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Exploring Links Between Innovation and Diffusion: Adoption of NO_X Control Technologies at US Coal-fired Power Plants

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Abstract While many studies have looked at innovation and adoption of technologies separately, the two processes are linked. Advances (and expected advances) in a single technology should affect both its adoption rate and the adoption of alternative technologies. This paper combines plant-level data on US coal-fired electric power plants with patent data pertaining to NO_X pollution control techniques to study this link. As in other studies of environmental technologies, the effect of other explanatory variables is dominated by the effect of environmental regulations, demonstrating that the mere presence of environmental technologies is not enough to encourage its usage. Nonetheless, I do find that technological advances are important for the adoption of existing combustion modification technologies. However, these advances are less important for the adoption of newer post-combustion control techniques, which are adopted only when needed to comply with the strictest emission limits.

Keywords Air pollution · Environmental policy · Expectations · Technology transfer

JEL Classification L94 · O31 · O33 · Q53 · Q55

In recent years, economists have paid increasing attention to the links between environmental policy and technological change. More stringent environmental regulation can be expected to both increase levels of innovation directed at environmentally friendly technology and encourage increased adoption of such technologies. While many studies have looked at environmental innovation or diffusion separately, these processes are clearly linked—adoption of a new technology cannot take place until innovation has taken place. This paper explores

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linkages between available technologies and adoption of one of two air pollution control technologies by coal-fired electric power plants, considering both the availability of control technologies, as well as expectations about future technological progress.

The diffusion of a new technology is a gradual, dynamic process. New technologies are not adopted *en masse*. Rather, adoption usually begins with a few early adopters, followed by a more rapid period of adoption, with the rate of adoption leveling off once most potential users have adopted the technology. This process generates the well-known S-shaped diffusion curve.[1] Early attempts to explain this process focused on the spread of information (*epidemic models*, such as Griliches 1957) and differences among firms (*probit* models, such as David 1969).

Recent models combine these explanations while adding potential strategic decisions of firms.[2] Karshenas and Stoneman (1993) discuss three potential dynamic interactions. The *rank* effect derives from probit models—potential adopters are ranked by their gross benefits, and those with the greatest benefits go first. *Stock* and *order* effects relate to the cumulative number of adopters. Both deal with strategic interactions—those who adopt faster face less competition and receive first mover advantages. As a result, early adopters gain greater net benefits than later adopters. For example, both Karshenas and Stoneman (1993) and Kerr and Newell (2003) find that the percentage of firms already adopting the technology negatively affects the probability of adoption, which they attribute to these first-mover advantages.

These explanations, however, ignore a potential benefit of waiting. Those that adopt later receive the benefit of technological advances and may adopt technologies superior to those chosen by early adopters (see, for example, Rosenberg 1976). While previous models implicitly consider such advantages (such as through falling costs, which are often modeled as quality-adjusted), few empirical studies of diffusion consider the potential benefits of improved technology.[3] One exception is Weiss (1994), who uses survey data to show that expectations of more rapid technological change to come delay adoption. In contrast, this paper uses publicly available patent data to measure technological progress. By including a direct measure of technological progress, the methodology used potentially allows the study of technological progress and diffusion across a wide range of technologies.

This paper uses patent data to examine the role that technological advances play in the adoption of technologies designed to reduce nitrogen dioxide (NO_X) emissions at coal-fired electric power plants in the United States. This adoption decision is of interest for several reasons. Most importantly, unlike most other pollutants, US NO_X regulations have historically lagged behind those of other nations, particularly Japan and Germany. As a result, the path of innovations in each country differed (Popp 2006). To meet the more stringent regulations in Japan and Germany, post-combustion emissions treatment techniques were developed. In contrast, innovations in the US focused on modifications to the combustion process. Such modifications are cheaper, but do not reduce emissions as well as post-combustion treatment. Thus, combustion modifications are more useful when NO_X regulations are less stringent. After the 1990 Clean Air act strengthened NO_X emission rules, US firms began to develop their own innovations for post-combustion treatment, as well as develop improved methods for combustion modification. As such, potential adopters of either technology were faced

[1] See, for example, Karshenas and Stoneman (1995).

[2] Examples include Hannan and McDowell (1984), Rose and Joskow (1990), Karshenas and Stoneman (1993), and Kerr and Newell (2003).

[3] Examples of theoretical models including technological expectations include Balcer and Lippman (1984), Ireland and Stoneman (1986), Tsur et al. (1990), and Lissoni (2000).

with an existing technology base that was changing due to increased US innovation after the 1990 Clean Air Act (Popp 2006).

Compared to other technologies, another advantage of studying the adoption of technology by coal-fired electric power plants is that we can study the links between technological advances and adoption in isolation, without concern for the more strategic stock and order effects often considered in the literature. Many plants operate in regulated markets, and most serve dedicated areas with little competition. Furthermore, the choice to adopt environmental technology is driven by regulatory pressures (Gray and Shadbegian 1998; Kerr and Newell 2003; Snyder et al. 2003). The benefit that firms receive from adopting an environmental technology is increased compliance with regulation. For these reasons, strategic considerations, such as first-mover advantages, are less important here than for other technologies.

The lessons from this research should be of interest to a wide range of economists. For environmental economists, the links between environmental policy and technological change have become important research areas.[4] However, the bulk of these research efforts have focused on innovation, rather than on the diffusion of technology. For economists studying technological diffusion more generally, the paper offers new empirical methodologies designed to explicitly model the benefits of delaying adoption in return for the opportunity to adopt a better technology in the future. While the results in this paper suggest that regulatory influences are more important determinants of pollution control equipment adoption, it is hoped that the methodology presented will be of interest to economists studying adoption of other technologies as well.

