Technology Diffusion and Environmental Regulation:

The Case of Coal-Fired Scrubbers

Elaine F. Frey, Ph.D. Candidate[1]

Department of Economics
George Washington University
1922 F Street, NW
Old Main, Suite 208
Washington, DC 20052
Phone: (202) 566-2359
effrey@gwu.edu

June 22, 2007

Abstract

This research examines the technological diffusion of scrubbers, a sulfur dioxide (SO_2) abatement technology, under Title IV of the Clean Air Act. Specifically, I use a survival analysis framework to determine how technology diffusion responds to changes in regulatory structure and regulatory stringency, controlling for the expected cost of installing a scrubber. I find that electric generating units with strict pre-Title IV command-and-control regulations and low expected scrubber installation costs have a high probability of installing a scrubber. Also, individual generating unit characteristics such as age and size are also important factors in this decision. These findings suggest that, although Title IV has encouraged diffusion, many scrubbers have been installed because of state regulatory pressure. Since policies are often evaluated based on the incentives they provide to promote adoption of new technologies, it is important that policy makers understand the relationship between technological diffusion and regulatory structure to make informed decisions in the future.

[1] This research is an essay from my dissertation and has been funded in part by the U.S EPA, National Center for Environmental Economics. Opinions expressed in this paper are solely those of the author and do not necessarily represent those of the U.S. EPA. I would like to thank my dissertation advisor, Arun Malik, dissertation committee members Frederick Joutz and Wallace Mullin, Ron Shadbegian and members of the GWU Microeconomics Seminar for useful comments and suggestions for this paper. I would also like to thank Nathaniel Keohane for providing data.

I. Introduction

Research that concerns the effects of policy on technology diffusion, especially in the area of environmental policy, has increased in recent years. Economists' interest in this area spawns from the fact that the diffusion of new technologies has the potential to change environmental conditions and because implementing environmental regulation often induces or alters the diffusion path of an abatement technology. This study will contribute to this body of work by determining the effects of regulatory type and stringency on the diffusion of technology. Specifically, I will examine the effect of Title IV of the 1990 Clean Air Act Amendments on the diffusion of scrubbers by coal-fired generating units. Scrubbers, also known as flue gas desulfurization units, are designed to remove sulfur dioxide (SO_2) from boiler and furnace exhaust gases of electric generating units. Scrubbers can be highly effective and can be designed to remove up to 99 percent of SO_2 from a generating unit's emissions stream.

Title IV, also known as the Acid Rain Program, presents a unique regulatory regime which established the first nationwide tradable pollution permit system in the U.S. This was significantly different from the emission rate standards and abatement technology requirements that were in place previously. The purpose of Title IV was to mitigate the negative effects of SO_2 emissions from electric power plants by cutting emissions by 40 percent from 1980 levels. Title IV was implemented in two phases. Phase I required the 263 largest and dirtiest generating units, known as Table A units, to reduce emissions via a permit market beginning in 1995. Each unit was allocated permits sufficient to achieve an emission rate of 2.5 lbs of SO_2/mmBtu (based on average heat input in 1985-1987), where one permit allows the unit to emit one ton of SO_2. Allocated permits can then be used, banked, or traded. Phase II began in 2000 and includes all units larger than 25 MW (megawatts of nameplate capacity). Under Phase II, each unit is allocated permits sufficient to emit at a rate of 1.2 lbs of SO_2/mmBtu. Prior to Title IV, newly constructed generating units had to follow the New Source Performance Standards (NSPS), which established rigid technology and emission restrictions that required the installation of scrubbers. In addition, existing sources were subject to state level emission rate standards or command-and-control regulations. State level emission rates were established under State Implementation Plans (SIPs) as part of the National Ambient Air Quality Standards (NAAQS). These restrictions were essentially overridden under Title IV, although existing sources still have to comply with state regulations.

Theory suggests that market-based policies such as Title IV give firms more incentives to adopt new technologies, relative to command-and-control regulations (see Milliman and Prince, 1989; Jung et al., 1996; Downing and White, 1986; Fischer et al., 2003; and Keohane, 2006). But because there have been so few market-based regulations in place in the U.S., there is little empirical evidence to support this claim. This research will examine the technological diffusion of scrubbers, a SO_2 abatement technology, under Title IV of the Clean Air Act. I use survival analysis to determine how technology diffusion responds to changes in regulatory structure and changes in regulatory stringency, controlling for the expected cost of installing a scrubber. I find that electric generating units with strict state command-and-control regulations have a high probability of installing a scrubber. Moreover, the expected cost of installing a scrubber is an important factor in this decision; as expected, those units that have very low expected costs are more likely to adopt. Finally, individual generating unit characteristics such as age and size are also important factors in this decision.

The remainder of this paper is organized as follows: Section II provides a brief overview of technological diffusion models and empirical evidence, Section III establishes the theoretical and empirical model and discusses the data used in this study, Section IV presents the results of the empirical estimation and Section V concludes.

II. Literature Review

In this section, I will give an overview of relevant empirical findings that relate to my research. Throughout the text, I will follow Schumpeter's definition of technology change and technology diffusion. Schumpeter (1942) describes three stages of technological change: i) invention, the creation of a new product or process; ii) innovation, advances in technologies and techniques used in production; and iii) diffusion. I will use the term adoption as the act of installing a particular technology; a single firm adopts a technology and the combined adoption decisions of firms are referred to as technological diffusion. Much of the work on diffusion does not explicitly model policy effects, but rather, concerns itself with explaining why some technologies are diffused more quickly than others and why some firms will adopt more quickly than others. Four types of effects have been developed to explain these patterns of technology diffusion over time: epidemic, order, stock and rank effects. Some empirical research exists, which tests one or more of these effects on diffusion and a small subset of these studies also incorporates the effect of policy of the diffusion process. I will first discuss the epidemic, order, stock and rank effects in more detail and then give an overview of the major empirical findings in this area.

II.A. Epidemic, Order, Stock and Rank Effects

Epidemic, order, stock and rank effects have traditionally been the basis for technology diffusion models for the purpose of explaining the pattern of diffusion over time.[2] These models each follow the well-known diffusion pattern, the S-curve, which reveals that firms find it optimal to adopt a particular technology at different times. The first generation of models used the epidemic approach, finding that technological diffusion is self-propagating and occurs through a process of information exchange among firms (Griliches, 1957). Under this framework, diffusion is analogous to the spread of an infectious disease; as the infected (adopters) come into contact with non-infected individuals (non-adopters), they spread the disease (technology). However, the epidemic model does not explain any underlying economic behavior, assumes that all firms are homogeneous and provides no theoretical explanation for why some firms would adopt a technology faster than others.

Models that incorporate stock and order effects assume that a firm's adoption decision is dependent on the actions and adoption decisions of other firms. For this reason, both types of models are often termed game-theoretic models. To make the adoption decision, firms compare their profits with adoption to their profits without adoption, given the decisions of other firms. In this model, the benefits of adoption are also dependent on production levels of the firm and production levels are dependent on other firms' adoption behavior. Although profits differ between adopters and non-adopters, firms within

[2] See Stoneman (2001), Hall and Khan (2003) and Geroski (2000) for an in-depth review of the diffusion literature. In addition, Jaffe et al. (2002) provide an overview of the relationship between technological change and environmental issues.

each group have the same profit levels.[3] The order model assumes that the present value of adoption depends on the firm's order of adoption, relative to other firms. Thus, benefits of adoption decrease as adoption increases and eventually, no firms find it profitable to adopt (barring any other changes in the quality or cost of the technology). Unlike the stock model, Fudenberg and Tirole (1985) argue that the profit levels of firms differ such that those firms that adopt early have higher profits than firms that adopt later. The model implies that there are first-mover advantages to adoption, in that the first to adopt can influence the outcomes of other rival firms.

