Johnsson, 2011	PRIMES	85% Reduction relative to 1990 emissions by 2050.	Europe	26
Kitous et al, 2010	POLES	Stabilization at 400ppm by 2100	Global	26

6. Costing Analysis

6.1 Cost Trends

Figure 15 below demonstrates the cost trend for FGD units from the sample, normalized by unit size (MW), using the GDP deflator (base year 1982) to account for the general inflation level and its impact on costs.

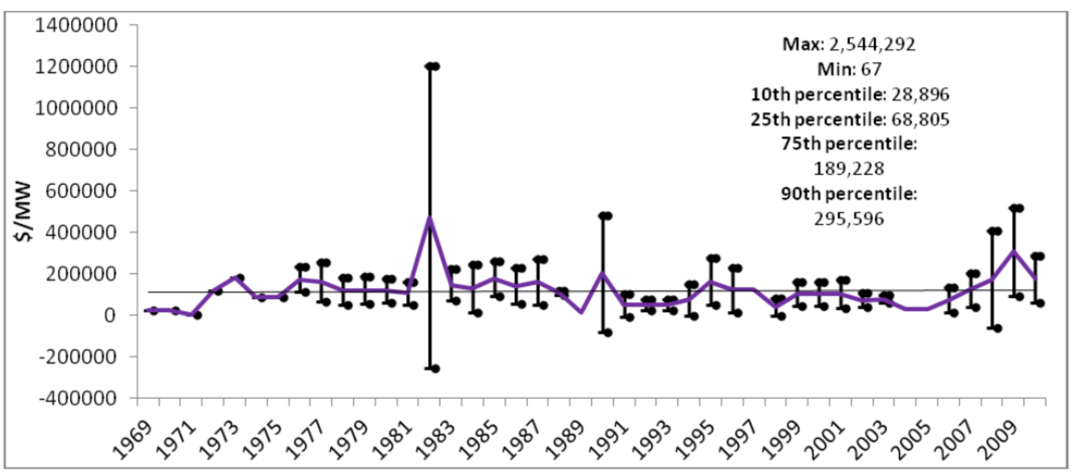

FIGURE 15. COST/MW FOR FGD UNITS (ANNUAL AVERAGES)

Cost data obtained from (EIA, 2011) while unit capacity data was obtained from (EPA, n.dc). Indexing and unit cost calculations performed by author (see supplementary materials 2).

Evidently, costs/MW are both high and increasing over time. This has some interesting implications for supposed learning-by-doing in the installation of FGD units, for if capital costs are increasing over time, where is the learning? This increase in normalized costs, it should be noted, is not consistent across the choice of deflator, with a GDP deflator and a general PPI commodity index yielding an increasing price while a PPI Chemical price index and a Handy-Whitman price index yield a decreasing cost. With all indicators, however, the trend is not very steep- hence the sensitivity to deflator. The graphs showing the cost trend for these other indicators is located in Appendix D.

This, of course, does not mean that learning is not an important phenomenon for this technology. A large number of factors influence cost simultaneously and, thus, downward cost pressure from learning could be overshadowed by other cost-inflating factors. The regression analysis, which follows, is an attempt to understand these cost dynamics, and account for the numerous factors which influence costs over time. Finally, learning-by-doing can also manifest itself through a decline in the variance of the cost of FGD units over time. Here we do see a weak negative trend in the variance of costs (correlation coefficient of -0.04 to -0.16 between time and annual cost standard deviations) which is consistent across deflators. This is demonstrated by the error bars in figure 12 above. However, as also evident by these error bars, as well as by the box in figure 12 reporting some common measures of dispersion, the variance of the dependent variable in the sample is immense, a fact further highlighted by a scatterplot of the dependent variable in table D4 of Appendix D, which also superimposes annual means and $10^{th}/90^{th}$ percentile values of the data.

The broad movements in costs over time are also consistent across deflators. Initially, we see a rapid increase in cost to about 1973, where there is a slight decline before costs spike again around 1982. After this spike, however, costs experience a significant decline until about 1994, before beginning a second rise from 1995 to the present. Figures 16, 17, and 18 disaggregate the above cost trend (using the GDP deflator) into finer intervals that correspond to some key intervals in the diffusion of a technology. These are:

a) The early formative years of a technology (1969-1979)
b) The period of core market growth and expansion (1980-1998), and
c) The post 2000 period (1999-2010) where almost all energy technologies have seen substantial cost increases.

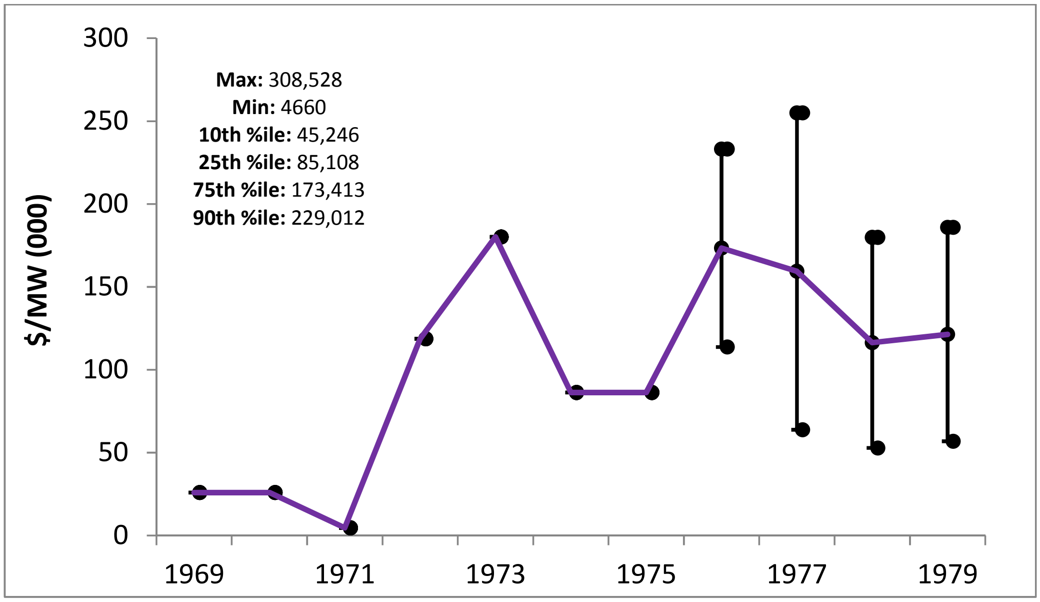

FIGURE 17. COST TRENDS 1969-1979

Cost data obtained from (EIA, 2011) while unit capacity data was obtained from (EPA, n.dc). Indexing and unit cost calculations performed by author (see supplementary materials 2).

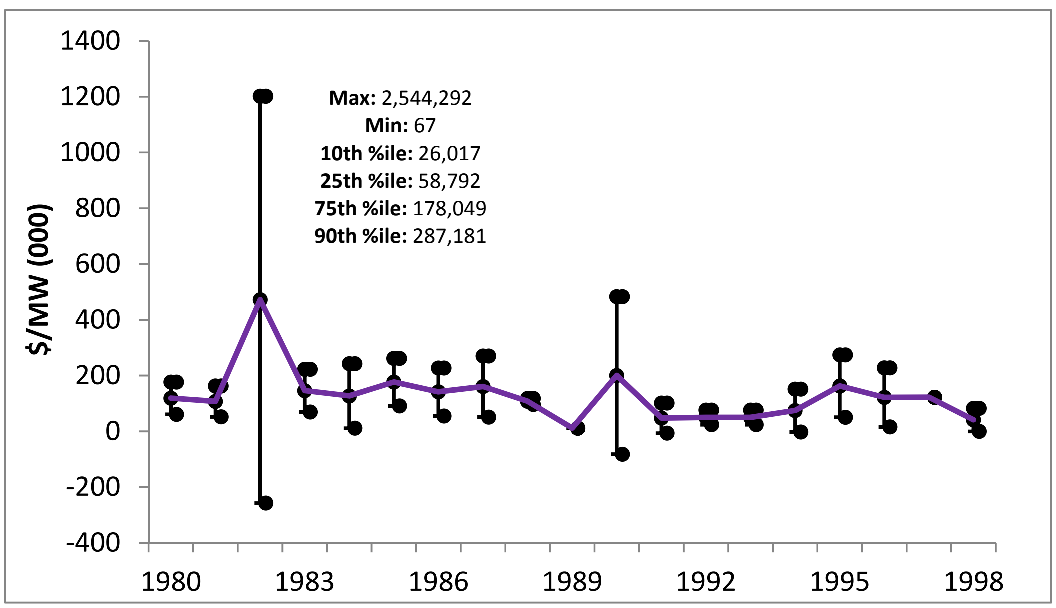

Figure 18. Cost Trends 1980-1998
Cost data obtained from (EIA, 2011) while unit capacity data was obtained from (EPA, n.dc). Indexing and unit cost calculations performed by author (see supplementary materials 2).

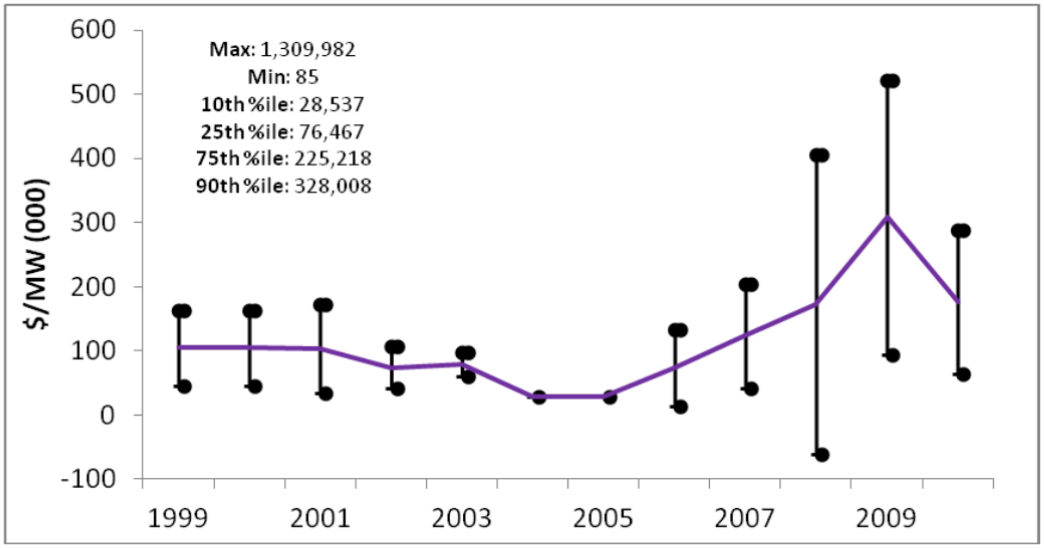

FIGURE 19. COST TRENDS 1999-2010

Cost data obtained from (EIA, 2011) while unit capacity data was obtained from (EPA, n.dc). Indexing and unit cost calculations performed by author (see supplementary materials 2).

6.2 Regression Results (Core Model 1969-2010)

The base model regression results, summarized in column 1 of Appendix E, provide some interesting insights concerning FGD cost trends over time. Apparent immediately is the poor fit of the model, with an adjusted R^2 of only 0.1. Thus, variation in my independent variables explains only 10% of the variation in the dependent variable. This was an unexpected result, for this core model contains many of the key variables identified by economists and engineers in the literature as important determinants of FGD cost. The implications of this low goodness of fit will be elaborated upon further in the discussion section.

Most key variables-unit size, sulphur content of the coal, average firm size, and removal efficiency- are not of the expected sign. All else being equal, one would expect a greater concentration of sulphur in the coal to result in facilitated emissions control relative to a more dilute strain. Likewise, the expectation of economies of scale implies a negative sign for both unit scale and output per firm. Furthermore, according to the model, higher removal efficiencies lead to lower FGD prices, which is counterintuitive as we would expect higher costs in building a more advanced design. Fortunately none of these variables are statistically significant at any conventional significance level. Of the twelve independent variables in the model, only two are significant at conventional significance levels. Whether the unit is wet or dry FGD technology is significant at the 1% level, and the number of spare absorber trains per MW capacity was significant at the 5% level. The experience variable, while of the expected negative sign, was not statistically significant. Thus, after controlling for other key engineering and economic parameters, learning did not lead to any cost declines which were statistically noticeable.

A white test, as well as results from Breusch-Godfrey and Durbin Watson tests, indicate that heteroskedasticity (non-constant variance of the error) is an issue with this dataset, but not serial correlation (systemic movements in the error term). . Consequently, all results reported in Appendix E have corrected for heteroskedasticity (using Huber-White standard errors). In addition, some severe multicollinearity exists between a few of the variables, with trains and unit size yielding a correlation coefficient of -0.78 and with the energy price and cumulative capacity yielding a correlation coefficient of 0.91.