1 NO_X Regulations and Technology

NO_X emissions are produced from the combustion of fossil fuels by three separate mechanisms. Fuel NO_X forms when nitrogen contained in the fuel combines with oxygen during the combustion process, and is the dominant source of NO_X emissions from coal-fired power plants. Thermal NO_X forms from the combination of nitrogen in combustion air with oxygen in the flame. Prompt NO_X is formed at the flame front through the reaction of hydrocarbon radicals (Wu 2002). NO_X emissions can be reduced either by making modifications to the combustion process or by using post-combustion control techniques. This section reviews major legislative efforts to combat NO_X emissions from power plants, as well as the technologies used to do so.

1.1 Regulations[5]

In the US, NO_X is one of six criteria pollutants regulated by the Clean Air Acts (CAA). However, NO_X emissions were primarily seen as a local issue until the 1990 Clean Air Act. NO_X emissions results in two major environmental problems—the formation of ground-level ozone and acid rain. As such, US NO_X regulations have focused on areas where these two problems are primary concerns—California (ozone) and the eastern United States (acid rain). US NO_X regulation typically takes the form of emissions per unit of input, rather than emissions per output or total environmental performance. For NO_X, the 1970 CAA established a limit of 0.7 lb/mmBtu of NO_X for power plants. The 1977 CAA tightened the standard

[4] Jaffe et al. (2003) provide a review.

[5] Except where noted, information in this section comes from a series of publications on emission standards published by the International Energy Agency Clean Coal Centre: Vernon (1988), Soud (1991), McConville (1997), and Sloss (2003).

slightly, lowering the limit to 0.5–0.6 lb/mmBtu.[6] In addition, removal of at least 65% of NO_X emissions was required.

It was not until the 1990s that NO_X regulations were strengthened, and even then the focus was on regions of primary concern. The 1990 CAA established the Ozone Transport Commission (OTC), made up of members from 11 northeastern states and the District of Columbia. The OTC was charged with designing a plan to reduce NO_X emissions in the northeastern US The resulting plan, announced in September 1994, called for reductions in affected eastern states to 0.2 lb/mmBtu beginning in May 1999, and reductions to 0.15 lb/mmBtu by May of 2003, and allowed trading of NO_X emission permits across plants in the region.[7] In addition, the 1998 NO_X SIP Call expanded additional NO_X reductions to 22 eastern states.[8] These reductions were to begin in 2003, and would be achieved using permit trading, as part of the NO_X Budget Trading Program (NBTP; USEPA 2004).[9] At the national level, the 1990 CAA tightened emission standards to as low as 0.4–0.46 lb/mmBtu by 2000.[10] Unlike previous legislation, these reductions applied to both new and existing plants.

1.2 Technologies to Reduce NO_X Emissions

NO_X emissions can be controlled via modifications to the combustion process or by treatment of flue gas after combustion. The primary post-combustion techniques are selective catalytic reduction (SCR) and selective non-catalytic reduction (SNCR). In both processes, an ammonia-based reagent is injected into the flue gas stream. A chemical reaction between the NO_X gases and the reagent produce nitrogen and water. SCR uses a catalyst to produce this reaction, allowing it to work at lower temperatures than SNCR technology. SCR has a higher capital cost than SNCR, but can reduce emissions by as much as 80–90%, compared to just 30–40% reduction from SNCR technologies (Wu 2002; Afonso et al. 2000). As such, SCR is the technology of choice for plants facing strict NO_X emissions restrictions.

In contrast to post-combustion techniques, combustion modification techniques, which change the combustion process to reduce the amount of NO_X formed by combustion, are less costly. Typically, such modifications work by adjusting the mix of air and fuel used in combustion, which reduces the peak flame temperature and results in lower NO_X formation. Commonly used techniques include low-NO_X burners and overfire air, in which combustion air is separated into primary and secondary flows. These techniques reduce emissions by 30–40% from uncontrolled levels (Wu 2002; Afonso et al. 2000). Other techniques used include flue gas recirculation, in which some of the flue gas is recirculated and mixed with combustion air, and fuel staging techniques such as reburning, which use a secondary fuel directed at a section of the furnace to burn remaining waste gases. In addition, different

6 Different limits applied depending on the type of coal burnt. The higher 0.6 limit applied to bituminous coal, which is most commonly used at US coal-fired electric plants.

7 Affected states are Maine, New Hampshire, Vermont, Massachusetts, Connecticut, Rhode Island, New York, New Jersey, Pennsylvania, Maryland, Delaware, and the District of Columbia.

8 In addition to the 11 OTC states, additional SIP states are Alabama, Illinois, Indiana, Kentucky, Michigan, North Carolina, Ohio, South Carolina, Tennessee, Virginia, and West Virginia.

9 Rather than operate two separate markets, the OTC trading market became part of the NBTP in 2003. Due to court challenges, enforcement of emission reductions was postponed until 2004 for SIP Call states. However, plants clearly made investments in anticipation of the 2003 market, as many of the coal-fired power plants studied in this paper installed abatement technologies in 2003, and none installed new technologies in 2004.

10 This regulation was phased in, with slightly higher standards between 1996 and 1999. Also, note that the requirements vary by plant. The standards presented apply to tangentially fired boilers and dry bottom wall-fired boilers respectively. These are the most common boiler types in the US Other boilers are allowed more NO_X emissions.

combustion techniques can be combined to achieve greater reductions, making it possible to comply with stringent regulations without using post-combustion techniques (Wu 2002; Afonso et al. 2000).