Finally, models that integrate rank effects, beginning with the work of David (1969), assume that potential adopters have heterogeneous characteristics, which affect the benefits they receive from adoption. The benefits of adoption can be influenced by the firm's location, previous investments and technologies, management decisions and knowledge, market conditions, the regulatory environment, firm organizational type, expectations of future market conditions and the firm's discount rate. In this model, adoption occurs if the net present value of adoption is positive and it is not more profitable to put off the adoption decision until another period. A diffusion path is created because over time, the benefits or costs of adoption change. Like the order model, those firms with the highest net benefits will adopt the technology first.

Stoneman (2001) suggests that empirical research on technological diffusion aims to prove that data is consistent with theory and to identify which factors are the most important in the diffusion process. Despite these objectives, there is no certainty as to which effect (epidemic, stock, order or rank) describes technology diffusion best. In the majority of empirical studies, the researcher simply chooses one model and applies the model to a particular diffusion case. In many instances, this is due to limited availability of data, which precludes the researcher from using a particular model. One exception is Karshenas and Stoneman (1993), who nest all four effects into one model. They find evidence to support rank and epidemic effects, but no evidence that the stock or order effects describe the diffusion process in that particular application.

[3] See Reinganum (1981) and Stoneman (2001) for more detail on stock models.

II.B. Empirical Evidence

Empirical studies often utilize probit or survival models, which contain variables that take into account one or more of the four effects described above. Variables that have been used to incorporate the rank effect (i.e. firm heterogeneity) include firm characteristics such as firm size, age, ownership type and the complexity of a firm's operations. Firm size is thought to have an effect on diffusion; a number of authors find that large firms are more likely to adopt than smaller firms (Rose and Joskow, 1990; Karshenas and Stoneman, 1993; Popp, 2006; Snyder et al., 2003; Kerr and Newell, 2003; and Fuglie and Kascak, 2001).

There is some evidence that firm age has a negative effect on the instance of adoption (Popp, 2006), but, Karshenas and Stoneman (1993) and Dunne (1994) find that age is not statistically significant. Rose and Joskow (1990) find that ownership structure affects diffusion rates; however, results from Karshenas and Stoneman (1993) do not show ownership type to have a statistically significant effect. Complexity of the firm's operations is also thought to be an important predictor of adoption but the results are mixed. Snyder et al. (2003) find that complexity has a negative effect on the probability of adoption, but Popp (2006) and Kerr and Newell (2003) show a positive effect.

The cost of installing new technology also seems to have a negative effect on technology adoption (Stoneman and Karshenas, 1993; Stoneman and Kwon, 1994; Kerr and Newell, 2003); but measuring costs accurately is often difficult, due to data constraints. Previous studies have used firm characteristics, such as firm size, as proxies for the differences in adoption costs across firms. My research differs in that the expected cost for scrubber installation will be explicitly estimated.

Stoneman and Karshenas (1993) show that the number of firms that have previously adopted the technology can be used to measure both stock effects and order effects. Order effects are also captured by a variable for the expected number of adopters in the next period. Although, as Popp (2006) points out, including both number of firms that have adopted the technology and regulation variables in the estimation may lead to endogeneity, since regulatory stringency may directly affect the number of adopters. For this reason, my estimation will exclude the number of previous adopters as an explanatory variable.

Other empirical work has supported the theoretical finding that market-based policies, such as Title IV, create more incentives for technological adoption than command-and-control policies. Popp (2001) uses detailed data on patents of electric generating units that have installed scrubbers since 1985 to test if Title IV caused innovation and adoption of more efficient technologies. He finds that although the number of patents did not increase because of the permit system, more efficient scrubbers were installed because of Title IV, leading to lower abatement costs. Bellas (1998) finds no evidence of technological advances in scrubbers in new electric generating units under the command-and-control regulations in place before Title IV was implemented.

Keohane (2005) provides an empirical simulation of abatement choices under different regulatory schemes. He finds that the type of regulation implemented is an important determinant of abatement choice. Specifically, he finds evidence that total abatement costs are lower under a permit system because of the types of technologies; his primary focus is on coal-switching technologies and the installation of scrubbers. This provides evidence that permit systems grant more incentives for increased technological adoption than an alternative command-and-control policy. Similarly, Gray and Shadbegian (1998) find that in the paper industry, state environmental regulations do have an effect on the technology choice of firms. In particular, strict regulations have a large impact on technology choices of new plants, but regulatory stringency has little to no effect on existing plants.

Kerr and Newell (2003) provide empirical evidence on the dynamic effects of environmental regulation on technology diffusion, using data from oil refineries. Their survival model differs from similar models in that it incorporates the effect of market-based regulation versus command-and-control regulation on technological adoption. Consistent with theory, they find that increased regulatory stringency has a positive effect on the adoption of the new technology and that firms are more likely to adopt the technology under the permit system than under a performance standard.

Popp (2006) uses a survivor model for technological adoption of two types of nitrous oxide (NO_x) emission controls for electric power plants. His estimation controls for expected quality increases of scrubbers, using patent data as a proxy for increased future technological improvements. His results show that regulatory stringency is the most important predictor of technology choice. In addition, he finds that available knowledge of emerging technologies, from domestic innovations and knowledge from abroad, has a small but significant effect on adoption decisions.

Finally, Snyder et al. (2003) use a survival model to estimate the effects of environmental regulations on the diffusion of membrane cell technology, a cleaner technology for the production of chlorine. They model both the adoption of membrane cell technology at existing plants, as well as the exit of older plants using a survival model. Dummy variables are used to control for the effects of each type of regulation on diffusion of new technologies and the exit of older chlorine facilities. They find that the presence of environmental regulations did not facilitate technological adoption at existing facilities, but did increase the exit rate of facilities using older technologies.

My research will use the methods developed in the diffusion literature to explore the adoption of scrubbers by coal-fired electric generating units in response to Title IV of the Clean Air Act. This research differs from existing research in that it will provide empirical evidence that market-based policies, particularly pollution permit systems, encourage technological diffusion. Moreover, I will explicitly estimate the expected installation cost of scrubbers, which I believe is an influential determinant in the decision to adopt but has been missing from the literature. Because diffusion of abatement technologies can have a great impact on environmental quality, this research is not only important to the diffusion field but also contributes to the environmental field.

III. Modeling the Decision to Install a Scrubber

This section will outline the decision to install a scrubber and describe how diffusion will be modeled in this context. First, I will formally introduce a theoretical model, which provides a foundation for the focus of this research, the empirical model. I will also discuss how my model compares to other models in the diffusion literature. Furthermore, I will discuss how epidemic, rank, order and stock effects drive technological diffusion in my model. Specifically, I argue that rank effects will dominate the decision to adopt in the case of scrubbers. Then, I will describe the empirical model, which uses survival analysis to model the time to adoption of scrubbers. Finally, I will describe the data used to estimate the empirical model.

III.A. Theoretical Model

In my model, which follows from Kerr and Newell (2003), each plant manager, *i*, has the option to choose *T*, the adoption time of the scrubber. It is possible that firms with high expected installation costs (or low benefits) will never find it optimal to adopt. The expected cost of installing the technology, at time *t* for each *i* is $C_{it}(Z_{it}, t)$, where Z_{it} is a vector of unit-specific characteristics that influence the cost of installing a scrubber. In every period *t*, the manager faces regulatory restrictions R_{it} and decides to install a scrubber or to delay the decision to install until next period. Note that regulations R_{it} represent the unique regulatory requirements that were established by the State Implementation Plans (SIP), which vary across units and can vary across time for a single unit.[4] This vector of regulatory variables also reflects whether the unit was regulated under Phase I or Phase II of Title IV. This decision can be represented in the following dynamic optimization problem,

$$\max_T \int_0^T \left(B^0(Z_{it}, R_{it}, t)\right) e^{-rt}\,dt - C_{it}(Z_{iT}, T)e^{-rT} + \int_T^\infty B^1\left(Z_{it}, R_{it}, t\right)e^{-rt}\,dt \qquad (1)$$

where *r* is the unit's discount rate. Each manager is choosing the time of adoption, *T*, which will maximize its total net present value of returns.[5] The first term on the RHS captures *i*'s present value of benefits before the technology adoption, the second term represents the costs of adoption at time *T*, while the third term is the present value of *i*'s benefit stream, after the adoption takes place.