6.3 Sensitivity Analysis

In addition to the base model run, a number of alternative tests were performed to discern the model's sensitivity to alternative specifications. This sensitivity analysis was quite extensive and involved the following runs:

- Base Model + Regional variables (Run2)
- Base Model + Ownership category (Run3)
- Base Model + Simultaneous construction of multiple units (Run4)
- Base Model + Plant learning (Run5)
- Base Model + Utility learning (Run6)
- Base Model + Scale/Technology interactions (Run7)
- Base Model + By-product recovery (Run8)
- Base Model + HW Index (Run9)
- Base Model + Regulations (Run10)
- Base Model + Manufacturing firm dummies (Run11)
- Base Model + Manufacturing firm learning (Run12)
- Base Model + Flue gas/unit generating capacity (Run13)
- Base Model + Retrofit*Generating capacity interaction (Run14)
- Base Model + Bypass technology (Run 15)
- Base Model + Odixation Technology (Run 16)
- Base Model + Alternative Specification for Learning (Cumulative Capacity in MW (Run17)
- Base Model + Year dummies (Run 18)
- Base Model + Manufacturing firm dummies + other significant engineering factors (Run 19)
- Base Model + Patent Data (Run21)
- Base Model + Patent Data Lag1 (Run 21)
- Base Model + Patent Data Lag2 (Run 23)

A detailed description of each of the runs, and the respective data sources for each new variable specification, are located in Appendix F, while their results are summarized in columns 2-23 of tables E3 to E6 of Appendix E. For our purposes, the changes which were significant were learning at the utility level, the simultaneous construction of multiple units, whether the unit engages in by-product recovery or not, flue gas volume/generating capacity, the inclusion of firm dummies, the inclusion of year dummies, whether the FGD unit used forced/inhibited oxidation, the interaction of unit scale with the type of FGD system (wet or dry), and the inclusion of patent data. Of these, only two runs had practical significance, that is, with considerable implications on the explanatory power of the model- the inclusion of firm dummies, which increased the adjusted R^2 of the model to 25% from ~10% in the base case, and the inclusion of year dummies (column 18 of Appendix E), which increase the adjusted R^2 of the model to 19%.

If we take most of the above runs with statistically significant variables (I exclude the patent variables as they were estimated using a subset of the data-given their low practical significance, that is, their low impact on the adjusted R^2 for their respective runs- I do not expect them the affect the R^2 that much in the below exercise), and then combine them with our base model, we get a very large, non parsimonious model (column 19 in Appendix E) that explains only 30% of the cost variation. All things considered, this is quite a negative result, indicating that most of the economic and engineering factors identified in the literature as important determinants of the cost of FGD units explain a little less than one third of the actual variation in costs seen in the US FGD sample. The implications of this result are discussed further in section 7 below. Finally, while the experience variables were not statistically significant across any of the alternative runs, the sign did switch from negative to positive in runs 7, 10, 17 and 18- indicating the possibility of negative learning.

In addition to the above, I ran regressions for the time periods 1969-1979, 1980-1998, and 1999-2010. Due to degrees of freedom issues, especially pertaining to the 1969-1979 period which only had 44 observations, I limited my analysis to the base model and observed any changes relative to the base model for the whole sample period. Table E7 in the appendix contains the results. Immediately evident is how the explanatory power of the model changes across different timeframes, with adjusted R^2 values ranging from a high of 0.45 for the 1969-1979 period to only 0.14 for the 1999-2010 period. The 1980-1998 period is close to the low end, with an adjusted R^2 value of only 0.17. Furthermore, the significance, magnitude, and the sign of many variables change across timeframes. While the 1969-1979 period had a moderately high adjusted R^2, most of the statistically significant variables in this run were of the opposite sign, suggesting possible spurious results. The fact that severe multicollinearity was present among all combinations of the material price index, energy prices, industry concentration, and cumulative capacity makes it difficult for the regression to identify and isolate their individual effects on the dependent variable for this timeframe. Overall the breaking up of the core model into finer intervals continues the trend of negative results, doing little to aid the analysis. While learning becomes statistically significant at the 5% level in the 1969-1979 period, the sign remains positive indicating negative learning.

6.4. Further Learning Analysis

Table 6 below demonstrates the results of the simple bivariate model where cumulative capacity (measured using the alternative specification of cumulative units installed and cumulative MW capacity installed) influences costs. This was then repeated with the addition of an additional variable, unit size, to control for economies of scale which can be conflated with learning if the latter is measured by cumulative capacity in MW. All of these specifications above were then repeated with cost deflated using the Handy-Whitman Index.

TABLE 6. LEARNING CURVE ESTIMATES-VARIOUS SPECIFICATIONS

Row	Dep Variable	Indep Variable	Coefficient-Learning	Learning Rate	Coefficient-Unit Size
1	Cost/Mw Deflator	CCAP (Units)	-0.06	4.1%	NA
2	Cost/Mw Deflator	CCAP (Units) + Unit Scale	-0.06	3.8%	-0.02
3	Cost/Mw Deflator	CCAP (MW)	0.01	-1%	NA
4	Cost/Mw Deflator	CCAP (MW) + Unit Scale	0.02	-1.2%	-0.03
5	Cost/MW HWI	CCAP (Units)	-0.18	11.7%	NA
6	Cost/MW HWI	CCAP (Units) + Unit Scale	-0.18**	11.4%	-0.05
7	Cost/MW HWI	CCAP (MW)	-0.09	5.9%	NA
8	Cost/MW HWI	CCAP (MW) + Unit Scale	-0.08	5.1%	-0.07
9	Cost/Mw Deflator	Base Costing Model (Units)	-0.14	9%	0.09
10	Cost/Mw Deflator	Base Costing Model (MW)	0.28	-21%	0.12

Comparing Rows 1 and 3 with rows 9 and 10, we see that the single explanatory variable model yields a considerably different learning rate than that derived from the base model that was estimated in Section 6.2. For instance, regressing cumulative units on unit costs yields a learning rate of 4.1%- that is, a 4.1% cost decline for every doubling of cumulative units. The corresponding rate for the base model, however, is a learning rate of 9%.

After changing the specification from cumulative units to cumulative capacity (in MW), we see an even greater discrepancy between the single explanatory variable model and the base costing model. In both of these specifications- the learning variable switches sign, going from negative to positive or, going from actual (positive) learning to so-called negative learning. Here, the full model gives a negative learning rate of 21%, relative to only 1% in the bivariate case (row 3). Controlling for unit size further results in less learning than the one variable case, however, this impact is constant across the two specifications of experience- cumulative MW's and units. Evident from the above analysis is that learning/experience rates is highly sensitive to the specification chosen- something which needs to be accounted for in future learning studies. Note also, how the results from row 5 correspond well with the learning rates found in the literature for

FGD systems- that of 11% in the Rubin et al., (2004) paper, and 12.1% in the Lohwasser and Madlener (2010) paper.

7. Discussion

The scaling results provide some interesting insights into the nature of both industry and unit scaling of pollution control technologies. Firstly, even though these technologies were forced into the market through various regulations, their rates of diffusion in core markets were no different than the more market driven technologies. The consistency of this observation across technologies, across countries, and thus, across regulatory regimes, is particularly noteworthy. Of course, this finding cannot be generalized. Policies are a product of human agency and thus can be varied in their intensity to promote rapid or slow diffusion. However, this ability is, in practice, limited by important factors such as political and economic acceptability (the costs of policy). With this in mind, a possible interpretation of the aforementioned findings of the consistency of rates of diffusion is that the political-economic constraining factors preclude an overambitious and rapid introduction of environmental add-on control technologies, which results in diffusion rates similar to technologies competing in the marketplace. Another possible interpretation is that, even in the presence of moderate regulations, new technologies need a certain amount of time to overcome the slow initial growth inherent with new technologies that causes the pervasive S-shaped diffusion pattern, particularly with long-lived capital assets such as power plants which often precludes premature retiring of the capital stock and results in diffusion rates resembling a “natural” rate of capital turnover

The above has interesting implications for CCS, for if CCS’s rate of diffusion is expected to range 20-40 years in core markets, policies conducive to CCS need to start to be implemented soon (immediately) in order for CCS to make a dent in emissions by 2050. The prospects of CCS are furthered hampered by the fact that many low GHG technologies- biomass, renewable etc.- have already undergone substantial debugging and increased user familiarity from their having already diffused into niche markets. This has given them a head start relative to CCS in the path to widespread diffusion. This of course is not to say that there are no advantages to CCS relative to these technologies (cost, dispatchability, political acceptability in fossil fuel producing regions etc.), however, it is a significant disadvantage which could hinder its adoption.

Secondly, the speed of industry diffusion of the add-on technologies examined in non-core jurisdictions, relative to that for other technologies, was evident and pronounced (yet faster diffusion catch-up than that observed for other technologies). The likely reason for this is that these technologies are add-on technologies, with no additional requirements in terms of supporting infrastructure, and that can benefit thus somehow more from standardization effects and from learning (knowledge) spillovers from core regions. Thus, once the technology has diffused substantially in a core market, where FGD manufacturers and installers have worked out many of the kinks and risks inherent in new technology, and once a sufficient policy framework is in place in non-core markets, diffusion in these non-core regions occurs quite rapidly.

The exemplary case for this was Germany which saw rapid diffusion of FGD and SCR technologies. Germany was able to implement stricter standards than the US and Japan due to almost 20 years experience of those two regions with these technologies. Consequently, what would potentially be a policy perceived to be of great economic cost to society was made acceptable and achieved with less.

Finally, the scaling analysis illustrated the rapid upscaling at the unit level for pollution control technologies. Wilson (2009, 2012) observed that the increase in scale at the unit level is often preceded by a lengthy formative phase which sees the build out of multiple smaller units where experimentation and learning can occur. Shorter formative phases occur if the potential cost decline arising from economies of scale exceeds the potential cost decline arising from learning in an extended formative phase (Wilson, 2012).

Putting this together with some of the regression work, FGD's rapid upscaling was unlikely due to economies of scale due to the lack of significance and the wrong sign of the unit scale variable across the regression runs (the exception being the unit scale/wet interaction term, suggesting that perhaps wet FGD units may experience economies of scale while dry FGD units do not). A more plausible explanation was that FGD units, being an add-on technology, were built to a scale that matched the size of existing coal-fired boilers. This is analogous to the concept of derived demand in economics (where the demand for a product is driven from a product it is commonly associated with) except it is "derived" scaling, where the scale of the pollution control technology is driven by factors influencing the scale of the underlying technology of power plants they are combining with.

Another interesting finding from the regression analysis was the learning variable, which was only statistically significant in four of the twenty-six runs. For all intents and purposes, even when we control for other factors, there was no learning effect in driving the costs of FGD and, potentially, there was "negative learning". This is a significantly different dynamic than what is commonly assumed in many modelling studies, and so modellers may want to reconsider this assumption. A possible reason for this was the extremely short formative phase for FGD technologies prior to the rapid upscaling seen at the unit level. This rapid upscaling, in turn, may have meant insufficient time to adequately debug the technology, leading to errors and dead ends with greater consequences due to their occurring at a larger scale.

The major finding from the regression, however, was its lack of explanatory power, indicating that much of the economic and engineering factors identified as important determinants of the cost of FGD units explain little of the cost variation seen in the sample. This is even the finding after running some very generous regression specifications. For instance, the specification of binary variables for each FGD manufacturing firm- simply implying that different firms in the FGD industry have different costing/pricing strategies and that these should, in turn, explain a non-trivial part of the cost variation over time- explains only 24% of the variation in cost.

The likely reason for these poor results is a number of site specific factors that influence FGD costs which are unobservable given available data. For instance, differences in boiler location within a given plant could make it more difficult, and thus more costly, to retrofit. Similarly, other site specific factors such as local labour market conditions, local geography, and distance from suppliers would play a key role in explaining differences in FGD installation costs across the sample. Katzberger and Jayaprakash noted in an article in COALPower Magazine how critical labour shortages in key positions such as boilermakers and welders have contributed to the recent cost rise of FGD systems (Katzberger and Jayaprakash, 2007). In many of the technical analysis of FGD systems cited earlier in this paper, site specific factors were frequently mentioned as important determinants of FGD installation costs.

8. Conclusions and Policy Implications

The oft stated goal is for climate policies to be technologically neutral, due to the poor precedent of governments selecting “technological winners” (Azar and Sanden, 2011). In practice, however, this goal is rarely achieved and so, should society introduce policies to promote CCS, the above research indicates some challenges they may face, adopting as analogy the case of FGD, i.e. sulfur removal technologies.