2 Estimating the Determinants of Adoption

To consider the effect of knowledge on the adoption decision, we consider a coal-fired electric plant, i, facing NO_x emission regulations. In each period t, the plant must decide whether or not to install one of two pollution abatement equipments: combustion modification (CM) or post-combustion emission treatment (PT). Its gross profits in any given year τ, denoted $g_{i\tau}$, are a function of the level of regulation at time τ, $\mathbf{R_i}(\boldsymbol{\tau})$, a vector of fixed firm characteristics $\mathbf{C_i}$, and a vector of time-varying firm characteristics $\mathbf{X_i}(\boldsymbol{\tau})$. In addition, the effectiveness of any pollution abatement equipment installed depends on the quality of the technology at the time in which it was installed (period t). I use $K_j(t)$ to represent the quality of technology at time t for technology j, where $j = \text{CM}$ or PT. The present value of installing technology j at time t is then:

$$G_{i,j}(t) = \int_t^\infty g_{i,j}\left\{\mathbf{C_i}, \mathbf{X_i}(\boldsymbol{\tau}), \mathbf{R_i}(\boldsymbol{\tau}), K_j(t)\right\} \mathrm{e}^{-r(\tau-t)}\mathrm{d}\tau \tag{1}$$

Following Karshenas and Stoneman (1993), define the net present value of adoption as $Z_{i,j}(t)$, where

$$Z_{i,j}(t) = G_{i,j}(t) - P_j(t) \tag{2}$$

Here, $P_j(t)$ represents the price of technology j at time t.[11]

For simplicity, consider first the decision to adopt a technology for which there is no substitute. Adoption is profitable[12] if:

$$Z_{i,j}(t) = G_{i,j}(t) - P_j(t) \geq 0 \tag{3}$$

At the same time, adoption must meet the arbitrage condition. This states that not only is adoption profitable today, but that it is not more profitable to postpone adoption until some future date. Formally, this is expressed as:

$$y_{i,j}(t) = \frac{\partial Z_{i,j}(t)\mathrm{e}^{-rt}}{\partial t} \leq 0 \tag{4}$$

To derive an expression for the arbitrage condition, y, first define $p(t)$ as the expected change in price over time, $\mathbf{r(t)}$ the expected change in regulations over time, and $k(t)$ as the expected

[11] Note that $P_j(t)$ may include adjustment costs as well as direct costs of capital, as investment is often found to be a lumpy process (e.g. Cooper et al. 1999; Nilsen and Schiantarelli 2003). For instance, one might expect plants to be more likely to install pollution abatement equipment when a unit is shut down for other maintenance, typically performed at a plant's half-life of about 20 years. To test for this, variations of the model in this paper were run including a dummy variable for plants that are 19–21 years old. This variable proved to be insignificant, suggesting that adjustment costs are less important than the need to comply with changing regulations. I thank an anonymous referee for this suggestion.

[12] Note that the model need not imply that a plant operate in an unregulated environment where only profit maximization matters. While many plants operate in regulated environments, all that matters here is that the plant adopts a technology if it perceives it will be better off with the technology than without. In practice, different regulatory environments can be included as part of the variable R.

change in the knowledge stock over time.[13] Taking derivatives yields

$$y_{i,j}(t) = rP(t) - p(t) - g(t) + \int_t^{\infty} g(\tau) \cdot \{k(t) + \mathbf{r(t)}\} e^{-r(\tau - t)} d\tau \qquad (5)$$

From Eqs. (3) and (5), we observe that adoption is a function of firm characteristics, current and expected regulations and knowledge, and current and expected prices for the technology in question. At any given time, some firms will find adoption profitable, while others will not. Over time, we expect that adoption will become more desirable, even if other firm characteristics remain the same, as technological advances improve the profitability of the technology. Thus, firms for which adoption is most desirable will adopt first, while additional firms adopt as the benefits of adoption rise. In the adoption literature, this is known as the *rank effect* (Karshenas and Stoneman 1993). In these models, firm heterogeneity leads to a distribution of expected return from adopting the new technology. From this, I define the hazard function, $h_{i,j}(t)$, which captures the conditional probability that firm i will adopt technology j in time t, given that it has not previously adopted the technology, as

$$h_{i,j}(t) = f\left\{\mathbf{C_i}, \mathbf{X_i(t)}, \mathbf{R_i(t)}, \mathbf{r_i(t)}, K_j(t), k_j(t), P_j(t), p_j(t)\right\} \qquad (6)$$

This approach, while similar to other models in the adoption literature, differs in that I explicitly model the possibility of technological improvements. As in other models, only firms above a threshold great enough to justify the costs of adoption will choose to adopt the technology at any given time. Over time, the technology gets cheaper, and its quality improves, so that more firms cross the adoption threshold. However, this decrease is typically modeled exogenously.[14] In the empirical work that follows, I use instrumental variables to control for the endogenous links between innovation and regulation.[15]

Now, consider a plant that can choose between either of the two technology options. In addition to the profitability and no arbitrage conditions (Eqs. 3, 5), it must also be the case that it is *more profitable* to adopt technology j than the competing technology, l. For example, using data on the adoption of multiple machine tool technologies, Stoneman and Kwon (1994) and Stoneman and Toivanen (1997) find significant cross-technology effects – changes in the price of one technology affect adoption rates for both technologies. In addition, since a plant may decide against investment in technology j if it anticipates major advances in the competing technology, the arbitrage condition should include expectations

[13] For simplicity, we assume that expectations for future firm characteristics are the same as current characteristics. That is, firms do not anticipate future changes in operations or revenues.

[14] Ireland and Stoneman (1986) provide a theoretical example of such a model. They consider both supply and demand of a new technology, and consider how adoption changes when expectations over future prices occur. However, costs fall exogenously over time, and improvements in the quality of technology are only considered implicitly, by assuming prices to be quality-adjusted. Similarly, Tsur et al. (1990) use the possibility of learning by using to model the evolution of technology. Modeling technological progress via learning by using leads to opposite conclusions about timing. If experience is necessary to improve the technology, firms may find it beneficial to adopt technologies that result in short-term losses in hopes of long-term benefits. Here, firms may decide to postpone adopting beneficial technologies if future benefits, due to technological progress, will be even greater.