[4] SIPs are established by each state in order to comply with National Ambient Air Quality Standards (NAAQS) and are usually imposed in the form of standard emission rates. These emission rates were set anywhere between 0.006 and 12.6 lbs SO_2/mmBtu. It is not uncommon for these emission rate standards to change over time for a given unit, as states try to adjust for any noncompliance areas or other local circumstances that may arise.

[5] The time of adoption, *T*, varies for each plant manager, *i*. Thus, the precise notation would include a subscript for *i* on *T*. To simplify notation, I have omitted this subscript, but it is implied throughout the text.

Adoption is dependent on two conditions. First, adoption will occur at *T* as long as it is not more profitable to wait and adopt at a later period. This is commonly known as the arbitrage condition and is given by the derivative of Equation (1) with respect to *T*.[6] Second, adopting the technology must result in positive profits (the second order condition).[7] The arbitrage condition is a sufficient condition if the installation cost is nondecreasing and convex and the gross value of adoption is nondecreasing with respect to time. In other words, the second derivative of Equation (1) must be greater than or equal to zero.

Equation (1) captures the rank effect that was described in the literature review. Generating units are heterogeneous and therefore have different benefits and costs of technology adoption. The plant manager will choose to adopt at time *t* if the net present value of adoption is positive and it is not more profitable to postpone adoption. This simple model suggests that as the costs of adoption increase, *i*'s benefit from adoption will decrease. Therefore, for any adoption cost, there will always be some units that do not find it profitable to adopt at any given time, due to heterogeneous benefits across firms. My model indicates that technological diffusion is affected by unit and plant level characteristics, which are represented by the vector Z_{it}, regulatory structure and stringency encapsulated in R_{it} and the expected cost of the technology, $C_{it}(\cdot)$. The empirical model will provide a method to test these assertions.

Scrubbers typically have a lifespan of 15 years (Daniel Mussatti, U.S. Nuclear Regulatory Commission, personal communication, May 16, 2007). Although, my data show that they often operate longer than that, there was a 34 year-old scrubber that was still operating in 2003 and 50 percent of the scrubbers in the sample were older than 20 years. However, in the model, I assume that the plant manager faces an infinite time horizon, rather than a finite time horizon. In other words, the technology adopted will have an infinite physical life and the technology does not become obsolete. Given a normal

---

[6] The first order condition is: $\left[B^1(Z_{iT}, R_{iT}, T) - B^0(Z_{iT}, R_{iT}, T)\right] - rC(Z_{iT}, T) + \frac{\partial C(Z_{iT}, T)}{\partial T} \geq 0$. The expression in brackets can be interpreted as the gross value of the adopted technology at time *T*, while the second two expressions represent the costs incurred from adoption at time *T*

[7] The second order condition is: $\int_T^\infty \left[B^1(Z_{it}, R_{it}, t) - B^0(Z_{it}, R_{it}, t)\right] e^{-rt}\, dt - C(Z_{iT}, T)e^{-rT} > 0$.

scrubber lifespan, an infinite time horizon is a sensible approximation, given a reasonable value of the discount rate. This also allows simplification of the problem without changing the implications of the model, according to Stoneman (2001). This assumption is made throughout the literature, with the exception of Ireland and Stoneman (1986), who explicitly examine technological diffusion by introducing the probability that obsolescence can occur in any given time period. In their general equilibrium model, they find that increasing firm expectations of the obsolescence of the technology will diminish the extent of technology diffusion in an industry under certain market conditions.

As described in the previous section, epidemic effects depict the diffusion process as an automated process where firms adopt as a result of coming into contact with firms that have already adopted. This type of process may be justified if a technology is not known to all possible adopters; when potential adopters meet adopters, information about the technology is disseminated and technology is adopted by those who have acquired the new information. However, in the case of electric power plants, scrubbers are a known abatement technology to all possible users. Because of the NSPS that began in 1978, all new units were required to install scrubbers. By 1990 when Title IV was passed, over 50 scrubbers had already been installed in the industry, ensuring that all potential adopters were well aware of the technology. Therefore, my model does not incorporate epidemic effects.[8]

Although I do not include stock and order effects in my model, they can easily be incorporated into the theoretical model presented above, following Stoneman and Karshenas (1993), by adding two arguments that represent the stock and order effects. The first, $S(T)$, reflects the order effects, where for a given firm *i*, benefits of adoption are dependent on the number of firms that have already adopted at *i*'s adoption date. The second variable, $K(t)$, reflects stock effects and captures the fact that the returns to a firm will depend on the number of other users at that date *t*. To incorporate these effects in the model, the

[8] Although epidemic effects are not incorporated in the theoretical model, Hannan and McDowell (1987) argue that empirically, epidemic effects can be incorporated by using a logistic baseline hazard function or a hazard rate that is increasing with duration. As I will discuss in the empirical results, I do not find that this type of model is appropriate for the data.

two variables would be arguments in the benefits before and after adoption or $B^0(\cdot)$ and $B^1(\cdot)$, respectively.[9]

The cost of adopting a new technology is thought to be a driving factor in a unit's technology choice, but is not measured in much of the diffusion research. The cost estimates derived will be controlled for directly in the scrubber choice econometric model. I will explicitly measure the expected cost of scrubber installation, which is the relevant cost measure for making adoption decisions in the diffusion literature (Stoneman, 2001).[10] This is distinct from abatement costs, defined as the loss of profits from reducing emissions, which are commonly used in the environmental literature. The installation cost estimate, $C_{it}(\cdot)$, will simply be estimated by a log-linear function, which will depend on a vector Z_{it}, *i*'s unique characteristics. This vector will include factors such as capacity of the unit, quality of coal used by the generating unit, the removal efficiency of the installed scrubber, the age of the scrubber and regional variables, which are thought to be important determinants of cost (Bellas, 1998; Keohane 2005). Cost data are only available for units that have already adopted the technology. But, using the coefficients measured in the cost equation above, I derive expected installation costs for all units, even those that did not install the technology. Due to space limitations, I omit the results for the installation cost equation, but results are available upon request.[11]

My model is distinct from other models in the use of the installation cost of scrubbers, represented in Equation (1) by $C_{it}(Z_{iT}, T)$. I assume that the installation cost depends upon time and on the individual characteristics of the generating unit, which follows from Kerr and Newell (2003). Some

---

[9] Thus the model that incorporates epidemic, rank, stock and order effects becomes:

$$V_{it} = \max_T \int_0^T \left(B^0(Z_{it}, R_{it}, K_t, S_T, t)\right)e^{-rt}\,dt - C_{it}(Z_{iT}, T)e^{-rT} + \int_T^\infty \left(B^1(Z_{it}, R_{it}, K_t, S_T, t)\right)e^{-rt}\,dt \,.$$

[10] According to Stoneman (2001), the cost of installation is defined as "the price that has to be paid to acquire new capital goods that embody the new technology", this is also termed the acquisition cost. I have chosen to follow the diffusion literature and use installation costs in the estimation of scrubber choice. Therefore, I exclude yearly operation and management costs in this analysis.