Firstly, the primacy of site-specific factors on costs makes it very difficult for policymakers or engineers to manipulate costs through traditional economic or engineering channels. This is because, by definition, these factors are idiosyncratic and cannot be applied on mass across to FGD and CCS projects alike. Secondly, like the case for FGD units, the learning potential for CCS may well range from low to non-existent, and thus the potential of demonstration projects to start riding the learning curve may be misguided investments. Thirdly and finally, it appears that promoting the early and rapid up-scaling up of these technologies may be misguided as economies of scale do not appear to be very important in governing their costs, at least when judging the results of my “after the fact” analysis of the history of FGD technology in the US. As was potentially the case with FGD, rapid unit upscaling may result in an insufficient formative phase which implies less learning and increasing costs (or at the minimum higher costs than would be the case otherwise)

Thus, while the policy implications presented here are purely negative- what policymakers should not do- they guide us towards other areas of research which could supply the necessary information for helpful policy recommendations. In particular, the rapid diffusion of FGD units in Germany deserves greater attention and thus, a similar costing and scaling analysis for Germany would be most informative.

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Appendix A: Herfindahl-Hirschmann Index (HHI) construction

The HHI Index is a measure of market concentration with the following formula:

$HHI = (S_1)^2 + (S_2)^2 + \ldots.. + (S_n)^2$

Where:
HHI= Herfindahl-Hirschmann Index
S_n= Market share of nth firm.

Thus, the HHI index is simply the sum of the squares of the market shares of all the firms in the market for a given period. In estimating my HHI Index for each year, I calculated the market share for each firm for the past five years in order to smooth the annual fluctuations which would otherwise occur.

Appendix B: Material Price Index Construction

To calculate an index of the price of the material inputs used in FGD units, I required three things: the types of materials used in the construction of FGD units, how this basket of materials changes over time, and price data for the various materials in the basket. Table B.1 provides the weights for the various steels used in construction of FGD units by decade. The most common Stainless Steel Alloy used in FGD construction, prior to 2000, in SS317L and the most common Nickel Alloy used is Alloy22 (Dene et al., 2011).

B1. PROPORTION OF MATERIALS USED IN FGD CONSTRUCTION (%)

	1969-1980	1981 to 1990	1991 to 2000	2001 to 2010
Stainless Steel	19	58	57	46
Nickel Alloy	0	5	14	0
Tile Lined	0	5	11	38
Fibreglass	0	0	4	11
Flakeglass Carbon Steel	54	18.5	3.5	5
Rubber lined Carbon Steel	27	13.5	10.5	0

Data from Weilert and Meyer (2010)

Unfortunately, I was unable to find price data for such specialized materials. Consequently, an article by Milobowski (1997) provided the price of these materials relative to the price of steel for 1991, allowing me to obtain their 1991 price. From this point, I had the option to simply keep this ratio constant over the sample period, or, attempt to vary this ratio based on changes of the underlying raw materials that comprise the steel or the alloy. Using commodity indices for molybdenum, chrome, nickel, and iron ore taken from the United States Geological Society (Kelly & Matos, 2011). I varied the price of the specialized steel/alloys from its 1991 value according to variations in the price of the raw materials making up the steel. It must be noted that this is only an approximation of the prices of these materials as changes in demand conditions and their market concentration will also cause variation in their price. Furthermore, for some specialized materials-tile lined carbon steel, flakeglass carbon steel, and rubber lined carbon steel- I kept their ratio to the price of steel constant over the sample period as I couldn't find any reference to their underlying composition.

Once these prices were obtained, a combined "FGD material price" was obtained by weighing the price of the steel with the weights found in Table B1. This was then indexed to the base year 1982 to obtain the Material Price Index, which I lagged by 1 period in the regression.

Appendix C: Graphs of fitted logistic functions

Note: Dashed lines shown below represent the data segment used when estimating logistic parameters

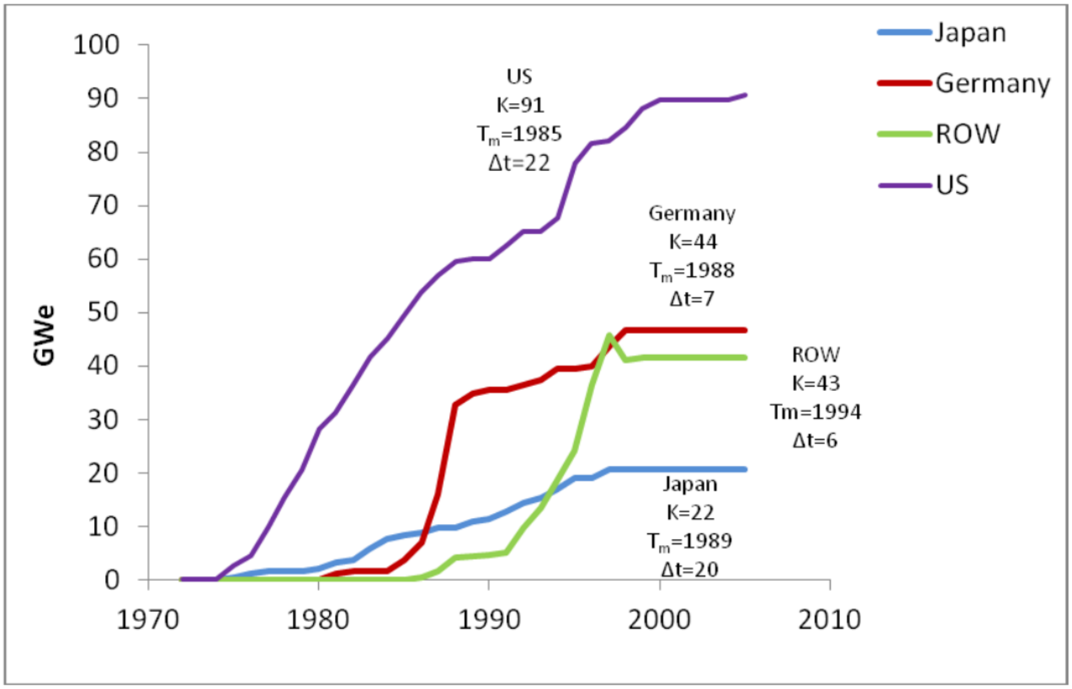


FIGURE C1. FGD WET DIFFUSION BY COUNTRY: 1972-2005

Data from: (Rubin et al., 2004)

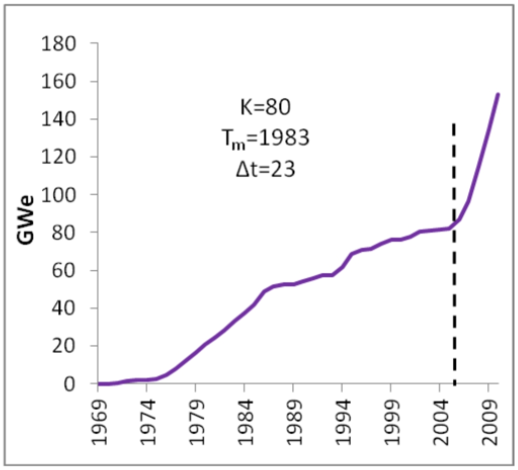


FIGURE C2. CUMULATIVE CAPACITY (US-FGD)-1969-2010

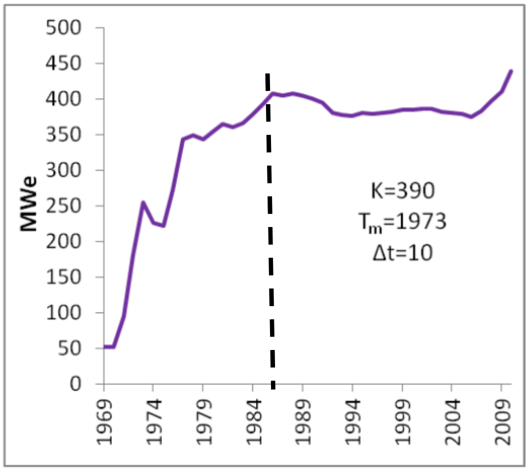
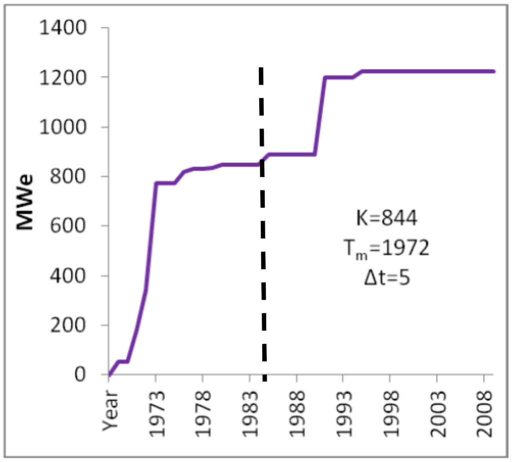


FIGURE C3. AVERAGE UNIT SCALE (US FGD)-1969-2010

Raw data from: (EPA, n.dc). Assembled in current format by author (see supplementary materials).



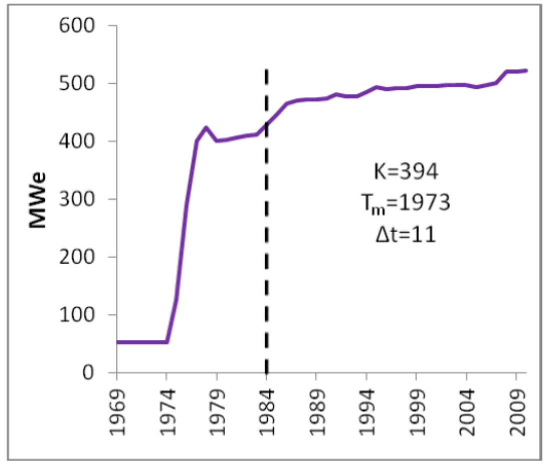
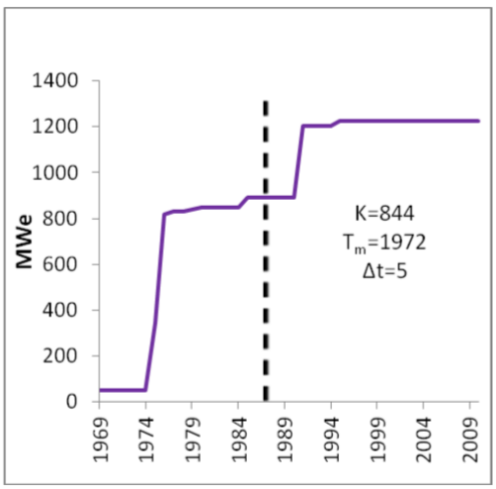


FIGURE C4. MAX UNIT SCALE (US FGD) 1969-2010

FIGURE C5: AVERAGE UNIT SCALE (US WET FGD) 1969-2010

Raw data from: (EPA, n.dc). Assembled in current format by author (see supplementary materials 1 and 2).



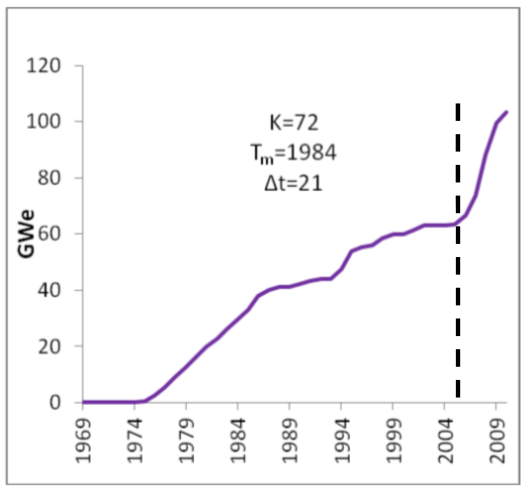
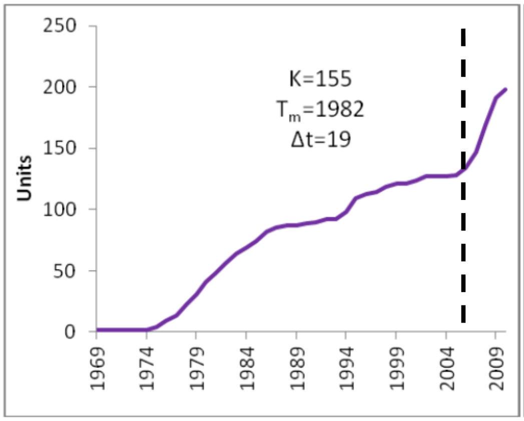


FIGURE C5: MAX UNIT SCALE (US WET FGD) 1969-2010

FIGURE C6: CUMULATIVE CAPACITY (US WET FGD) 1969-2010

Raw data from: (EPA, n.d c). Assembled in current format by author (see supplementary material 1 and 2).