[15] As noted earlier, models of adoption often explore *stock effects* and *order effects*, in addition to rank effects. Both are related to the cumulative number of adopters in an industry. Both address strategic advantages early adopters receive. Given that most electric plants face little competition, and many operate as natural monopolies in a regulated market, such strategic effects are likely to be unimportant in this study. However, for other applications, the model can be generalized to include stock and order effects by including variables relating to the number of adopters, as in Karshenas and Stoneman (1993).

for both technologies. From Eq. (6), note that only prices and knowledge are technology-specific. Thus, to know whether technology j is more profitable than technology l, we must also consider knowledge and prices for technology l. When faced with competing technologies the adoption decision is:

$$h_{i,j}(t) = f\left\{\mathbf{C_i}, \mathbf{X_i(t)}, \mathbf{R_i(t)}, \mathbf{r_i(t)}, K_j(t), k_j(t), P_j(t), p_j(t), K_l(t), k_l(t), P_l(t), p_l(t)\right\} \tag{7}$$

2.1 An Econometric Model

Recent work on diffusion use duration models to combine features of both epidemic models (e.g. Griliches 1957), in which the spread of information limits diffusion,[16] and probit models (e.g. David 1969), in which heterogeneity among firms determines diffusion rates. These newer models (e.g. Hannan and McDowell 1984; Rose and Joskow 1990; Karshenas and Stoneman 1993; Kerr and Newell 2003; Snyder et al. 2003) begin with the hazard function, which can be written as:

$$h(t, \mathbf{X_t}, \boldsymbol{\beta}) = \frac{f(t, \mathbf{X_t}, \boldsymbol{\beta})}{1 - F(t, \mathbf{X_t}, \boldsymbol{\beta})}. \tag{8}$$

Here, f is the continuous probability function of a random variable (such as the time to adoption), F is the cumulative probability function of this variable, $\mathbf{X_t}$ is a vector of explanatory variables, $\boldsymbol{\beta}$ is the vector of parameters to be estimated, and t represents time. Thus, like the probit model, adoption depends on individual firm characteristics captured by $\mathbf{X_t}$. By separating the hazard function into two parts, Karshenas and Stoneman (1993) combine features of the epidemic model with the hazard model by including a *baseline hazard function*, $h_0(t)$, that does not vary by firm. Combining the baseline hazard function with a hazard model that varies by firm characteristics yields a hazard function to be estimated of the form:

$$h(t, \mathbf{X_t}, \boldsymbol{\beta}) = h_0(t)\exp(\mathbf{X_t}'\boldsymbol{\beta}). \tag{9}$$

To estimate Eq. (9), the baseline hazard h_0 must be specified. Various specifications have been used in the adoption literature. Among the most common are the exponential, Weibull, and Gompertz distributions. The exponential distribution assumes the baseline hazard is constant over time, whereas the others assume that the baseline hazard is a function of time. Thus, the exponential distribution assumes that unmeasured learning effects are insignificant. In the results that follow, the exponential distribution is used.[17]

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[16] Using this framework, Griliches (1957) noted that the rate of diffusion is at least partially determined by economic factors, such as the expected rate of return for adoption. Other work using the epidemic model, such as Mansfield (1968), Davies (1979), and Oster (1982), typically focus on firm characteristics, such as firm size, to explain variations in the rate of diffusion.

[17] I also estimated models using the Weibull distribution. However, the models do not converge when including the knowledge stocks in the Weibull distribution, suggesting that collinearity between the stocks, which grow over time, and the baseline hazard is a problem when the baseline hazard is a function of time. Most importantly, the results for variables other than knowledge are unchanged when using the Weibull distribution while excluding the knowledge variables. The key assumption of using the exponential model is that the remaining explanatory variables capture any time-varying incentives to adopt. This is an empirical question, which can be tested by including other measures of experience, such as experience-based learning. Given that the technologies discussed have been well-known for some time, the assumption that unmeasured learning effects are small seems reasonable. In similar work, Kerr and Newell (2003) find learning effects to be insignificant for the adoption of isomerization technologies by oil refineries during the US phasedown of leaded gasoline.

Once the baseline hazard is specified, estimation of Eq. (9) is completed using duration data techniques.[18] Of particular importance is that, since not every observation ends in a decision to adopt, the data are censored. That is, we either observe that a plant adopts the technology, and thus leaves the data, or survives through the data period without adopting. We do not know, however, whether the plant will choose to adopt at some future point. Thus, the likelihood function used considers both adopters (denoted by α) and non adopters (denoted by $1 - \alpha$) as follows:

$$L(\boldsymbol{\beta}) = f(t; \mathbf{X}, \boldsymbol{\beta})^{\alpha}(1 - F(t; \mathbf{X}, \boldsymbol{\beta}))^{1-\alpha} \tag{10}$$

A plant contributes to the likelihood function in each year prior to adoption via $1 - \alpha$, and during the year of adoption through α. After a plant adopts, it is dropped from the data.