[11] There is potential for selection bias when predicting installation costs, since the scrubber sample is comprised of units that may have had lower installation costs than those who did not scrub and are thus not in the sample. However, I will control for this using a frailty model, which allows me to adjust for those unobservable characteristics of plants that makes them have lower installation costs and thus more likely to scrub.

studies (Stoneman, 2001; Popp, 2006) simplify the role of installation cost by allowing it to vary over time, but not across firms. Some studies simply omit the effect of cost on diffusion in the model (Rose and Joskow, 1990; Snyder et al. (2003); Fuglie and Kascak (2001).[12] Cost data have often been unavailable to researchers in the past, which may explain this simplification. In my study, unique cost data on scrubbers is available, which allows for a detailed look of the effect of installation cost on diffusion.

Stoneman and Karshenas (1993) point out that there is, in general, a missing link between empirical and theoretical work in technological diffusion. Many empirical diffusion studies do not specify theoretical models, for example Rose and Joskow (1990) and Snyder et. al (2003). However, the basic deterministic model depicted in Equation (1) has been the primary analytical model for those that do provide theoretical motivations for diffusion. The model that I present emphasizes the importance of the rank effect of diffusion. The rank effect allows for heterogeneity among potential adopters, so that firms will get different net benefits from the technology adoption. This explains the pattern of diffusion; not all firms will adopt at the same time, those with low net benefits may never find it profitable to adopt. Although the stock and order effects have found to be determinants of technological diffusion, there are several reasons that I believe these effects are not significant in the case of scrubbers. As explained by Popp (2006), stock and order effects assume that the decision to adopt a technology involves strategic interaction among firms. Specifically, there are strategic advantages to those who adopt early. But in the case of electric power plants, firms are fundamentally organized as local monopolies and do not engage in strategic interactions. Similarly, since scrubbers are purely abatement technologies and do not improve the productive efficiency of generation, it is not likely that strategic interaction would be a response, that is, they would not voluntarily install this technology to compete. Therefore, I believe the rank effect

[12] These studies will often use other prices to control for market conditions in the industry if cost data of the actual technology is not available. For example, Rose and Joskow (1990) use the annual market price of fuel as a proxy for the cost savings of a more energy efficient technology. Similarly, Snyder et al. (2003) use the annual market price of chlorine to control for market conditions. However, pure time series effects cannot be measured in the model that I adopt in this analysis.

should dominate the technological diffusion of scrubbers. The econometric model in the next section presents a framework for testing the rank effect on technological diffusion.

III.B. Empirical Model

Consistent with much of the recent literature on diffusion, I will use survival analysis to estimate the effects of the stringency and type of environmental regulation on the diffusion of scrubbers.[13] Survival models have become very useful for many economic applications that deal with transitions between events or the time to a particular event (see Kiefer, 1988; Beck, 1999; and Buis, 2006 for an overview of this class of models).[14] Fuglie and Kascak (2001), Popp (2006), Rose and Joskow (1990), Snyder (2003), Kerr and Newell (2003) and Karshenas and Stoneman (1993) have all used survival models to investigate technology diffusion. Survival models have been utilized because they are particularly helpful in measuring epidemic, rank, stock and order effects that have been described in the previous sections (Stoneman, 2001).

In survival models, the object of interest is the hazard function, $h_i(t)$. In the setting considered here, the hazard function is defined as the probability of plant manager *i* adopting the technology at time *t*, given that the adoption has not already occurred. More specifically, the hazard rate takes the following form:

$$h_i(t, X_{it}, \beta) = \frac{f(t, X_{it}, \beta)}{1 - F(t, X_{it}, \beta)} \tag{2}$$

where $f(t, X_{it}, \beta)$ is the probability density function for adoption, and $F(t)$ is the corresponding cumulative distribution function. $F(t, X_{it}, \beta) = \Pr(T < t, X_{it}, \beta)$ is the probability that the time of adoption, T has happened prior to the current time, *t*. β is a vector of parameters to be estimated. The

[13] Along with the survival models presented above, a logit model for scrubber choice was also contemplated. Similar results were obtained from the logit model in terms of significance and direction of the variables, but the hazard approach is more useful when interested in analyzing the speed or the rate of technological change over time.
[14] Survival models, also called duration models, arose in applications to the medical field where the term “failure” or the event that is being modeled is a fatality of a patient. In this context, the survivor function is the probability that the patient will survive past some point and time, given that the patient has survived up to this point.

vector X_{it} captures relevant firm characteristics and regulatory information. It includes the expected cost of adoption or installation cost, $C_{it}(\cdot)$, and *i*'s individual characteristics, Z_{it}, which captures size of the unit, type of technologies already in place, regional effects, age, type of ownership structure of the firm, and distance from a major low sulfur coal source, the Powder River Basin (PRB) in this case. In addition, X_{it} includes regulatory variables, R_{it}, that encapsulates regulatory structure and stringency. In other words, the vector X_{it} in the econometric model can be expressed as $X_{it} = \{Z_{it}, C_{it}(\cdot), R_{it}\}$.

The survival model captures the underlying decision process of each plant manager that was outlined in the theoretical model. That is, every time period *t*, given that a scrubber has not already been installed, the manager has the choice of either installing a scrubber or delaying the decision until the next time period. The estimation of the hazard rate in Equation (2) measures the effect of the explanatory variables introduced in the theoretical model on the conditional probability of adoption. In this estimation, the effect of the type and stringency of regulation on the diffusion of scrubbers will be the central interest. Notice that the benefits before and after adoption, denoted by $B^0(\cdot)$ and $B^1(\cdot)$ in the theoretical model, are not measured. These data are not observed and are thus omitted from the empirical model. Most studies omit benefits in the empirical model, due to the lack of data including Kerr and Newell (2003), Karshenas and Stoneman (1993), Fuglie and Kascak (2001), Snyder et al. (2003) and Popp (2006).

The proportional hazard model is commonly used in the diffusion literature and allows for convenient interpretation of the data. This model separates the hazard function into a baseline hazard rate, $h_0(t)$ and an exponential function, $\exp(X_{it}\beta)$ in which the covariates multiplicatively shift the baseline hazard. The proportional hazard function is given by

$$h_i(t, X_{it}, \beta) = h_0(t)\exp(X'_{it}\beta) \qquad (3).$$

The baseline hazard may be left unspecified (the semi-parametric approach) or can be assigned a functional form (the parametric approach). With the parametric approach, the baseline hazard function could be constant, increasing or decreasing over time, depending on the specific functional form; commonly used functional forms for the baseline hazard include exponential, Weibull, Gompertz or gamma distributions. Alternatively, with the semi-parametric Cox proportional hazard model, no assumption is placed on the relationship of the baseline hazard over time. However, for all proportional hazard models, it is assumed that the shape of the baseline hazard is the same for all decision makers in the model and the function is shifted by varying unit level characteristics. The semi-parametric analysis allows more freedom in terms of the shape of the hazard function, but parametric models produce more efficient coefficients, only if the functional form of the baseline hazard is specified correctly.

Ideally, theory would lead the researcher to choose one functional form over the other. However, in this application, there is no reason to assume any particular pattern for the hazard function. In this estimation, I chose the Cox proportional hazards specification, rather than a parametric model.[15] This decision was based on a comparison of the best fitting parametric model, which used the Weibull distribution and the Cox model. The Weibull model was the best fitting parametric model, based on the Akaike information criterion (AIC), which provides a method of comparing different distributional assumptions for parametric models (Akaike, 1974). To evaluate these two models, I estimated a smoothed hazard function from the data, which was increasing and then decreasing over analysis time. The same shaped function is obtained when estimating the hazard function in the Cox proportional hazards model. This shape differs from the function estimated with a parametric model and presents evidence that semi-parametric model is a better fit for the data.[16]

To generate the partial log-likelihood used in estimating the coefficients, assume first that each failure time is unique (or that there are no ties of failure times) and there is no right censoring.[17] Then, the sample contains K unique exit times from times from times $T_1,\ldots,T_K$ and the risk set includes $R(t_i)$

---

[15] Results for the parametric model are available upon request. The results of the empirical estimation were robust to changes in the model specification.