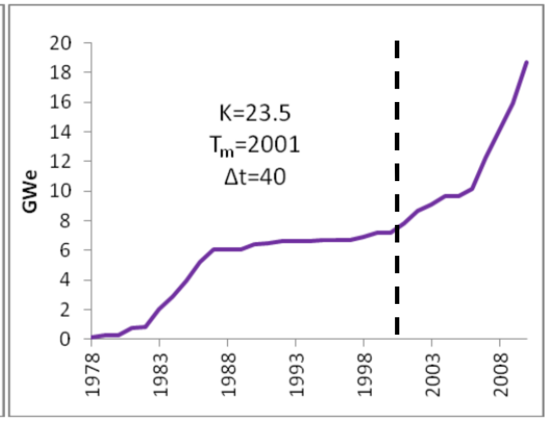


FIGURE C7: CUMULATIVE CAPACITY (US WET FGD) 1969-2010 –UNITS

Raw data from: (EIA, 2011)

FIGURE C8: CUMULATIVE CAPACITY (US DRY FGD) 1978-2010

Raw data from: (EPA, n.dc)

Raw data from: (EPA, n.dc). Assembled in current format by author (see supplementary materials 1 and 2).

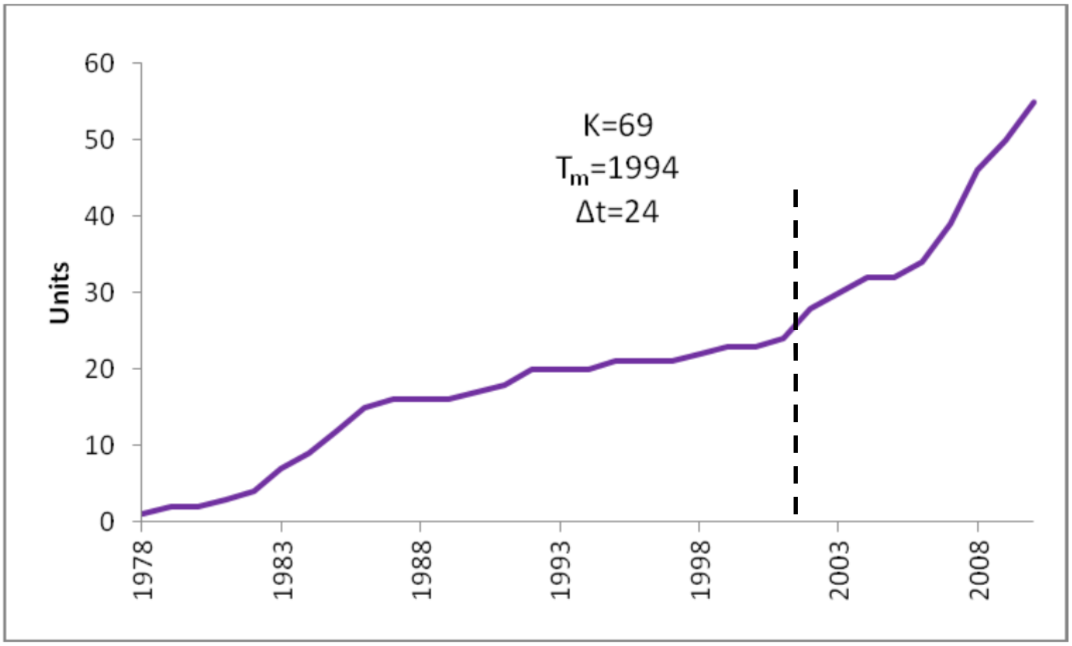
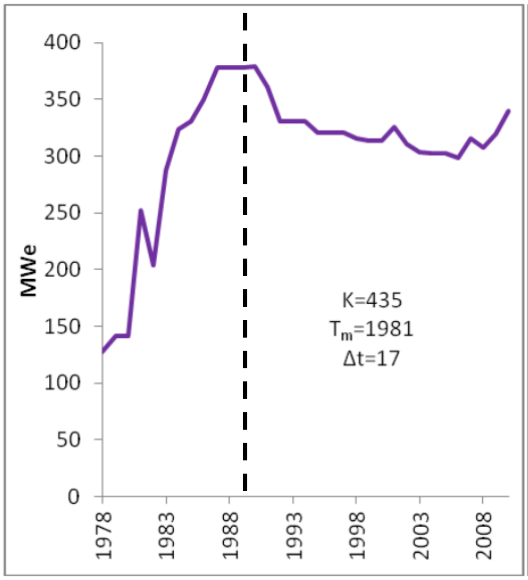


FIGURE C9: CUMULATIVE CAPACITY (US DRY FGD) 1978-2010 -UNITS

Raw data from: (EIA 2011). Assembled in current format by author (see supplementary materials 1 and 2).



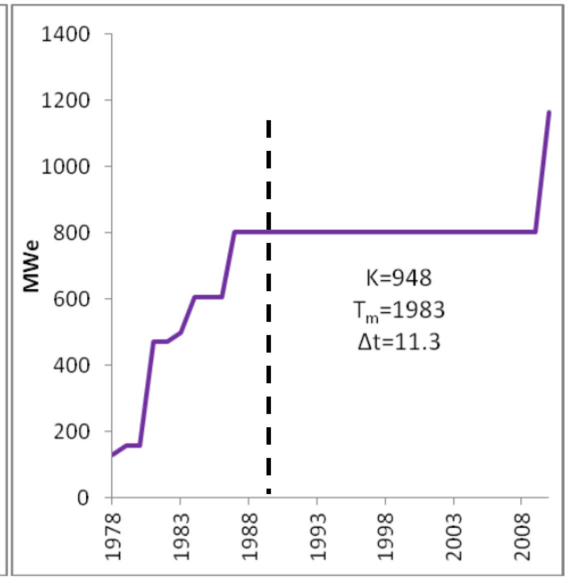


FIGURE C10. AVG UNIT SIZE (US DRY FGD) 1978-2010 **FIGURE C11. MAX UNIT SIZE (US DRY FGD) 1978-2010**

Raw data from: (EPA, n.dc). Assembled in current format by author (see supplementary materials 1 and 2).

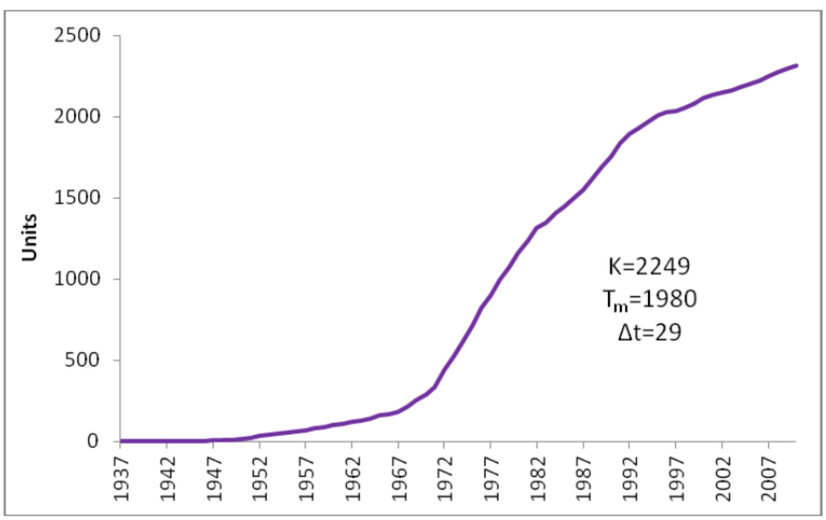


FIGURE C12. TOTAL US FGP CUMULATIVE CAPACITY (1937-2010)

Raw data from: (EIA, 2011). Assembled in current format by author (see supplementary materials 1 and 2).

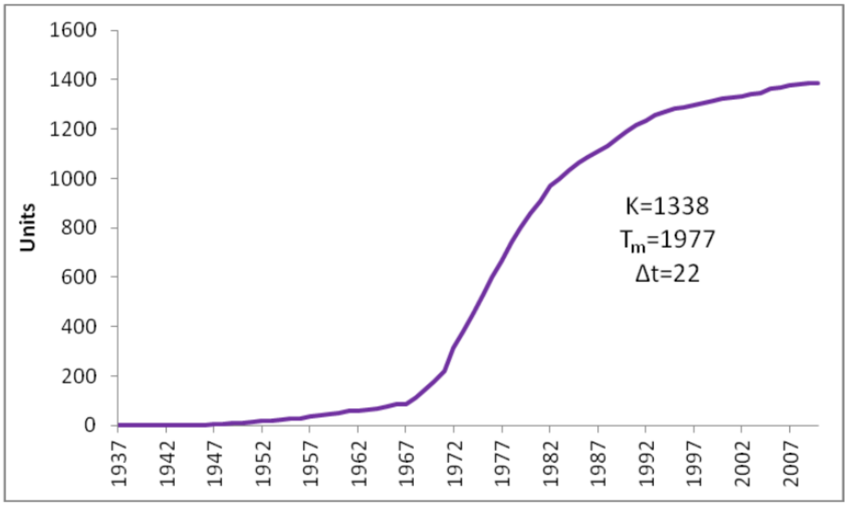


FIGURE C13. TOTAL US ELECTROSTATIC PRECIPITATORS CUMULATIVE CAPACITY (1937-2010)

Raw data from: (EIA, 2011). Assembled in current format by author (see supplementary materials 1 and 2).

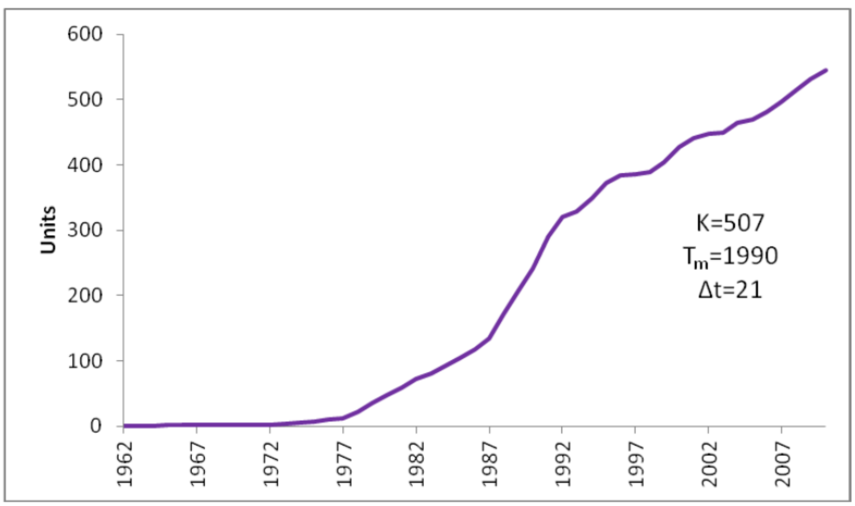


FIGURE C14. TOTAL US BAGHOUSE CUMULATIVE CAPACITY (1962-2010)

Raw data from: (EIA, 2011). Assembled in current format by author (see supplementary materials 1 and 2).

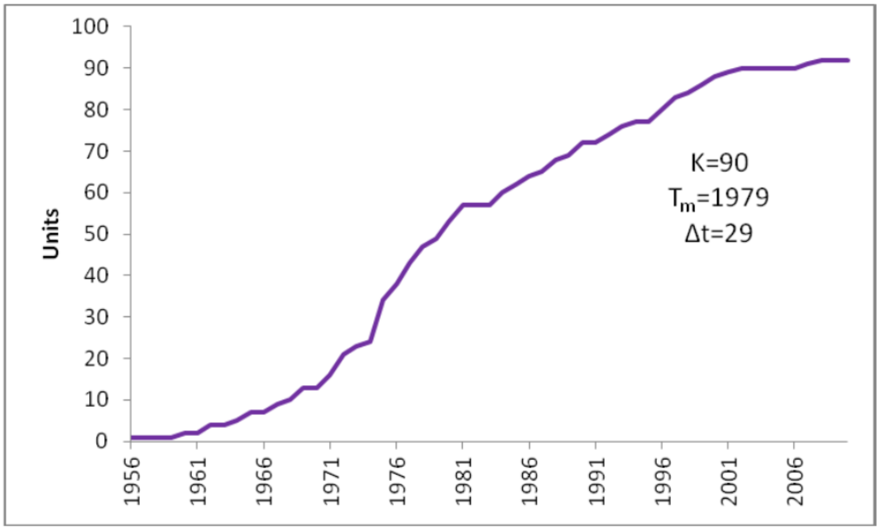


FIGURE C15. TOTAL US WET FGP SCRUBBER CUMULATIVE CAPACITY (1956-2010)

Raw data from: (EIA, 2011). Assembled in current format by author (see supplementary materials 1 and 2).