Equation (7) suggests the variables to include in $\mathbf{X_t}$. However, some modifications are necessary due to data constraints. Most importantly, the data set used does not contain information on the cost of technology, so that P_j is not observed directly. Instead, as I discuss in Sect. 3, the costs of NO_X control technologies are plant specific. Thus, plant characteristics help to control for variations in cost. Moreover, I assume that cost changes over time result from changes in technology, so that the effects of cost changes over time are picked up by the knowledge variables. Second, since expectations of future knowledge are not observed, I use the current growth rate in knowledge as a proxy.[19] Third, I include two dummy variables, $\mathrm{HASCM}_i(t - 1)$ and $\mathrm{HASPT}_i(t - 1)$, equal to one if the boiler uses combustion modification or post-combustion technology in the previous year. These dummies control for the fact that adoption of post-combustion treatment is less likely for a boiler that already has combustion modification (and vice versa).[20]

Finally, since the exponential distribution of the hazard assumes no unmeasured learning effects, it is important to control for any other learning that may take place. One important source of learning is within-firm experience. Utilities that have experience with a specific device at other plants may be more likely to install it elsewhere. To control for this, I define utility experience, $\mathrm{UtilExp}_{i,j}(t)$, as the total number of boilers owned by a utility using each technology in the previous year. I also include a measure of industry experience with each technology in the previous year, $\mathrm{IndExp}_j(t)$. This captures two potential time-varying effects. The first is the possibility that increased industry experience lowers the cost of abatement equipment through learning by doing, which would increase the likelihood of adoption over time. The second is that the benefits of increased emissions reduction may fall if other firms are also doing so, particularly when trading of permits is possible. Such competitive effects would decrease the likelihood of adoption. Lagged values of experience are used to avoid endogeneity problems. Modifying Eq. (7) to make use of these variables, the two hazard functions to be estimated are:

[18] For an introduction to duration data see Cox and Oakes (1985), Kiefer (1988), and Lancaster (1990).

[19] While other work including expectations, such as Karshenas and Stoneman (1993) use the change between current and future variables to proxy for expectations, doing so here is not possible without removing the last year of data from the regressions. Since much of the adoption of NO_X combustion treatment technologies occurs at the end of the sample, this is undesirable.

[20] Although combustion modification techniques do not achieve reductions necessary to meet the most stringent regulations in isolation, a boiler with existing combustion modification techniques may choose to add a second combustion modification technique. In combination, these technologies achieve emission reductions comparable to post-combustion treatment techniques (Wu 2001).

$$h_{i,\mathrm{CM}}(t) = f\left\{\mathbf{C_i}, \mathbf{X_i(t)}, \mathbf{R_i(t)}, \mathbf{r_i(t)}, K_{\mathrm{CM}}(t), k_{\mathrm{CM}}(t), K_{\mathrm{PT}}(t), k_{\mathrm{PT}}(t),\right.$$
$$\left.\mathrm{UtilExp}_{i,\mathrm{CM}}(t-1), \mathrm{IndExp}_{\mathrm{CM}}(t-1), \mathrm{HASPT}_{ii}(t-1)\right\} \quad (11)$$

$$h_{i,\mathrm{PT}}(t) = f\left\{\mathbf{C_i}, \mathbf{X_i(t)}, \mathbf{R_i(t)}, \mathbf{r_i(t)}, K_{\mathrm{PT}}(t), k_{\mathrm{PT}}(t), K_{\mathrm{CM}}(t), k_{\mathrm{CM}}(t),\right.$$
$$\left.\mathrm{UtilExp}_{i,\mathrm{PT}}(t-1), \mathrm{IndExp}_{\mathrm{PT}}(t-1), HASCM_{ii}(t-1)\right\} \quad (12)$$

Variables used to measure firm characteristics, regulations, and knowledge are discussed in Sect. 3. Table 1 presents descriptive data for these variables.

3 Data

3.1 Constructing the Knowledge Stocks

A main contribution of this paper is to add knowledge stocks to the traditional empirical models of technology adoption. To construct these stocks, I use counts of patents granted in the US. Economists have found that patents, sorted by their date of application, provide a good indicator of R&D activity (see, for example, Griliches 1990). Unlike R&D data, patent counts are available in highly disaggregated form. This makes it possible to distinguish between advances in combustion modification and post-combustion techniques. In addition, historical records of patent data are available for longer periods than R&D data, making it possible to construct a complete history of the development of these technologies. Popp (2005) discusses the advantages and disadvantages of using patent data when studying environmental technologies.[21]

When patents are granted, they are given technology classifications and subclassifications by various patent offices. These classifications can be used to identify patents pertaining to each of the technologies described in Sect. 1. Relevant patents were identified using the European Classification System (ECLA).[22] Using esp@cenet, the EPO's on-line database, I obtained a list of all patent numbers in relevant technology classes granted in the US since 1920. I construct separate list of patents for combustion modificationtechnologies and

[21] Among the disadvantages, note that not all successful innovations are patented, as inventors may choose to forgo patent protection to avoid disclosing proprietary information. Levin et al. (1987) report significant differences in the propensity to patent across industries. Fortunately, this is less problematic when studying the development of a single technology than when using patents to study inventive activity across technologies, as the only assumption needed is that the propensity to patent within the industry has remained similar, so that changes in overall level of knowledge in the field are correlated with changes in patenting activity. Moreover, note that the quality of individual patents vary greatly. Indeed, many individual patents never result in a profitable product. Thus, the effects of knowledge in this paper are best interpreted as the average effect of all accumulated knowledge, rather than the effect of any specific invention.

[22] The ECLA is based upon the well-known International Patent Classification system (IPC), but provides additional detail necessary to distinguish between the types of pollution controlled by various technologies. For example, IPC classification B01D 53/86 includes catalytic processes for pollution control. ECLA class B01D 53/86F2 specifies catalytic processes for reduction of NO_X, and B01D 53/86B4 specifies catalytic processes for reduction of SO_2. Moreover, as new classifications are added, the European Patent Office (EPO) updates the ECLA of older patents in its database. This is important, as classifications distinguishing pollution control techniques for specific pollutants were not added until recently.