[16] Recall that if the hazard is increasing over time, there is evidence of epidemic effects. Since the hazard rate in the Cox proportional hazards model does not increase over time, I do not find evidence of epidemic effects in this model.

[17] My data is right censored. That is, at the end of the observed time period, there are units left in the sample that have not adopted a scrubber.

individuals at time t_i, which includes all those individuals that have not exited yet or $R(t_i)=\{j: t_i \geq T_k\}$. Then, the probability that an individual will fail at time T_k, conditional on only one individual failure is $\Pr(t_i = T_k \mid R(t_i)) = \dfrac{e^{\beta X_i}}{\sum_{j \in R(t_i)} e^{\beta X_j}}$. The estimates of β are a result of maximizing the partial log-likelihood function $\ln L = \sum_{k=1}^{K} \left(\beta X_k - \ln \sum_{j \in R(t_i)} e^{\beta X_j} \right)$, which does not rely on the baseline hazard function. Of course, this is a simplified equation. In my analysis, the Breslow method for ties is used, since not all failure times are unique and the partial likelihood function is modified slightly to account for right censoring.

I also consider the shared frailty model, in order to control for unobserved heterogeneity. That is, units that were chosen to install scrubbers may possess some unobserved characteristic that make them a lower cost unit and is therefore more likely to adopt. This is controlled for by introducing an error term that enters multiplicatively into the model and affects how fast a unit will adopt a scrubber. Error terms can also be equal across groups within the sample (the firm is the group in this case), since units within a firm have similar risks for adopting a technology; this is similar to random-effects in a linear model.

III.C. Description of Data

The Energy Information Administration (EIA) gathers a large amount of data for the purpose of analyzing economic and environmental factors of energy and makes these publicly available. This research utilizes EIA's Form-767: Steam Electric Plant Operation and Design Report, which is available from 1985 onward. Data is not available prior to 1985. EIA-767 includes all generating units that have a nameplate capacity of 10 MW or more.[18] From this annual survey, important unit and plant characteristics are gathered, including age, nameplate capacity, boiler type, technology usage, type of ownership and location. Other yearly production specific variables in the survey include heat input, emissions of major pollutants and characteristics and quantity of fuels used and detailed information on

[18] Units that have nameplate capacity between 10 MW and 100 MW are only required to fill out a portion of the survey; units that are greater than 100 MW must complete the entire form. The information needed for this study was required by all units with a capacity of 10 MW or greater, so this does not affect thee sample size.

installed scrubbers. Finally, regulatory information such as the unit's phase, state-level emissions standards and NSPS status are also gathered.

In my model, 1990 is the beginning of analysis time for all firms, since Title IV was signed into law in this year. Prior to 1990, firms would only install scrubbers in order to comply with NSPS. In addition, in the period 1990 through 1996, only Phase I units were at risk for scrubbing, since they were the only units required to reduce emissions. After 1996, all units were at risk for scrubbing.[19] The data used for the scrubber choice analysis includes all coal-fired units from 1990 to 2002 that are at risk of installing scrubbers in order to comply with Title IV. Units that were not at risk for scrubbing and are not included in the sample are primarily units that were regulated under New Source Performance Standards (NSPS). These units had emissions below 1.2 lbs of SO_2/mmBtu, which is the rate that was targeted using permit allocations in Phase II; if a unit had an emissions rate lower than the allocation, there would be no need to install a scrubber in either Phase I or Phase II. For this reason, coal-fired units that were built between 1972 and 1977 and had emission levels below 1.2 lbs SO_2/mmBtu or had installed scrubbers simultaneously with the construction of the unit were omitted from the sample. All new coal-fired units that were built after 1977 either had emission levels below 1.2 lbs SO_2/mmBtu or had installed scrubbers and are therefore also excluded. Essentially, the units included in the sample are at risk for retrofit scrubbing between the periods 1990 to 2002.[20] This results in 777 units in my sample, 42 of which installed retrofit scrubbers over the time period. Again, there were more scrubbers installed during this period, but only 42 scrubbers were retrofitted to existing generating units (as opposed to new units) in response to Title IV. Although the number of adoptions is relatively small compared to the sample size, the results below do show sufficient variation in the data to obtain reasonable parameter estimates. However, this will limit the degrees of freedom available in the model.

---

[19] Since I am modeling the decision to install a scrubber and not the unit's abatement choice, I will include all units that are regulated under Title IV and had not been affected by NSPS regulations. Although some units may decide to buy SO_2 permits or switch to low sulfur coal in a given year to comply with Title IV, these decisions do not preclude them from installing a scrubber, since they are not permanent actions.

[20] Besides being under different regulatory regimes, the costs of installing a scrubber with a new unit rather than a retrofitted scrubber are significantly lower. Therefore, the decision to install a scrubber with a new unit should be considered separately from the decision to install a retrofit unit.

There are some units that have a status of "cold standby", which means that it would take 3-6 months to reactivate them, or a status of "standby", which means the unit is not normally used but is available for service at any time. Standby units are kept heated so that they can start up quickly and are placed on standby in case of a failure of a currently operating boiler or in case of unusual periods of high demand. Units that are on cold standby are deactivated (mothballed) and not kept heated. Although this is not as common as standby units, a firm might keep a unit on cold standby if it is in poor condition, if it has uncompetitive heat rates or because abatement costs due to environmental regulations are high. These types of units (standby and cold standby) can have zero heat input for a year or several years at a time during the observation period. I assume that during these shutdown periods, units are not at risk for installing a scrubber, since they are not producing electricity and have no emissions during this period. Thus, I treat these instances of shutdown as a truncation problem.[21] There are also 18 units that permanently retire, which I assume is four or more consecutive years with zero heat input and no subsequent positive heat input;[22] these units are subsequently dropped from the sample in the first year of retirement.

Recall that each unit is not only regulated under Title IV, but also by State Implementation Plans (SIP), which are usually emission rate standards that the unit cannot exceed. These state regulations can be binding to units in the sense that it is restricted to the emission rate that the state sets; if the state emission rate is set tighter than federal regulation, it could effectively force a coal-fired unit to install a scrubber. These state regulations are reported in EIA-767 in four units of measurement: lbs SO_2 per million Btu (lbs SO_2/mmBtu), lbs of SO_2 emitted per hour, lbs of sulfur per million Btu and percent of sulfur content of fuel. To make the regulations comparable, all units were converted to lbs SO_2/mmBtu, EIA's preferred measure. Regulation variables in the model include a dummy variable for those units that

[21] There were 2 units are truncated from the left, 10 units have interval truncation or shutdown in the middle of the sample, 18 units permanently shutdown and 16 units shutdown at the end of the sample and it is not known if it is a permanent shutdown.
[22] This assumption is based on the data; there are no units in the data from 1985 to 2001 that had positive heat input after shutting down for four or more years.

were subject to an emission standard equal to or below 1.2 lbs SO_2/mmBtu and a dummy variable for units that were regulated under Phase I of Title IV.

One section of the EIA-767 survey provides annual data on those coal-fired units that have installed scrubbers; these data are also available from 1985 to 2002 and are used to construct the scrubber cost data set. Data include the age of the scrubber, SO_2 removal efficiency, type of scrubber, hours utilized, amount of electricity consumed by the scrubber, operating and management costs each year, installation cost, scrubber status and the amount of SO_2 emitted. Of course, the characteristics of the plant and unit where the scrubber was installed is known as well. There are several categories of scrubber status listed each year, including scrubbers that are in the planning stage, those that are being constructed and tested, currently operating, on standby and retired. I only use data from years that the scrubber is actually operating, since prior to and during construction of a unit, costs that are reported are estimated, not actual costs.[23] Moreover, units on standby or retired are not being used, and should not be compared to units that are fully utilized.