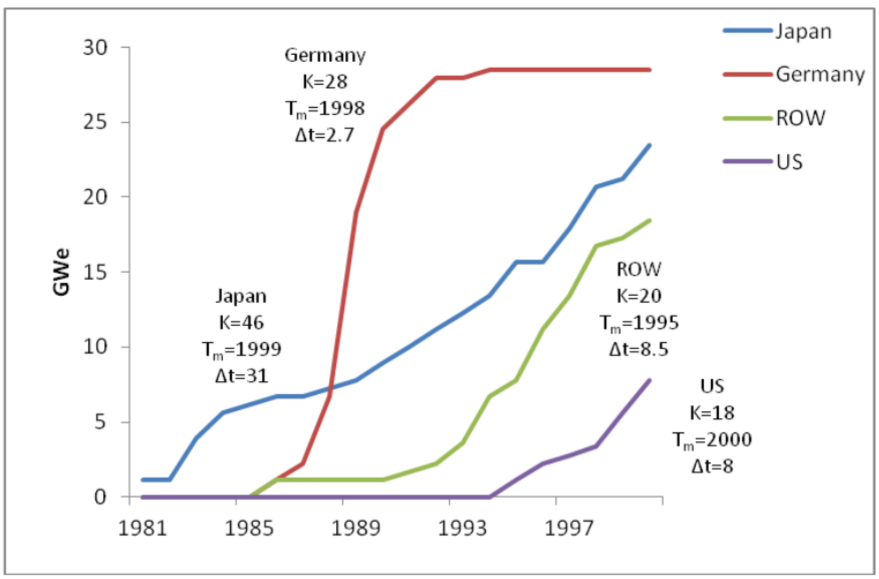


FIGURE C16. SCR CUMULATIVE CAPACITY

Data From: (Rubin et al., 2004)

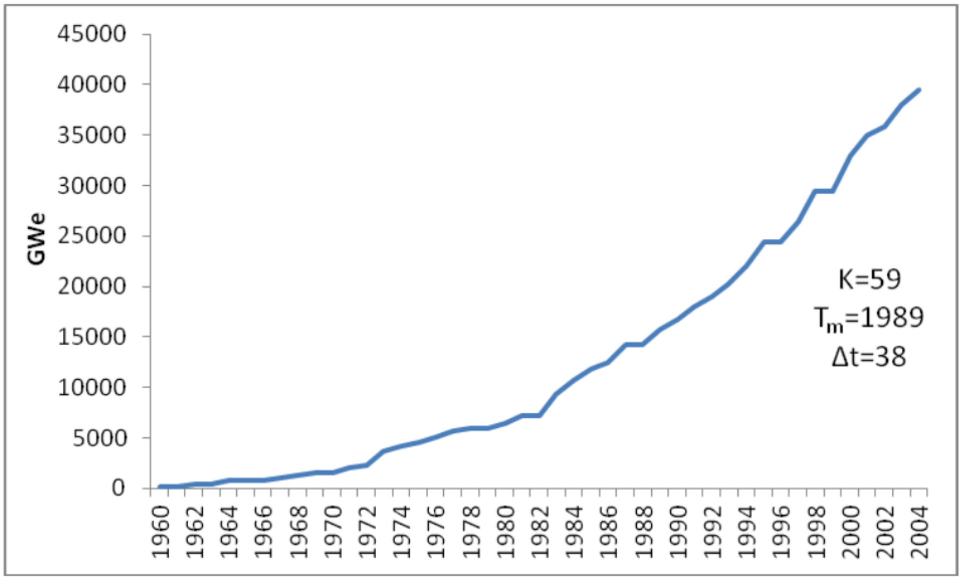


FIGURE C17. WET FGD CUMULATIVE CAPACITY (JAPAN 1960-2004)

Raw data from: (CRIEPI, n.d). Assembled in current format by author (see supplementary materials 1).

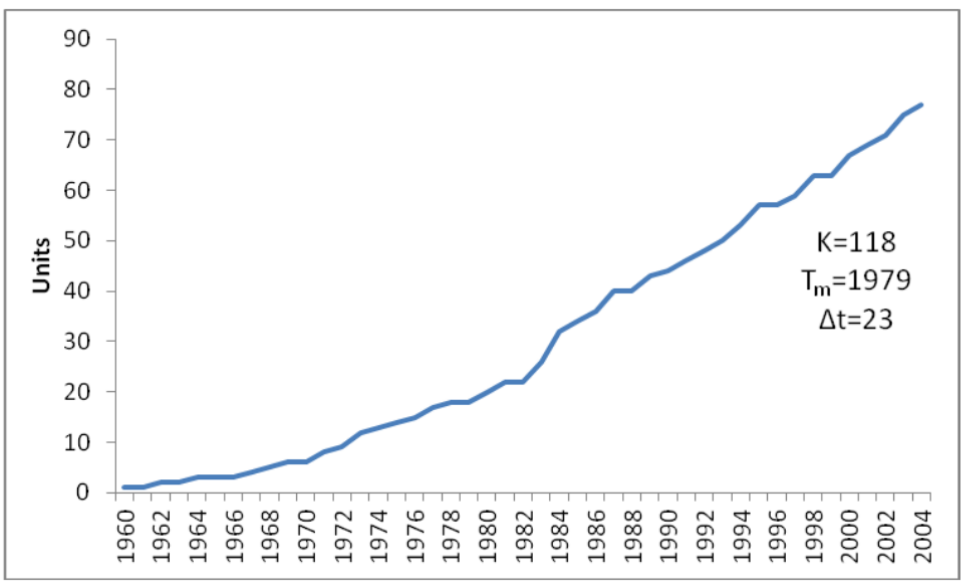


FIGURE C18. WET FGD CUMULATIVE CAPACITY (JAPAN 1960-2004)

Raw data from: (CRIEPI, n.d). Assembled in current format by author (see supplementary materials 1).

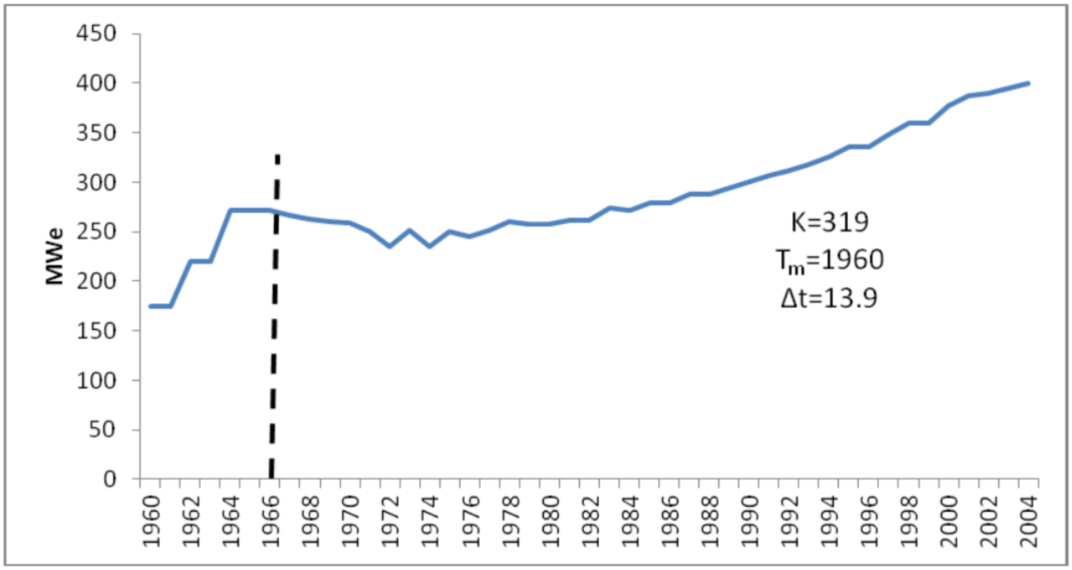


FIGURE C19. AVERAGE UNIT SIZE (JAPAN- WET FGD) 1960-2004

Raw data from: (CRIEPI, n.d). Assembled in current format by author (see supplementary materials 1).

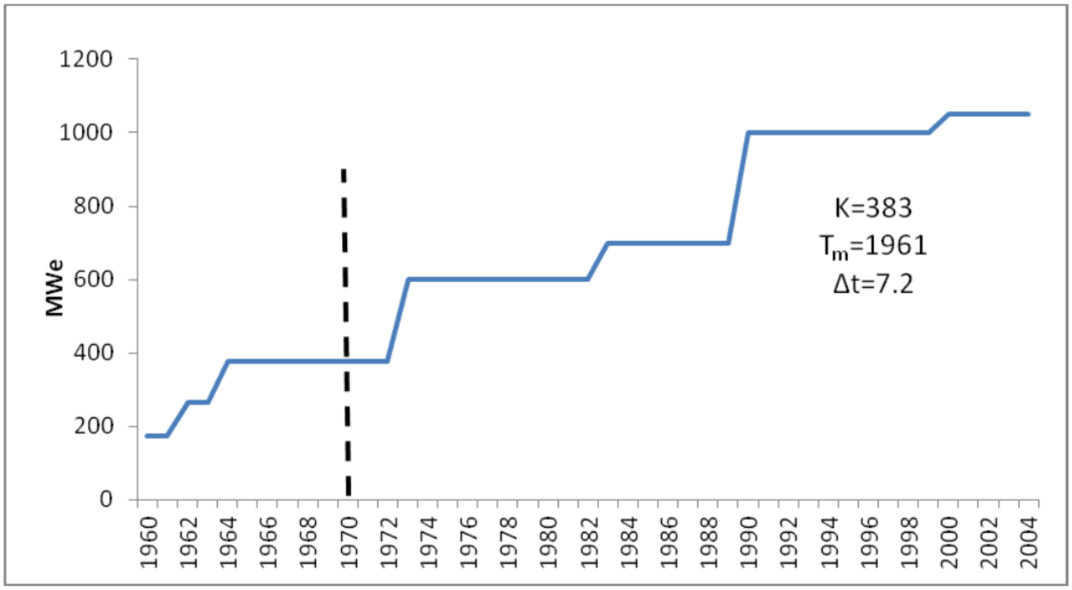


FIGURE C20. MAXIMUM UNIT SCALE (JAPAN- WET FGD) 1960-2004

Raw data from: (CRIEPI, n.d). Assembled in current format by author (see supplementary materials 1).

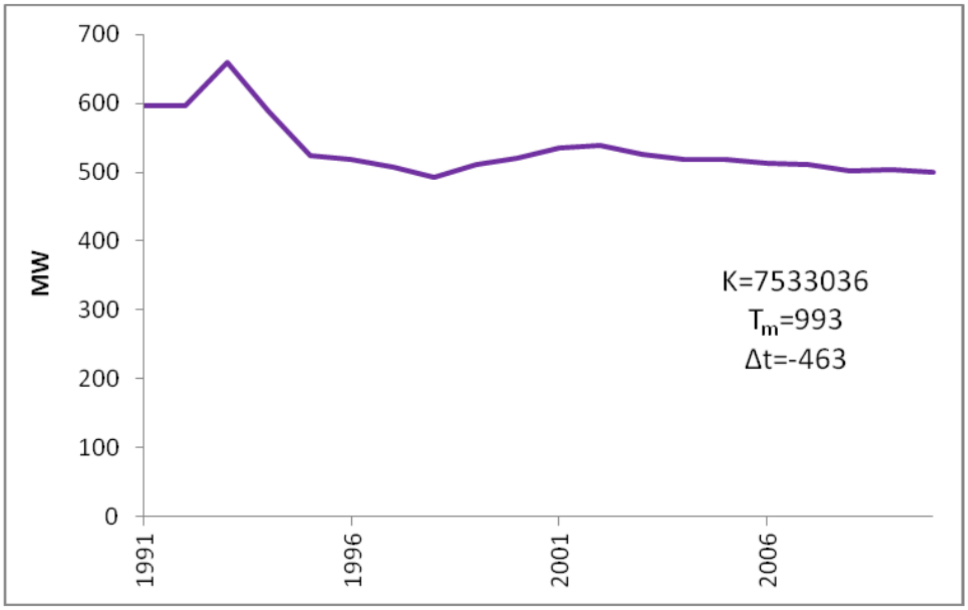


FIGURE C21. SCR AVERAGE UNIT SCALE (US 1991-2010)

Raw data from: (EPA, n.dc). Assembled in current format by author (see supplementary materials 1).