Table 1 Descriptive data

Variable	*N*	Mean	SD	Min	Median	Max
Dependent variables						
Has comb. mod.	13,196	0.472	0.499	0	0	1
Has post comb. treatment	13,196	0.023	0.148	0	0	1
Knowledge stocks*						
Combustion modification	14	149.027	38.690	84.486	157.616	197.818
Post comb. treatment	14	357.321	42.978	262.425	374.888	398.439
Growth CM stock	14	0.070	0.035	0.023	0.076	0.109
Growth PCT stock	14	0.037	0.037	−0.017	0.024	0.103
Regulations						
OTC expect	13,196	0.045	0.208	0	0	1
OTC phase I	13,196	0.042	0.201	0	0	1
OTC phase II	13,196	0.008	0.091	0	0	1
SIP phase I	13,196	0.182	0.386	0	0	1
SIP phase II	13,196	0.000	0.000	0	0	0
Has lb/mmBTU reg	13,196	0.517	0.500	0	1	1
lb/mmBTU level**	6,827	0.655	0.392	0.045	0.5	6.600
Has lb/h reg	13,196	0.007	0.083	0	0	1
lb/h level**	92	1,886.54	1,507.62	235	1,360	5,920
Has ppm reg	13,196	0.005	0.074	0	0	1
ppm at stack level**	72	0.472	0.088	0.32	0.480	0.76
Boiler characteristics						
Company experience: CM	13,196	6.247	8.880	0	3	57
Company experience: PCT	13,196	0.123	0.561	0	0	5
Industry experience: CM	13,196	399.449	190.144	97	403	701
Industry experience: PCT	13,196	13.854	18.477	0	9	60
% Sulfur content of coal	13,196	1.219	0.907	0	0.930	13.353
Capacity (MW)	13,196	312.18	266.54	8	200	1,426
Tangential firing dummy	13,196	0.425	0.494	0	0	1
Reveunes (millions)	13,196	2,562.12	3,086.31	13.03	1643.22	40,137.52
Municipal plant	13,196	0.156	0.363	0	0	1
Compustat plant	13,196	0.052	0.223	0	0	1
Age of plant	13,196	32.199	12.213	0	34	69

* Descriptive statistics from knowledge stocks faced by any firm in a given year (1990-2003)
** Statistics for positive values only

post-combustion treatment technologies.[23] "Appendix 2" lists the technology classifications used and their definitions.[24] I merged these patent numbers with additional data from Delphion's on-line database and the US Patent and Trademark Office (USPTO) website to obtain

[23] The database can be found at http://ep.espacenet.com

[24] Keyword searches of recent patents were used to identify relevant classes. When identifying classes, two types of errors are possible. One is omitting potentially relevant classes, so that not all patents are included in the dataset. The second is including classes that include not only relevant technologies, but also other, unrelated

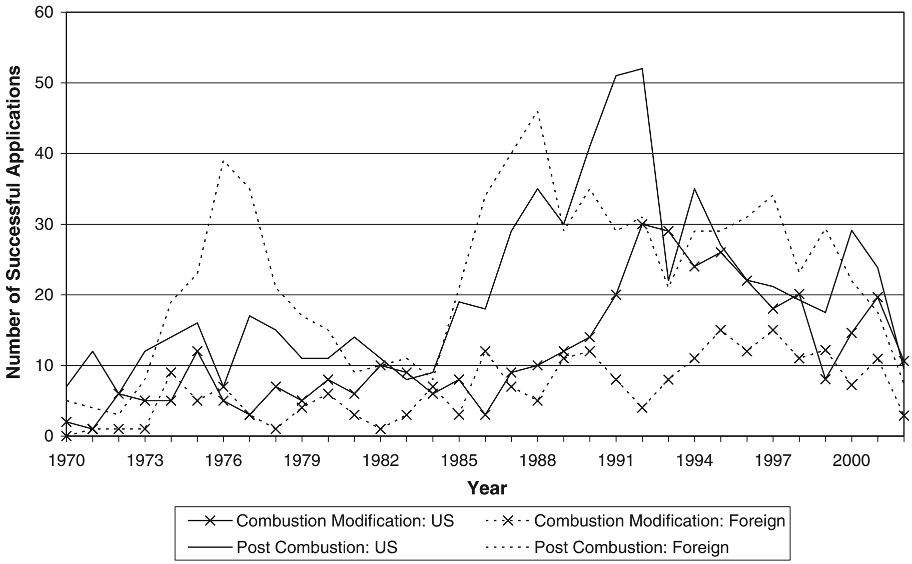

Fig. 1 NO_X pollution control patents by year. The figure shows all patents granted in the US for each of the two NO_X pollution control technologies. Patents are sorted by their year of application, and only successfully granted patent applications are included. The data for recent years are scaled to account for applications not yet processed, as described in footnote 26

descriptive data on these patents, such as the country of origin and their application date. Because US inventors will respond to the same US regulations that determine adoption, patents from US inventors are likely endogenous. Thus, I separately identify patents from domestic and foreign inventors. In Sect. 4, I use foreign patents as an instrument for predicting domestic patenting activity. All patents assigned to US inventors are considered domestic, and all others are considered foreign patents.[25] Figure 1 shows US and foreign patent applications for each technology. As noted in Popp (2006), foreign inventors respond to regulations in their home country, rather than to US regulatory changes, suggesting that foreign patents can be treated as exogenous. Most notably, foreign post-combustion treatment patents peak in the mid-1970s, after passage of NO_X regulations in Japan, and again in the mid 1980s, after passage of even more stringent NO_X regulations in Germany. There is little response of foreign patents to US policy changes in the 1990s.

As is traditional in research using patent data, I sort patents by their application year. Using the application year avoids differences in the length of time it takes to process a patent application, which varies both over time and across inventors from different countries. Moreover, the application year tends to corresponds with the date actual inventive activity (see, for example, Griliches 1990). Because patents were only published in the US upon grant until 2001, no public record exists of unsuccessful US patent applications. Thus, the data only

Footnote 24 continued
technologies. For our purposes, only the second is problematic, as any relevant patents in classes not included should follow the same trends as those included. However, including non-relevant patents is problematic, as trends in these patents may be subject to different forces. As such, care was taken to not include classes covering unrelated technologies, such as NO_X reduction for internal combustion engines.