These data are an unbalanced panel, since many scrubbers were built after 1990, due to Title IV. The cost data set includes 192 scrubbers. The initial data set had 241 scrubbers but for various reasons, 49 were dropped from the sample.[24] Because of the limited number of existing scrubbers, this sample does not exclude scrubbers that were constructed at the same time as the unit itself. This means that many of these generating units were not in the risk set for installing scrubbers under Title IV; only 42 of the retrofit scrubbers were installed to comply with Title IV, the remaining scrubbers were installed due to

[23] I only dropped the years that a scrubber was being planned or under construction under between the years of 1985-2002. Therefore, only three scrubbers were dropped entirely from the sample because they were in the planning stages in 2001 or 2002 and had not begun to operate before the end of 2002.

[24] Eleven scrubbers were installed on units that burned fuels other than coal as their primary fuel (wood, oil and refuse) and would presumably have different operating and maintenance costs and technological designs than coal-fired scrubbers. Seventeen scrubbers were dropped because there were no years in the sample where the scrubber was operating (i.e. the scrubbers status was standby, under construction, retired or planned between 1985 and 2002). An additional 14 scrubbers were dropped because capital cost data were missing. Note that average size of the units that were dropped was very close to the average size of units that were in the sample, so there was no relationship between those units that were dropped and size. Finally, seven more units were dropped because there was no matching plant and unit found in the EIA-767 production data.

regulations set by NSPS.[25] Following Keohane (2005), the installation cost data were deflated using the Handy-Whitman Electric Cost Index publicly provided by the U.S. Census Bureau and are expressed in 1996 dollars.

IV. Empirical Results

The covariates used to estimate the semi-parametric model include individual generating unit characteristics and regulatory variables. Unit characteristics include the natural log of nameplate capacity in megawatts (MW), age of the unit as of 2002, the distance from the plant to the Powder River Basin (PRB), the natural log of expected scrubber installation costs in dollars per lbs of SO_2 abated if installation occurs and an indicator variable for units with very low expected installation costs (those in the lowest quartile). I use a natural log transformation for size and installation cost because these variables are skewed heavily to the right. Regulatory variables include a binary indicator for those units that are regulated under Phase I and an indicator variable for those units that have very strict state regulations (equal to or below 1.2 lbs SO_2/mmBtu).

Descriptive statistics for these variables are provided in Table 1 and are stratified by Phase I and Phase II units. The descriptive statistics show that there are important differences between Phase I and Phase II units. Phase I units tend to be larger and slightly younger than Phase II units. Moreover, Phase I units have considerably higher pre-Title IV emission rates but tend to also have higher emission standards than Phase II units (i.e. Phase I units have less stringent state standards than Phase II units). There is a positive correlation between pre-Title IV emission rates and emission standards imposed on the unit. This pattern may have emerged because states were protecting their local coal markets. For example, in Ohio, there are large supplies of high sulfur coal. To encourage plants to buy local coal, a non-binding emissions rate is set so that plants continue to burn Ohio coal.[26] Finally, the estimated installation cost of scrubbers is lower for Phase I units than Phase II units. Since this cost estimate is expressed in terms of

[25] Although I include all scrubbers in the sample, when I estimate the equation for installation costs, I use a dummy variable to control for those units that are retrofit scrubbers.
[26] I use the term "non-binding" emission rate loosely in this context. I am referring the fact that often a very high, lenient emission rate will be set for the unit and even with a very high-sulfur coal, would be able to meet the emission rate standard.

dollars per ton of SO_2 abated, this shows that larger, dirtier firms generally have lower expected scrubber installation costs; that is, there seems to be some economies of scale for scrubbers.

Table 2 gives the results for four separate semi-parametric hazard models. The first model tests all 777 units that are at risk for installing scrubbers when Title IV was enacted in 1990. The second model is a frailty model, where the frailty is gamma distributed and enters multiplicatively on the hazard function to control for unobserved heterogeneity. Frailties for all units within a firm are assumed to be equal; that is, units owned by the same firm face the same risk of scrubbing. The third model uses a restricted sample where those plants that are in three NERC (North American Reliability Council) regions that have no scrubbing activity are omitted.[27] The three regions omitted include 64 subjects in the Electric Reliability Council of Texas (ERCOT), the Mid-Continent Area Power Pool (MAPP) and the Southwest Power Pool (SPP). The units in these regions are omitted because they are potentially not in the risk set. That is, these plants face certain regional and regulatory conditions that would make scrubbing an unattractive option. Strictly speaking, the restricted sample is biased in terms of representation of the entire population of generating units since it excludes three entire regions. However, estimates may be closer to the true population values, under the assumption that units in these regions were never at risk for scrubbing. Since no scrubbing activity is observed within these regions, omitting these 64 observations does not create biased estimates and there is no loss of explanatory power. The fourth model is a frailty model, using this restricted sample.

The four Cox proportional hazards models in Table 2 show similar results. In all models, age, phase, state regulations and low expected installation costs are statistically significant and are the major factors that drive scrubber adoption. The effect of age on the likelihood of scrubbing is negative, similar to findings by Popp (2006). Other studies, for example, Fuglie and Kascak (2001), Snyder et al. (2003) and Rose and Joskow (1990) do not include age in the estimation. Karshenas and Stoneman (1993) and Dunne (1994) find that the coefficient on age is not statistically significant. With my data, the negative

[27] Prior to 2006, plants in the risk set spanned 10 NERC regions. There have since been several major changes in NERC region boundaries and names. I will use the pre-2006 definitions, since this resembles conditions when plants were at risk for scrubbing.

sign on age is expected because all generating units in this sample were installed before 1977. The oldest units in the sample are approaching retirement age; the expected economic benefits to install a costly scrubber on a unit that will soon be retired are negative.

The size of the unit, or the natural log of nameplate capacity (in MW), does not have a statistically significant effect on the hazard but has a positive coefficient. However, this may be due to a high negative correlation between age and size. When capacity is used without the age variable, it is statistically significant and still has a positive effect on the hazard rate.[28] This is consistent with the prevailing literature; a number of studies report a significant positive effect due to firm size (Rose and Joskow, 1990; Popp, 2006; Snyder et al., 2003; Kerr and Newell, 2003; Dunne, 1994; and Fuglie and Kascak, 2001). Karshenas and Stoneman (1993) find that the coefficient on size is positive but not statistically significant. They argue that size should have a net positive effect on the hazard as a result of three effects on adoption behavior. First, large firms are more likely to adopt because there are positive scale effects of adoption and can adopt new technology at a lower cost. Also, large firms are willing to undertake more risk than smaller firms, and are therefore more likely to adopt. In the opposite direction, larger firms may have more rigid managerial approaches, and may actually be less likely to adapt to changes, relative to smaller firms. In my study, I do find evidence of positive scale effects, since larger units do have lower expected scrubber installation costs, but I have no data on risk or managerial preferences.