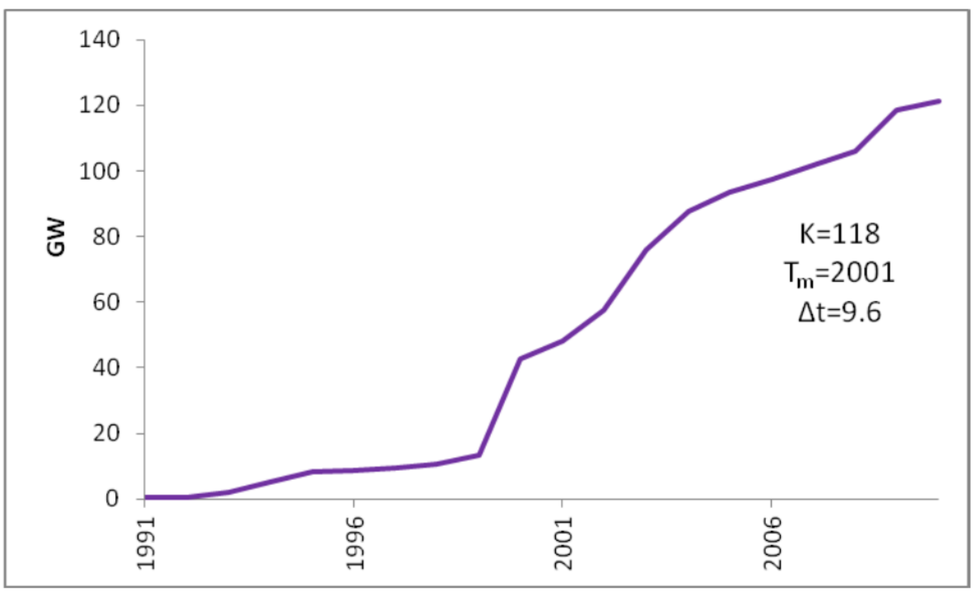


FIGURE C22. SCR CUMULATIVE CAPACITY (US 1991-2010)

Raw data from: (EPA, n.dc). Assembled in current format by author (see supplementary materials 1).

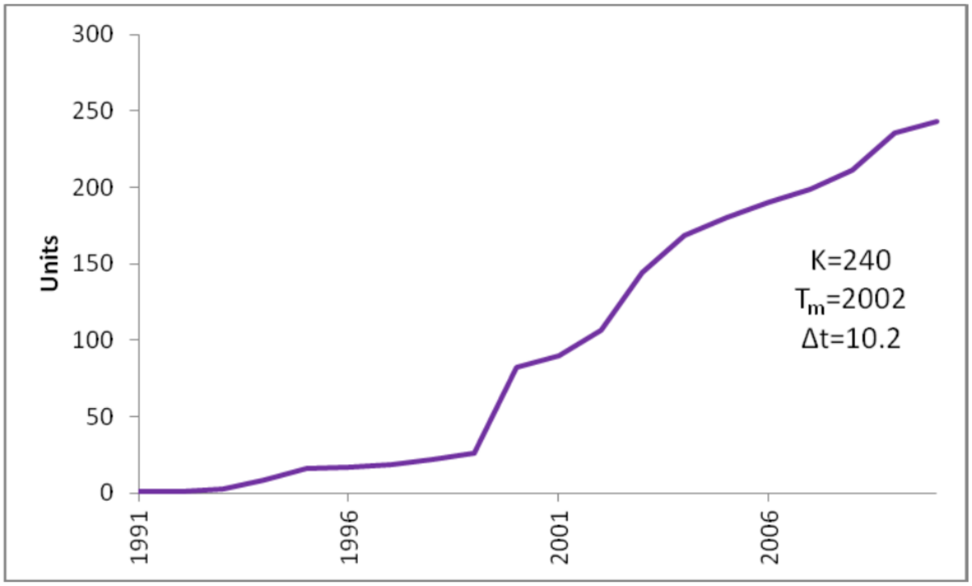


FIGURE C23. SCR CUMULATIVE CAPACITY (US 1991-2010)

Raw data from: (EPA, n.dc). Assembled in current format by author (see supplementary materials 1).

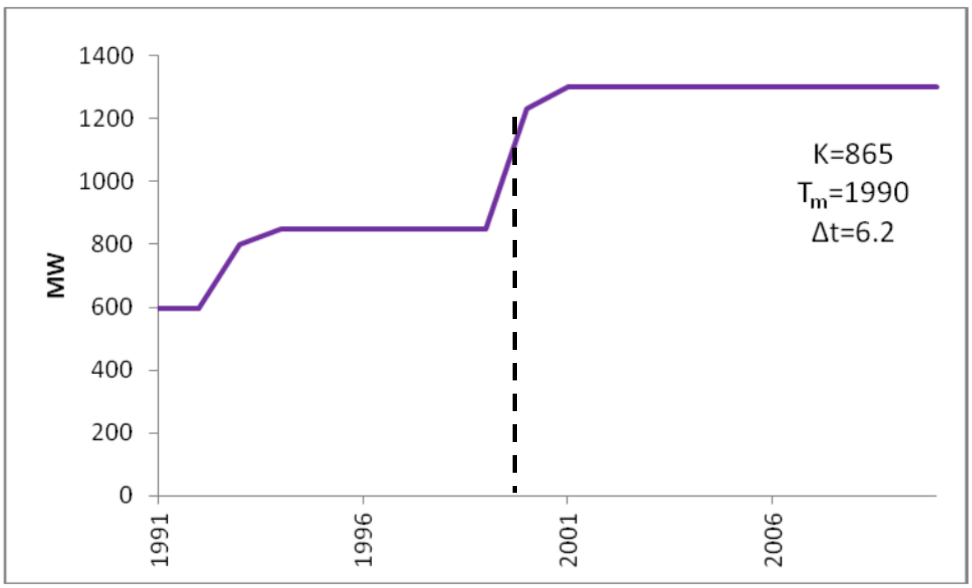


FIGURE C24. SCR MAXIMUM UNIT SCALE (US 1991-2010)

Raw data from: (EPA, n.dc). Assembled in current format by author (see supplementary materials 1).

Appendix D: FGD Costs- Other Indices

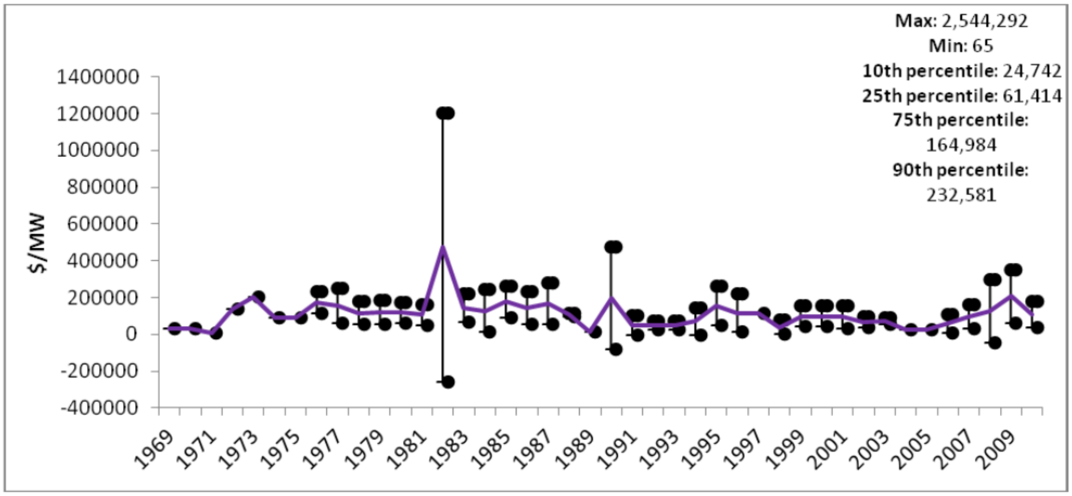


FIGURE D1. COST/MW FOR FGD UNITS (HANDY-WHITMAN INDEX)

Cost data obtained from (EIA, 2011) while unit capacity data was obtained from (EPA, n.dc). Indexing and unit cost calculations performed by author (see supplementary materials 2).

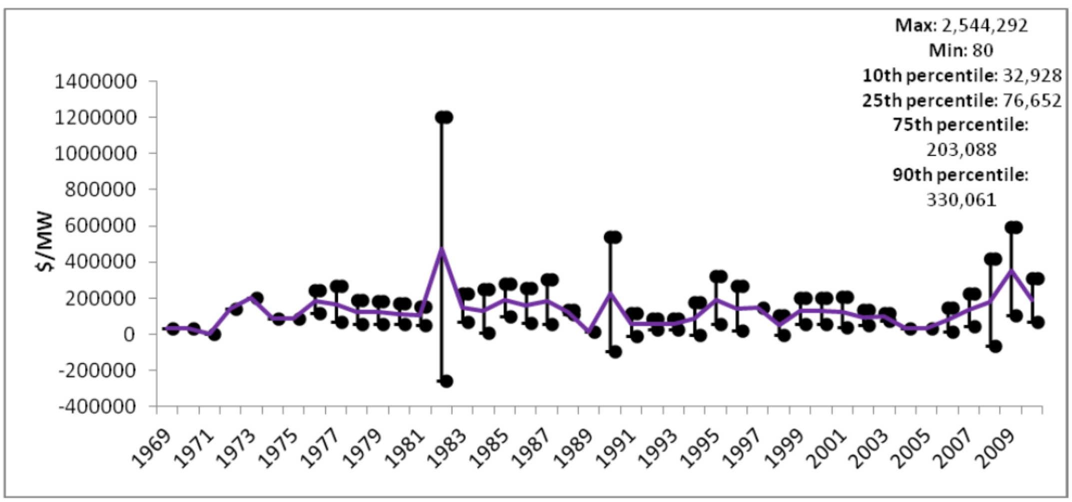


FIGURE D2. COST/MW FOR FGD UNITS (PPI COMMODITY INDEX)

Cost data obtained from (EIA, 2011) while unit capacity data was obtained from (EPA, n.dc). Indexing and unit cost calculations performed by author (see supplementary materials 2).

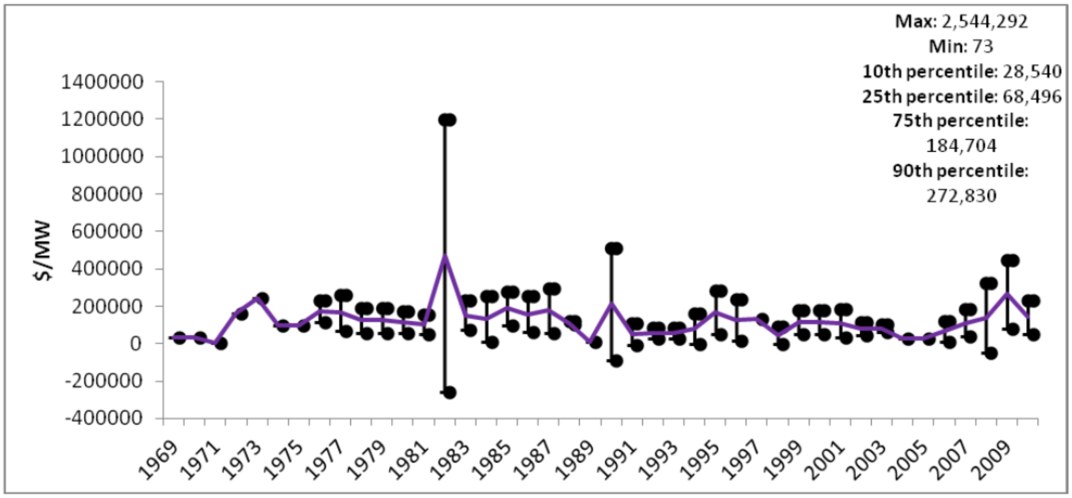


FIGURE D3: COST/MW FOR FGD UNITS (PPI CHEMICAL INDEX)

Cost data obtained from (EIA, 2011) while unit capacity data was obtained from (EPA, n.dc). Indexing and unit cost calculations performed by author (see supplementary materials 2).