[25] In most cases, these inventors come from manufacturers of pollution abatement equipment. Popp (2006) provides greater detail on the source of patents in this sector.

include patent applications that were subsequently granted. Since many recent applications have yet to be granted, data for later years are scaled to avoid truncation problems.[26]

Using these patent data, I create separate stocks of knowledge for combustion modification and post-combustion technologies. I use a rate of decay, represented by β_1, to capture the obsolescence of older patent and a rate of diffusion, β_2, to capture delays in the flow of knowledge, such as the time necessary for a patented idea to be converted into a commercially available technology. Defining s as the number of years before the current year, the stock of knowledge at time t for technology j is written as:

$$K_{j,t} = \sum_{s=0}^{\infty} \mathrm{e}^{-\beta_1(s)} \left(1 - \mathrm{e}^{-\beta_2(s+1)}\right) PAT_{j,t-s}. \tag{13}$$

The rate of diffusion is multiplied by $s + 1$ so that diffusion is not constrained to be zero in the current period. The base results presented below use a decay rate of 0.1, and a rate of diffusion of 0.25 for each stock calculation.[27] In previous work, I have used similar knowledge stocks to estimate the effect of energy-saving technology on industrial energy consumption (Popp 2001) and to estimate the effect of sulfur dioxide scrubber technology on coal-fired electric plants (Popp 2003).

Descriptive data for the knowledge stocks, presented at the top of Table 1, shows how the value of the stocks faced by any firm varies throughout the sample period (1990–2003). While mean values of the stocks of post-combustion patents are higher than for combustion modification, levels across technologies are not directly comparable, as the number of patents depends on the number of relevant patent classifications for each technology. Rather, variation in the stocks across time, as shown in Fig. 2, is important. Growth rates of each stock, defined as $(K_t - K_{t-1})/K_{t-1}$, control for expectations of future knowledge stocks. Average growth rates are higher for combustion modification, which grows consistently throughout the sample period. In contrast, growth of the post combustion stock levels off midway through the 1990s.

3.2 Power Plant Data

Data on individual power plants comes from the Energy Information Administration (EIA), the Federal Energy Regulatory Commission (FERC), and Compustat. I use the results of an EIA survey of power plants, EIA Form 767, to get information on plant characteristics. This survey includes data on fuel usage, electricity production, NO_X emissions standards, and pollution control equipment. The survey asks which techniques, if any, have been adopted to reduce NO_X emissions, and lists 11 possible technologies that may be used. Of these, nine qualify as combustion modification, and two are post-combustion techniques (SCR and

[26] I do this by first calculating the average grant lag for patents in the data set. Separate scales are created for foreign and domestic patents. From this, I estimate the percentage of pending patents for each year, and augment the data by this percentage. Fortunately, I have patent data through 2006. The analysis in this paper uses data through 2003. Over 90% of patents in these technologies are granted within 3 years, and over 95% within 4 years. Thus, the scaling only has a small effect in the last years of the sample. Moreover, as we will see below, these patents receive little weight in the knowledge stocks, as their diffusion process is just beginning. As such, the scaling has no effect on the main results of this paper. This has been verified using sensitivity analysis to different scaling techniques, as well as running the model without 2003 data. In all cases, the results are virtually unchanged.

[27] These rates are consistent with others used in the R&D literature. For example, discussing the literature on an appropriate lag structure for R&D capital, Griliches (1995) notes that previous studies suggest a structure peaking between 3 and 5 years. The rates of decay and diffusion used in this paper provide a lag peaking after 4 years. "Appendix 1" presents sensitivity analysis with respect to the rates of decay and diffusion.

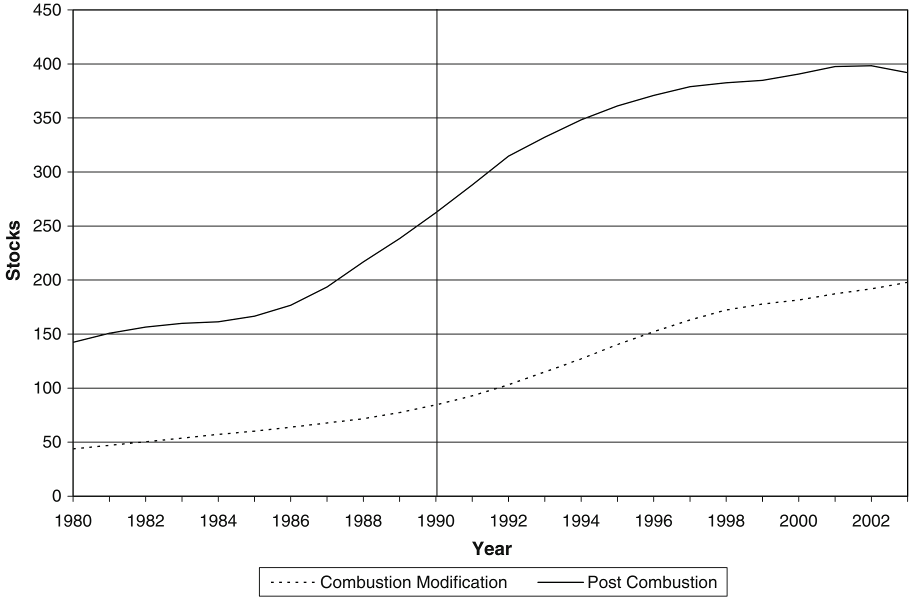

Fig. 2 Knowledge stocks over time. The figure shows how each knowledge stock varies over time. Note that both domestic stocks increase soon after passage of the 1990 Clean Air Act, but that growth of the post combustion stock soon levels off