The regulatory structure and stringency facing a unit is found to be very influential on the decision to adopt scrubbers in all models. Units that are regulated under Phase I are more likely to install scrubbers than units regulated under Phase II. This is an expected result; Phase I units are generally larger and have higher emission rates, lower costs per ton of abatement and thus are more likely to install scrubbers. The state regulation, which is expressed as a dummy variable for units with an average

[28] When the estimation excludes the age variable, there are no significant changes in the coefficient values.

emission rate standard is below 1.2 lbs SO_2/mmBtu, is positive.[29] Moreover, the magnitude of the coefficient is very high which suggests that units that face strict state regulations are very likely to install scrubbers. In my sample, 13 units out of the 42 units that installed a scrubber also had state emissions rate restrictions at 1.2 lbs SO_2/mmBtu or below. Again, this is an expected result and is consistent with findings from Popp (2006), Kerr and Newell (2003) and Snyder et al. (2003). That is, strict emission standards induce firms to adopt cleaner technologies. I also explored an alternative regulation variable, the average emission rate (in lbs SO_2/mmBtu) imposed by the state between 1990 and 2001. This variable was negative and statistically significant as expected, which shows that increasing the stringency of the command-and-control variable increases the hazard rate. This variable was not used in Table 2, because various specification tests showed that the dummy variable was a better fit for the model. Given the strong influence of command-and-control regulations on the adoption of scrubbers, it is not unreasonable to wonder how many scrubbers there would have been if all of the states imposed very strict regulation on plant emissions. Using the estimated coefficients, it is possible to predict the number of scrubbers, given that all units had strict state regulations. Using Model 1 in Table 2, this prediction resulted in over ten times more units adopting scrubbers. This indicates that if all states had adopted strict regulations, there would be considerably more scrubbers adopted, ceteris paribus.

The variables used to represent expected scrubber installation cost in the model includes the natural log of expected installation cost per ton of SO_2 abated (if a scrubber was installed) and a dummy variable that equals one if this expected installation cost was in the lowest quartile of the sample. The estimated coefficient on the expected installation cost has a negative effect on the hazard rate and is only statistically significant in Model 2. The coefficient on the low cost dummy variable is statistically significant and positive for all models. This suggests that units that have very low expected installation costs are more likely to install scrubbers than those with higher expected costs. This result is in

[29] Recall that in Phase II, units are allocated enough SO_2 permits to emit 1.2 lbs SO_2/mmBtu. If emissions exceed this amount, the unit must either abate or buy more permits (although all units face the same permit price at any given time). Therefore, I consider a state regulation that requires emission rates to be below 1.2lbs SO_2/mmBtu to be strict.

accordance with the few empirical and theoretical diffusion studies that have used installation costs, including Kerr and Newell (2003), Keohane (2005), Stoneman (2001) and Jaffe and Stavins (1995). Finally, the distance to the Powder River Basin (PRB) has a near zero effect on the hazard rate. Since the PRB is a major source of low sulfur coal, those plants that are closer to the PRB would have lower transportation costs of low sulfur coal, which would presumably make scrubbing less attractive. Nonetheless, in this estimation, distance to PRB is not a determinant in the decision to install a scrubber.

Several diagnostic tests were performed to assess the model specifications and assumptions. First, I performed an omitted variables test (the link test) and found that the correct variables are incorporated in the model. To check the proportional hazard model assumption, I interacted all variables with time and tested the null hypothesis that the coefficients on the interacted variables were equal to zero. The null hypothesis could not be rejected at the 0.10 level, which means that there is no evidence of violating the proportional hazards assumption. An alternative test, based on the Schoenfeld residuals confirms this finding for all variables except the natural log of expected cost and the distance to PRB. Finally, I tried two graphical tests that assess the proportionality of hazards for discrete covariates shows that the phase dummy and the low cost dummy may have violated the proportional hazard assumption for one of these tests. But, since these variables have passed other tests of the proportional hazards assumption, I do not put great importance on this finding alone. Overall, I conclude that the Cox proportional hazard model is a reasonable specification for the data.

I have also tried to use a number of other covariates in this model including the type of ownership structure that the plant faces, NERC region of the plant and variables that capture the quality of coal in the region surrounding the plant. The inclusion of these variables had little, if any, effect on the magnitude and statistical significance of the coefficients presented in Table 2. No notable insights were obtained from the inclusion of these variables and were thus excluded from the final results.

Shared frailty models in this context seem particularly appropriate. As previously explained, shared frailty models control for unobserved heterogeneity by introducing an error term in the hazard function that enters multiplicatively. Under the shared specification, observations in the same group (i.e.

units in the same firm) are correlated, which is analogous to a random-effects model. Examining the shared frailty estimates in Table 2, the parameter theta is the estimated frailty variance in the model. The null hypothesis that theta equals zero is tested, using a likelihood-ratio test. In both frailty models, the null hypothesis is rejected. Thus, I conclude that there is correlation between units that are owned by the same firm. Also, examining the data in more detail, out of the 21 firms that had adopted at least one scrubber, only six of these firms adopted only one scrubber. Therefore, it seems appropriate to control for this unobserved heterogeneity using the shared frailty model.

In Table 2, I present estimates for the entire population of generating units that were at risk for scrubbing (Model 1 and Model 2) and a subset of the population that omitted two NERC regions that had no scrubbing activity (Model 3 and Model 4). Choosing between these two samples is a judgment call. That is, the subset of generating units should be used only if the probability of the omitted units installing a scrubber over its lifetime is zero. Otherwise, if units had a positive probability of adopting, omitting them will result in biased estimates of the coefficients. In this case, although it seems highly unlikely that units in the omitted NERC regions (ERCOT, SPP and MAPP) would adopt, I also see no reason why they would not scrub, if the cost of scrubbing was low enough. Notice that all three of these regions are in the mid-west region on the U.S., which has enjoyed less stringent state regulations (none of the plants in these regions have emission rate restrictions below 1.2 lbs SO_2/mmBtu) or simply have very few at-risk coal fired units in the region (ERCOT only has 4 generating units at risk). Moreover, these three regions are in close proximity to cheap, low-sulfur coal, which may have deterred them from scrubbing in this period. Given that the coefficients from both models are very close and there is no change in statistical significance, I believe that either sample is appropriate.

V. Conclusion

In this study, I estimate the effects Title IV of the Clean Air Act on the diffusion of scrubbers. Regulations imposed on electric generating units are the most important determinants for installing scrubbers. With this particular technology, Title IV has directly caused 42 units to install scrubbers as an abatement strategy. However, units in Phase I were more likely to install scrubbers than units under

Phase II. Moreover, those units that faced strict state regulations were much more likely to install scrubbers than those that had less stringent regulations. Therefore, state and federal regulations had a large influence on scrubbing behavior.

Two unit characteristics were also important factors in the decision to install scrubbers. First, those units that faced relatively low expected installation costs were more likely to install scrubbers. Secondly, units in the sample that were relatively older were less likely to install a scrubber. This is a result of the long life of scrubber technologies; it would not make sense for units close to retirement to install a technology that would outlive the generating unit. Although the importance of other unit characteristics was tested, none had a statistically significant effect on the decision to install a scrubber.

Policies are often evaluated by the incentives they provide for the adoption of new technologies. In the case of scrubbers, although Title IV required units to reduce SO_2 emissions, having very strict state regulations is a strong determinant of whether or not a scrubber would actually be installed. Evaluating programs, such as Title IV which implements flexible market-based policies and understanding the resulting diffusion patterns will be particularly useful to policy makers when considering future climate change policy.