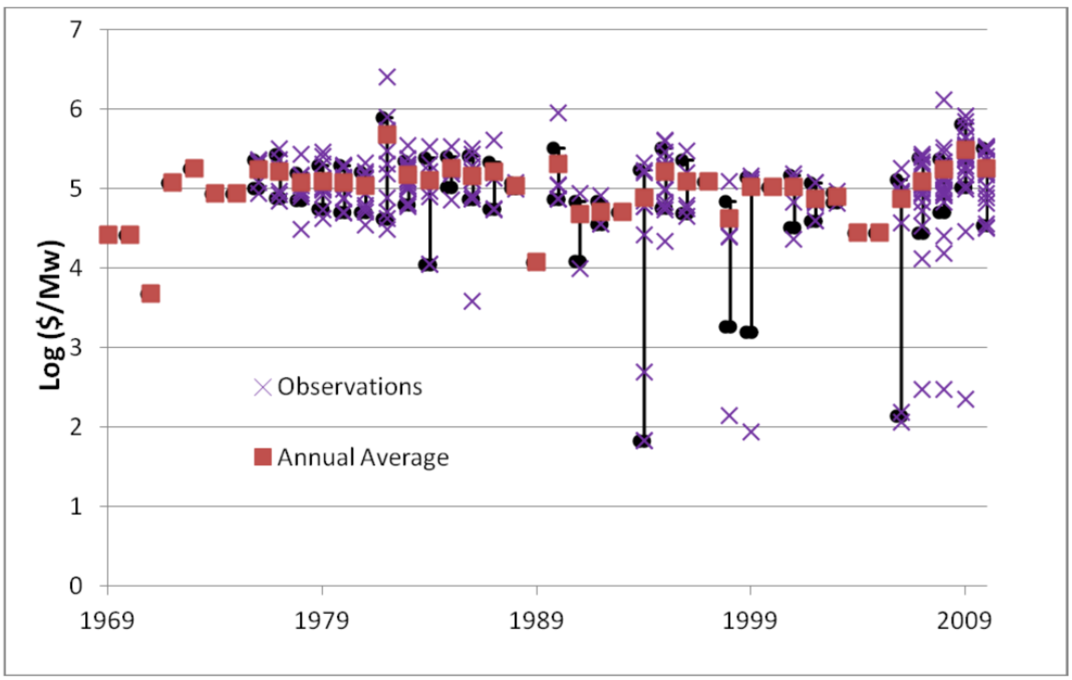


FIGURE D4: COST/MW DISPERSION (GDP DEFLATOR)

Cost data obtained from (EIA, 2011) while unit capacity data was obtained from (EPA, n.dc). Indexing and unit cost calculations performed by author (see supplementary materials 2). *Error bars show $10^{th}/90^{th}$ percentiles.

Appendix E: Regression Results

TABLE E1. REGRESSION RUNS 1-5

	1.	2.	3.	4.	5.
	LN(COST/MW)	LN(COST/MW)	LN(COST/MW)	LN(COST/MW)	LN(COST/MW)
WET	0.78(0.19)***	0.76(0.2)***	0.79(0.2)***	0.77(0.19)***	0.84(0.2)***
LN(UNSIZE)	0.09(0.12)	0.08(0.12)	0.09(0.12)	0.06(0.12)	0.12(0.12)
LN(PLCON)	-0.03(0.05)	-0.02(0.05)	-0.03(0.05)	-0.02(0.05)	-0.03(0.05)
LN(REMEFF)	-0.44(0.58)	-0.59(0.55)	-0.45(0.58)	-0.27(0.55)	-0.54(0.58)
LN(TRAINS)	0.49(0.24)**	0.48(0.25)*	0.49(0.25)**	0.47(0.23)**	0.51(0.24)**
LN($COALSO_2$)	0.12(0.09)	0.17(0.13)	0.11(0.1)	0.11(0.09)	0.10(0.09)
RETROFIT	0.23(0.18)	0.21(0.18)	0.21(0.17)	0.30(0.18)*	0.21(0.18)
LN(EXP)	-0.14(0.31)	-0.14(0.32)	-0.16(0.31)	-0.10(0.31)	-0.11(0.32)
LN(STEEL)	0.7(0.44)	0.78(0.45)*	0.64(0.45)	0.82(0.45)*	0.72(0.44)*
LN(AVGUNI)	0.84(0.55)	0.8(0.57)	0.86(0.55)	0.86(0.56)	0.82(0.55)
LN(INDCON)L	0.04(0.23)	0.05(0.24)	-0.01(0.26)	0.08(0.23)	0.03(0.23)
N(ENER)	0.53(0.58)	0.54(0.62)	0.54(0.58)	0.41(0.56)	0.5(0.59)
CONSTANT	14.29(3.63)***	15.05(3.41)***	14.11(3.67)***	13.58(3.49)***	14.49(3.64)***
PACIFIC		0.15(0.43)			
SATLANTIC		-0.12(0.28)			
NCENTRAL		-0.14(0.31)			
SCENTRAL		0.01(0.42)			
PLATEAU		0.05(0.35)			
IOWNED			0.18(0.3)		
MUNIICIP			0.09(0.3)		
COOP			0.06(0.38)		
#BUILTSIM				-0.34(0.17)**	
PLANTLRN					-0.29(0.2)
Number of Observations	303	303	303	303	303
Adj. R^2	0.1	0.09	0.09	0.11	0.1
DW Stat	1.97	1.97	1.97	2	1.98
White	115.19**	160.73	155.42**	126.43*	136.45**

TABLE E2. REGRESSION RUNS 6-9

	6.	7.	8.	9.
	LN(COST/MW)	LN(COST/MW)	LN(COST/MW)	LN(COST/MW)-HWI
WET	0.85(0.19)***	2.96(1.01)***	0.65(0.19)***	0.77(0.19)***
LN(UNSIZE)	0.16(0.13)	0.39(0.18)**	0.1(0.12)	0.09(0.12)
LN(PLCON)	-0.03(0.05)	-0.02(0.05)	-0.06(0.05)	-0.03(0.05)
LN(REMEFF)	-0.59(0.59)	-0.4(0.61)	-0.53(0.6)	-0.44(0.57)
LN(TRAINS)	0.53(0.25)**	0.55(0.22)**	0.48(0.24)**	0.51(0.24)**
LN($COALSO_2$)	0.09(0.1)	0.14(0.09)	0.08(0.1)	0.12(0.09)
RETROFIT	0.28(0.18)	0.21(0.18)	0.2(0.18)	0.23(0.18)
LN(EXP)	-0.08(0.32)	0.05(0.32)	-0.1(0.31)	-0.21(0.31)
LN(STEEL)	0.66(0.44)	1.01(0.46)**	0.83(0.46)*	0.45(0.44)
LN(AVGUNI)	0.88(0.54)	0.78(0.54)	1.02(0.55)*	0.69(0.55)
LN(INDCON)	0.02(0.23)	0.11(0.22)	0.04(0.23)	-0.12(0.23)
LN(ENER)	0.5(0.59)	0.29(0.6)	0.29(0.56)	0.43(0.58)
CONSTANT	14.41(3.61)***	12.1(3.9) ***	13.82(3.6)***	14.48(3.59)***
UTILLRN	-0.3(0.14)**			
DISPOSAL			0.5(0.21)**	
LNSIZE*WET		-0.39(0.18)**		
Number of Observations	303	303	303	303
Adj. R^2	0.11	0.11	0.12	0.09
DW Stat	1.98	1.96	1.97	1.97
White	125.22*	121.45*	131.63**	116.11**

TABLE E3. REGRESSION RUNS 10-13

	10.	11.	12.	13.
	LN(COST/MW)	LN(COST/MW)	LN(COST/MW)	LN(COST/MW)
WET	0.8(0.19)***	0.86(0.24)***	0.78(0.19)***	0.79(0.19)***
LN(UNSIZE)	0.05(0.13)	0.16(0.13)	0.09(0.12)	0.07(0.12)
LN(PLCON)	-0.02(0.05)	0.02(0.04)	-0.03(0.05)	-0.01(0.05)
LN(REMEFF)	-0.45(0.59)	0.2(0.6)	-0.45(0.57)	-0.51(0.59)
LN(TRAINS)	0.42(0.26)*	0.44(0.23)*	0.49(0.24)**	0.45(0.23)*
LN($COALSO_2$)	0.10(0.1)	0.14(0.1)	0.11(0.09)	0.12(0.09)
RETROFIT	0.28(0.17)*	0.24(0.18)	0.23(0.18)	0.27(0.18)
LN(EXP)	0.28(0.51)	-0.44(0.34)	-0.12(0.31)	-0.21(0.31)
LN(STEEL)	1.13(0.57)**	0.7(0.43)*	0.72(0.45)	0.69(0.42)
LN(AVGUNI)	0.86(0.52)	0.48(0.47)	0.86(0.53)	0.88(0.55)
LN(INDCON)	-0.45(0.74)	0.12(0.24)	0.04(0.23)	0.06(0.22)
LN(ENER)	0.02(1.12)	0.98(0.64)	0.52(0.58)	0.54(0.58)
CONSTANT	11.84(4.61)**	13.56(3.57)***	14.22(3.59)***	12(3.55)***
NSPS1979	-0.87(0.64)			
CAA1995	-1.33(0.95)			
CAA2000	-0.38(0.62)			
CAIR2005	-1.14(0.62)*			
FIRMLEARN			-0.03(0.08)	
FLUEGAS/GENCAP				0.26(0.12)**
AA		0.73(0.68)		
ABB		0.46(0.34)		
AL		-0.17(0.29)		
AM		-0.45(0.42)		
AP		0.95(0.44)**		
BL		0.59(0.4)		

BW		-0.18(0.24)		
CA		-1.55(0.79)*		
CC		-0.28(0.38)		
CE		-0.51(0.34)		
CO		-0.46(0.42)		
EE		1.36(0.49)***		
FL		-1.06(0.66)		
FM		0.11(0.36)		
FW		2.42(0.6)***		
GE		-1.25(0.9)		
HA		-0.28(0.41)		
HT		0.25(0.24)		
IH		-0.2(0.34)		
JO		0.58(0.39)		
KE		0.06(0.33)		
LLB		0.46(0.35)		
MI		-1.24(1.03)		
MX		0.08(0.34)		
OT		0.58(0.24)**		
PB		-1.04(0.55)*		
RC		0.04(0.34)		
RS		0.19(0.7)		
SHU		1.39(0.34)***		
TH		0.14(0.4)		
UO		-0.32(0.34)		
WA		-6.84(0.39)***		
WAP		0.34(0.26)		
Number of Observations	303	303	303	303
Adj. R^2	0.1	0.24	0.1	0.11
DW Stat	1.99	1.93	1.97	1.97
White	169.29**	NA	145.79***	123.27*

TABLE E4. REGRESSION RUNS 14-17

	14.	15.	16.	17.
	LN(COST/MW)	LN(COST/MW)	LN(COST/MW)	LN(COST/MW)
WET	0.79(0.19)***	0.79(0.19)***	0.5(0.23)**	0.85(0.2)***
LN(UNSIZE)	0.09(0.12)	0.09(0.12)	-0.05(0.12)	0.12(0.11)
LN(PLCON)	-0.03(0.05)	-0.03(0.05)	-0.04(0.05)	-0.04(0.05)
LN(REMEFF)	-0.43(0.58)	-0.44(0.58)	-0.47(0.59)	-0.61(0.54)
LN(TRAINS)	0.49(0.24)**	0.49(0.25)**	0.38(0.23)*	0.53(0.24)**
LN($COALSO_2$)	0.12(0.1)	0.12(0.1)	0.12(0.9)	0.12(0.09)
RETROFIT	0.6(1.42)	0.23(0.18)	0.08(0.2)	0.26(0.19)
LN(EXP)	-0.13(0.32)	-0.14(0.32)	-0.37(0.33)	
LN(STEEL)	0.73(0.44)*	0.69(0.44)	0.64(0.46)	1.16(0.4)***
LN(AVGUNI)	0.84(0.55)	0.84(0.54)	0.81(0.52)	0.94(0.54)*
LN(INDCON)	0.04(0.23)	0.03(0.23)	0.02(0.23)	0.26(0.25)
LN(ENER)	0.52(0.59)	0.52(0.59)	0.73(0.61)	-0.17(0.46)
CONSTANT	14.15(3.63)***	14.27(3.64)***	15.82(3.75)***	11.56(3.7)***
RETROFIT*GENCAP	-0.05(0.2)			
BYPASS		-0.04(0.17)***		
FORCEDOXIDATION			1.18(0.29)***	
INHIBOXIDATION			1.44(0.3)***	
CCAP(MW)				0.28(0.21)
Number of Observations	303	303	303	303
Adj. R^2	0.1	0.1	0.13	0.1
DW Stat	1.97	1.97	1.96	1.99
White	142.95***	142.43***	169.42***	119.06**

TABLE E5. REGRESSION RUNS 18-19

	18.	19.
	LN(COST/MW)	LN(COST/MW)
LN(UNSIZE)	0.21(0.14)	0.27(0.17)
LN(PLCON)	0.05(0.05)	0.04(0.05)
LN(REMEFF)	0.08(0.54)	-0.43(0.59)
LN(TRAINS)	0.95(0.25)***	0.33(0.20)
LN($COALSO_2$)	0.07(0.12)	0.09(0.1)
RETROFIT	0.52(0.18)***	0.15(0.22)
LN(EXP)	1.15(1.13)	-0.23(0.37)
LN(STEEL)	(dropped)[16]	1.48(0.52)***
LN(AVGUNI)	(dropped)	0.66(0.48)
LN(INDCON)	-1.01(0.84)	0.22(0.244)
LN(ENER)	-1.07(2.88)	0.42(0.73)
CONSTANT	6.6(8.6)	10.71(3.83)***
FORCEDOXIDATION		0.76(0.38)**
INHIBOXIDATION		1.19(0.44)***
WET	0.57(0.23)**	4.08(1.29)***
#BUILTSIM		-0.23(0.21)
UTILLEARN		-0.1(0.12)
FLUEGAS/GENCAP		0.3(0.11)***
LNSIZE*WET		-0.62(0.22)***
DISPOSAL		0.5(0.21)**
AA		0.27(0.57)
ABB		0.6(0.4)
AL		-0.08(0.35)
AM		0.07(0.45)
AP		1.53(0.53)***
BL		1.83(0.46)***
BW		-0.02(0.32)
CA		-1.23(0.85)
CC		0.1(0.4)
CE		-0.25(0.38)
CO		1.6(0.62)***
EE		1.22(0.48)*
FL		-0.71(0.68)
FM		0.03(0.51)
FW		2.11(0.68)***
GE		-0.54(0.77)
HA		-0.59(0.53)
HT		0.53(0.36)
IH		-0.18(0.4)
JO		0.71(0.52)
KE		0.22(0.51)
LLB		0.57(0.42)
MI		-0.37(0.97)
MX		1.36(0.58)**
OT		0.97(0.56)*
PB		-0.73(0.56)
RC		0.34(0.43)
RS		-0.23(0.6)
SHU		1.5(0.43)***
TH		-0.06(0.37)
UO		0.26(0.39)

[16] Variables were dropped in this specification due to perfect collinearity with some of the year binary variables.

WA		-6.72(0.49)***
WAP		0.49(0.33)
1971	-0.38(0.73)	
1972	1.59(0.71)**	
1973	1.9(0.82)**	
1974	1.44(0.72)**	
1976	1.7(0.23)***	
1977	1.52(0.52)***	
1978	0.34(0.63)	
1979	0.09(0.91)	
1980	-0.23(0.84)	
1981	-0.37(0.43)	
1982	-0.031(0.38)	
1983	-0.30(0.32)	
1984	-0.73(0.57)	
1985	(dropped)	
1986	-0.58(0.36)	
1987	-0.73(0.43)*	
1988	-0.67(0.58)	
1989	-5.4(0.84)***	
1990	-0.97(0.79)	
1991	-1.72(0.87)**	
1992	-1.07(0.47)**	
1994	-2.7(1.11)**	
1995	-1.15(1.04)	
1996	-1.26(1.17)	
1997	-0.72(0.95)	
1998	-2.99(1.33)**	
1999	-2.1(1.61)	
2001	(dropped)	
2002	-0.23(0.29)	
2003	-0.58(0.31)*	
2004	-1.62(0.34)***	
2006	-1.83(1.13)	
2007	-0.3(0.91)	
2008	-0.16(0.88)	
2009	0.49(1.17)	
2010	0.42(1.12)	
Number of Observations	303	303
Adj. R^2		
DW Stat	0.19	0.3
White	2.13	2.01
	NA	NA

TABLE E6. REGRESSION RUNS 20-23 (PATENT SAMPLE)

	20.	21.	22.	23.
	LN(COST/MW)	LN(COST/MW)	LN(COST/MW)	LN(COST/MW)
LN(COALSO$_2$)	0.24(0.12)**	0.23(0.12)*	0.23(0.12)*	0.23(0.12)*
LN(TRAINS	0.52(0.34)	0.55(0.35)	0.55(0.35)	0.54(0.35)
LN(REMEFF)	-0.31(0.47)	-0.36(0.47)	-0.35(0.47)	-0.32(0.48)
LN(PLCON)	-0.12(0.09)	-0.13(0.1)	-0.14(0.1)	-0.13(0.09)
LN(UNSIZE)	0.18(0.17)	0.16(0.16)	0.16(0.16)	0.16(0.16)
WET	0.66(0.25)***	0.66(0.25)***	0.65(0.25)***	0.64(0.25)**
RETROFIT	0.01(0.22)	0.08(0.22)	0.08(0.22)	0.09(0.22)
LN(CCAP)	0.29(0.33)	-0.73(0.37)**	-0.64(0.36)*	-0.73(0.40)*
LN(STEEL(-1))	1.37(0.65)**	0.73(0.63)	0.63(0.64)	0.53(0.65)
LN(AVGUNI)	1.18(0.83)	1(0.74)	0.93(0.73)	0.83(0.68)
LN(INDCON)	-0.67(0.46)	-0.7(0.45)	-0.72(0.45)	-0.78(0.44)*
LN(ENER(-1))	-1.01(0.78)	-0.87(0.75)	-0.94(0.76)	-1.11(0.76)
CONSTANT	8.11(3.37)**	3.25(3.75)	4.82(3.5)	4.62(3.46)
PATENT		1.45(0.42)***		
PATENT(-1)			1.17(0.32)***	
PATENT(-2)				1.25(0.41)***
Number of Observations	188	188	188	188
Adj. R^2	0.11	0.12	0.12	0.12
DW Stat	1.96	2.06	2.06	12.07
White	143.83***	152.76***	152.09***	152.59***

TABLE E7. REGRESSION RUNS- ALTERNATIVE TIMEFRAMES

	1969-1979	1980-1999	1999-2010
	LN(COST/MW)	LN(COST/MW)	LN(COST/MW)
LN(COALSO$_2$)	0.01(0.12)	0.19(0.16)	-0.05(0.2)
LN(TRAINS	-0.03(0.19)	0.72(0.42)*	0.18(0.26)
LN(REMEFF)	0.67(0.49)	-1.2(0.61)*	2.64(2.83)
LN(PLCON)	0.09(0.1)	-0.17(0.11)	0.01(0.05)
LN(UNSIZE)	-0.05(0.14)	0.26(0.22)	-0.73(0.25)***
WET	NA (all obs wet)	0.68(0.27)**	0.8(0.35)**
RETROFIT	0.39(0.28)	0.27(0.26)	0.81(0.36)**
LN(CCAP)	1.12(0.43)**	0.75(0.69)	2.48(6.63)
LN(STEEL(-1))	49.33(24.47)*	1.45(1.2)	0(1.44)
LN(AVGUNI)	1.34(0.7)*	-0.97(2.12)	0.58(1.25)
LN(INDCON)	2.69(0.81)***	-3.03(1.13)***	1.46(1.14)
LN(ENER(-1))	-14.65(7.12)**	-1.55(1.06)	1.26(4.25)
CONSTANT	-3.61(5.41)	6.7(7.48)	-10.62(40.85)
Number of Observations	44	139	120
Adj. R^2	0.45	0.17	0.14
DW Stat	2.05	2.18	2.14
White	44	113.15*	100.11*

Appendix F: Sensitivity analysis run description

Run	Explanation and Rationale	Construction	Data
Base Model + Regional Variables (Run 2)	Dummy variables representing the region of the US the plant was located to test for regional labour market conditions or other regional factors influencing costs.	. The sample was divided into six regions based on the Handy Whitman Index. The North East region is the base case.	EIA 2011
Base Model + Ownership category (Run 3)	Used to determine whether there was systemic misreporting of costs based on whether the utility was investor owned, owned by a municipality, owned by the state, or a co-operative	Dummy variables representing whether the utility was investor owned, owned by a municipality, owned by the state, or a co-operative.	Platts 2011
Base Model + Simultaneous Construction (Run 4)	Costs associated with overhead and administration would be spread out over multiple units, thereby lowering costs.	A series of binary variables representing whether two, three, or more, FGD units were built (or planned) simultaneously. Assumed simultaneous construction if the variables were built within the same year or one year apart. The base case represents no simultaneous construction.	EIA 2011
Base Model + Plant Learning (Run 5)	Included to see if a history of constructing a FGP, a SCR, or a FGD unit by the *power plant* will influence cost. Assumes some of the knowledge/experience with installing pollution control devices garnered by plant operators will translate into lower costs.	A continuous variable which counts the number of pollution control devices built by the plant prior to the construction of the given unit.	EIA 2011
Base Model + Utility Learning (Run 6)	Included to see if a history of constructing a FGP, a SCR, or a FGD unit by the *utility* will influence cost. Assumes some of the knowledge/experience with installing pollution control devices obtained at the head office will translate into lower costs.	A continuous variable which counts the number of pollution control devices built by the utility prior to the construction of the given unit.	EIA 2011
Base Model +	Included to determine if	Interaction term between	EIA 2011, EPA

Scale/Technology interactions (Run 7)	scale economies change based on the type of technology utilized.	the unit scale variable with the Wet FGD binary variable.	n.dc
Base Model + By-product recovery (Run 8)	Included to determine the impact of the presence of waste/by product recovery on cost. It makes sense that the building of such functionality into the FGD design should raise costs relative to a system without such functionality.	Binary variable indicating whether the FGD unit includes a by-product recovery system.	EIA 2011
Base Model + Handy Whitman Index (Run 9)	Used an alternative index to deflate the dependent variable. As mentioned previously, the use of the Handy-Whitman index resulted in a different cost trend for the sample as a whole relative to GDP deflator.	Estimated the base model using the Handy Whitman index to deflate unit costs.	EIA 2011 for costs, EPA n.dc for capacity
Base Model + Regulations (Run 10)	The ever-expanding scope and scale of regulation of SO_2 in the US may have raised FGD costs by making it more favourable to build FGD units in plants where it previously was not economic to do so.	Binary variables representing the most recent regulation passed when the FGD unit was built. Variables are for the NSPS 1979, the 1995 CAA Amendments, the 2000 CAA Amendments, and the 2005 CAIR. The base case is the regulatory regime prior to 1979 (no regs for 1969 and for all others NSPS 1971).	NA
Base Model + Firm dummies (Run11)	Aimed at capturing impacts which are firm-specific but time invariant on cost. Reason to believe that some firms can produce FGD units cheaper/more expensive than others over the sample period due to differences inherent to the particular firms	A series of binary variables identifying the firm who built the unit. Relative to a base case using the company BPE.	EIA 2011
Base Model + Manufacturing firm learning (Run12)	This variable is to determine if the cumulative experience of FGD construction at a given plant results in lower costs per unit. In essence, this variable captures learning by doing at the	Cumulative summation of the number of FGD units built prior to the unit in question by the company who built the unit.	EIA 2011

	plant level rather than the industry level.		
Base Model + Flue Gas/unit generating capacity (Run 13)	Greater flue gas volume/unit generating capacity necessitates more duct work when installing FGD systems, which affects costs.	Divided the rate of the volume of actual flue gas per minute by the total generating capacity of the plant.	EIA 2011
Base Model + Retrofit*GenCapacity (Run 14)	Plants with smaller generating capacities (generally smaller plants in absolute size) may have less space to retrofit with FGD systems and thus, may see higher costs relative to retrofits in large plants.	Interaction term between generating capacity of the plant and its retrofit status.	Platts 2011 (for retrofit status), EIA 2011 for generating capacity.
Base Model + Bypass (Run 15)	Configuring the FGD system to account for the bypass of a fraction of the flue gas may cause higher costs to account for this additional functionality.	Binary variable for whether the FGD unit in question	EIA 2011
Base Model + Oxidation (Run 16)	Forced/Inhibited oxidation technologies have additional steel requirements associated with it, necessitating higher costs.	Binary variable for whether the FGD unit in question was forced oxidation. This necessitated the adjustment of the wet binary variable into three separate binary variables- one for forced oxidation, another for inhibited oxidation, and yet another for regular wet FGD. Dry FGD units remain the reference case.	Weilert et al., 2010. *If not reported, assumed was not forced oxidation.
Base Model + Cumulative Capacity (Run 17)	Replaced the experience variable (measured in cumulative units) with a cumulative capacity variable measured in cumulative MWe	Cumulative summation of the capacity of all FGD units built prior to the unit in question.	EIA 2011
Base Model + Year Dummies (Run 18)	To capture year specific effects which do not vary by location and which were not already captured in the base model.	A series of binary variables identifying the year the unit was built. Relative to a base case 1969.	EIA 2011
Base Model + Cumulative Patent Data (Run 20-23)	Test to see if the cumulative number of patents (taken contemporaneously and lagged by 1 and 2 periods)	Dataset compiled by Lohwasser & Madlener- used for analysis in Lohwasser & Madlener	Lohwasser & Madlener (2010)

	impacts unit costs as per the learning-by-researching phenomenon	(2010). In the contemporaneous case, a value of the number of cumulative patents up to that point in time is assigned to any FGD units built that year.	