Table 1: Descriptive Statistics

Variable Description	Phase I Units		Phase II Units		Total Sample	
	Mean	*St Dev*	*Mean*	*St Dev*	*Mean*	*St Dev*
Dependent Variable						
Scrub Indicator	0.09	0.28	0.03	0.17	0.05	0.23
Ave. Year Scrub (if installed)	1995	2	2000	2	1996	3
Unit Characteristics						
Nameplate Capacity	289.26	247.73	200.90	213.23	238.32	232.46
ln(Nameplate Cap.)	5.32	0.85	4.88	0.90	5.07	0.91
Age (in 2002)	41.18	9.22	43.70	9.33	42.63	9.36
Distance to PRB (in miles) †	1134.48	579.42	1189.52	649.96	1166.21	621.28
Expected Installation Cost (in dollars/ton of SO_2 abated)	108.27	128.69	145.31	232.32	129.63	196.03
ln(Exp. Installation Cost)	4.52	0.66	4.73	0.76	4.64	0.73
Low Cost Dummy	0.29	0.46	0.22	0.41	0.25	0.43
Regulatory Variables						
Ave. State Standard (in lbs SO_2/mmBtu)	4.63	2.05	2.80	1.53	3.57	1.98
Strict State Reg. Dummy	0.03	0.16	0.10	0.30	0.07	0.25
Number of Units	329		448		777	
Number of Plants	n/a		n/a		293	
Number of Firms	n/a		n/a		121	
Number of Scrubbers	28		14		42	

Source: EIA-767, 1985-2002

†These data were provided by Nathaniel Keohane.

Table 2: Parametric Model Results

Variables	Cox Model (1)	Cox with Shared Frailty (2)	Cox Limited Sample (3)	Cox Limited Sample and Frailty (4)
Age	-0.130*** (0.305)	-0.151*** (0.435)	-0.133*** (0.030)	-0.154*** (0.043)
ln(Nameplate Capacity)	0.212 (0.224)	0.367 (0.392)	0.174 (0.226)	0.327 (0.394)
Distance to PRB	0.000 (0.000)	0.001 (0.001)	0.000 (0.000)	0.001 (0.001)
ln(Expected Installation Cost)	-0.230 (0.476)	-1.192* (0.717)	-0.230 (0.484)	-1.327 (0.793)
Low Cost Dummy	0.930* (0.528)	1.390* (0.797)	0.921* (0.533)	1.327* (0.793)
Phase I Dummy	0.912** (0.374)	1.874*** (0.697)	0.863** (0.379)	1.802*** (0.670)
Strict State Reg. Dummy	2.582*** (0.398)	4.674*** (1.041)	2.487*** (0.402)	4.437*** (1.045)
Log Likelihood	220.021	207.284	218.719	206.709
Number of subjects	777	777	713	713
Theta[a]	n/a	3.887*** (1.687)	n/a	3.736*** (1.659)

Figures in parentheses are the standard errors of the coefficient estimates.
*** Significance at the 1% level
** Significance at the 5% level
* Significance at the 10% level
[a]Theta is the estimated frailty variance in the shared frailty model. The likelihood-ratio tests the null hypothesis that theta equals zero.

References

Akaike, H (1974). "A New Look at the Statistical Model Identification." IEEE Transaction and Automatic Control AC-19: 716-723.

Beck, Nathaniel (1999). "Modeling Space and Time: The Event History Approach". *Research Strategies in Social Science*, Oxford University Press.

Bellas, Allen S. (1998). "Empirical Evidence of Advances in Scrubber Technology". Resource and Energy Economics 20, 327-343.

Buis, Maarten L. (2006), "An Introduction to Survival Analysis". *Working Paper*.

David, P. (1969). "A Contribution to the Theory of Diffusion", *Center for Research in Economic Growth Research Memorandum*, No. 71, Stanford University.

Downing, Paul B. and Lawrence J. White (1986). "Innovation in Pollution Control". *Journal of Environmental Economics and Management*, 13, 18-29.

Dunne, Timothy (1994). "Plant Age and Technology Use in U.S. Manufacturing Industries". *The RAND Journal of Economics* 25 (3), 488-499.

Fischer, Carolyn, Ian W. H. Parry and William A. Pizer (2003). "Instrument Choice for Environmental Protection when Technological Innovation is Endogenous". Journal of Environmental Economics and Management, 45, 523-545.

Fuglie, Keith O. and Catherine A. Kascak (2001). "Adoption and Diffusion of Natural-Resource-Conserving Agricultural Technology". *Review of Agricultural Economics* 23 (2), 386-403.

Geroski, Paul A. (2000). "Models of Technology Diffusion". *Research Policy*, 29, 603-626.

Gray, Wayne B. and Ronald J. Shadbegian (1998). "Environmental Regulation, Investment Timing and Technology Choice". *Journal of Industrial Economics*, 46, 235-256.

Griliches, Zvi (1957). "Hybrid Corn: An Exploration in the Economics of Technological Change". *Econometrica* 24 (4), 501-522.

Hall, Bronwyn H. and Beethika Khan (2003). "Adoption of New Technology". *New Economy Handbook*, Chapter 10, Academic Press.

Hannan, Timothy H. and John M. McDowell (1987). "Rival Precedence and the Dynamics of Technology Adoption: An Empirical Analysis". *Economica*, New Series 54 (214), 155-171.

Ireland, Norman J. and Paul L. Stoneman (1986). "Technological Diffusion, Expectations and Welfare". Oxford Economic Papers, New Series 38 (2), 283-304.

Jaffe, Adam B., Richard G. Newell and Robert N. Stavins (2002). "Technological Change and the Environment". *Environmental and Resource Economics,* 22, 41-69.

Jaffe, Adam B. and Robert N. Stavins (1995). "Dynamic Incentives of Environmental Regulations: The Effects of Alternative Policy Instruments on Technology Diffusion". *Journal of Environmental Economics and Management*, 29, S-43-S63.

Jung, Chulho, Kerry Krutilla and Roy Boyd (1996). "Incentives for Advanced Pollution Abatement Technology at the Industry Level: An Evaluation of Policy Alternatives". *Journal of Environmental Economics and Management*, 30, 95-111.

Karshenas, Massoud and Paul L. Stoneman (1993). "Rank, Stock, Order, and Epidemic Effects in the Diffusion of New Process Technologies: An Empirical Model". *The RAND Journal of Economics* 24 (4), 503-528.

Keohane, Nathaniel O. (2005). "Environmental Policy and the Choice of Abatement Technique: Evidence from Coal-Fired Power Plants". *Yale University Mimeo*.

Keohane, Nathaniel O. (2006). "Environmental Policy Design and Technology Diffusion". *Yale School of Management Working Paper.*

Kerr, Suzi and Richard G. Newell (2003). "Policy Induced Technology Adoption: Evidence from the U.S. Lead Phasedown". *Journal of Industrial Economics* 51 (3), 317-343.

Kiefer, Nicholas M. (1988). "Economic Duration Data and Hazard Functions". *Journal of Economic Literature* 26 (2), 646-679.

Milliman, Scott R. and Raymond Prince (1989). "Firm Incentives to Promote Technological Change in Pollution Control". *Journal of Environmental Economics and Management*, 17, 247-265.

Popp, David (2001). "Pollution Control Innovations and The Clean Air Act of 1990". *NBER Working Paper Series*, #8593.

Popp, David (2006). "Exploring Links Between Innovation and Diffusion: Adoption of NO_x Control Technologies at U.S. Coal-Fired Power Plants". *NBER Working Paper Series* #12119.

Rose, Nancy L. and Paul L. Joskow (1990). "The Diffusion of New Technologies: Evidence from the Electric Utility Industry". *The RAND Journal of Economics* 21 (3), 354-373.

Schumpeter, J. (1942). *Capitalism, Socialism and Democracy*. New York: Harper.

Snyder, Lori, Noland Miller and Robert Stavins (2003). "The Effects of Environmental Regulation on Technology Diffusion: The Case of Chlorine Manufacturing". *The American Economic Review* 93 (2), 431-435.

Stoneman, Paul L. (2001). *The Economics of Technological Diffusion*. Blackwell Publishers: Massachusetts.

Stoneman, Paul L. and Myung-Joong Kwon (1994). "The Diffusion of Multiple Process Technologies". *The Economic Journal*, 104, 420-431.

U.S. Department of Energy, Energy Information Administration (EIA). 1985-2001. "Steam-Electric Plant Operation and Design Report". EIA Form 767.