SNCR). In addition to plant characteristics, several studies of diffusion suggest that financial characteristics of the firm matter. As such, I augment the data from EIA Form 767 with financial data on individual plants. FERC Form 1 provides this data for plants owned by regulated electric utilities. EIA Form 412 provides financial data for municipal, federally owned, and unregulated entities. Finally, because of shifts in ownership due to deregulation, data from Compustat are used to obtain financial data of the parent companies for plants owned by private corporations, such as Entergy or Duke Energy Corporation. The final unit of analysis is individual boilers within a plant. Each plant contains multiple boilers. These boilers are often of different vintages and may face different regulations, so that adoption of pollution abatement equipment is not uniform across boilers at a specific plant. The resulting data set includes observations for 996 coal-fired power plant boilers from 1990 to 2003.[28]

3.2.1 Technology Choice

Two dummy variables indicate whether a boiler has either combustion modification or post-combustion treatment technologies to reduce NO_X emissions. As shown in Table 1, combustion modification is more prevelant, being present in nearly one-half of the boiler-year observations. Figure 3 shows the percentage of boilers with each technology by year. The first panel shows overall trends, and the remaining panels separate the data by states that are part of the OTC and NO_X SIP call. Note that the percentage of boilers with combustion modification technologies grows steadily over the period analyzed, from 16% in 1990 to 67% in 2003. In comparison, no post-combustion treatment technologies were adopted

[28] Note that some boilers are not on-line for the entire period, so that the total number of possible observations is 13,196.

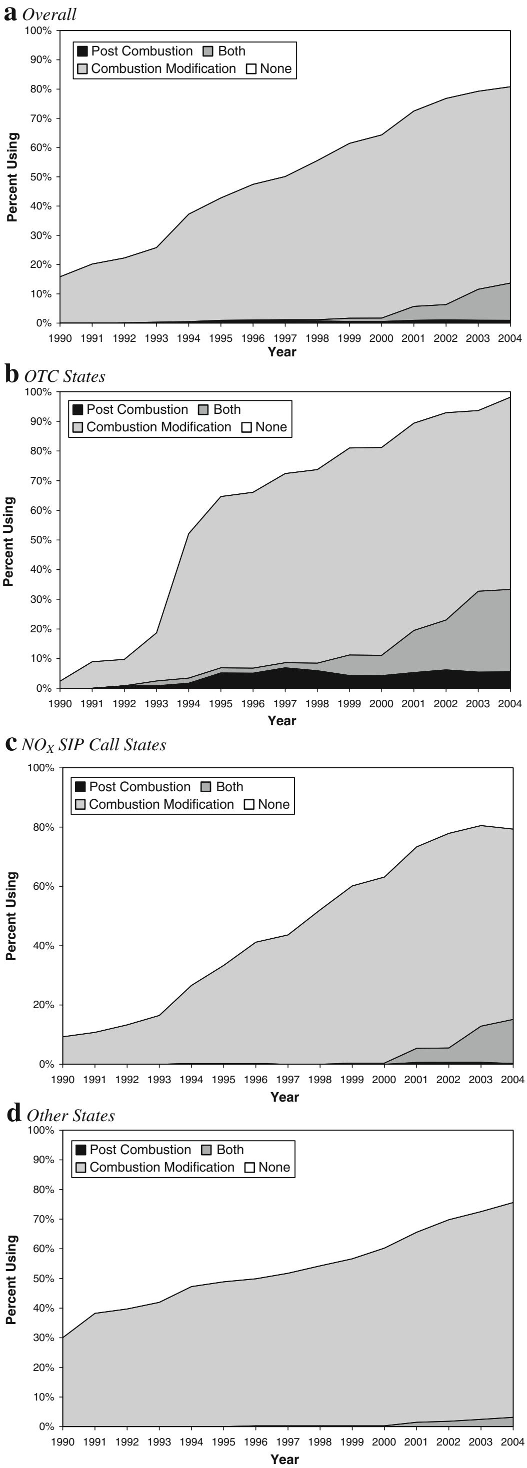

Fig. 3 Percentage of boilers adopting NO_X pollution control technologies. The figures show the percentage of boilers who have adopted each NO_X control technology by the year on the x-axis

until 1992. Most adoption occurs in recent years, as a result of recent increases in regulatory stringency. This does not simply represent a switch from one technology to the other, as adoptions of combustion modification technologies also increase at this time. In fact, about half of the post-combustion installations occur at boilers also using combustion modification (Popp 2006). Overall, just 12% of boilers use post-combustion treatment. Usage of post-combustion technologies is greatest in OTC states, where 33% of boilers use the technology by 2003. However, there is some adoption of post-combustion technologies in other states, with 13% of boilers using post-combustion techniques in SIP states, and 2.5% of boilers in states that are neither OTC or SIP states.[29] Note also that most boilers adopting post-combustion techniques in SIP states did so in 2003, the planned first year of expanded NO_X reductions under the NO_X SIP call.

3.2.2 Regulations

Of the other explanatory variables, perhaps most important are those variables measuring regulatory levels. Previous studies of diffusion of environmental technologies show that regulatory stringency matters (Gray and Shadbegian 1998; Kerr and Newell 2003; Snyder et al. 2003). Since NO_X emissions technologies provide no benefit to the plant other than reducing emissions, they are of little use unless a boiler is required to reduce NO_X emissions. Moreover, since post-combustion techniques reduce a greater percentage of emissions, but cost more than combustion modification techniques, the technology chosen should vary depending on regulatory stringency.

Boilers may face regulations at federal, state, and local levels. Form 767 includes the level of the most stringent of these regulations.[30] Because standards from various jurisdictions vary in the units by which they are defined, I include dummy variables for the presence of three types of regulations, as well as the allowable level of emissions regulated.[31] Most common are regulations specifying a maximum level of NO_X emissions per million Btus of fuel burned (lb/mmBTU). Nearly half of all boiler-year observations in the sample face such a limit. Other regulation types include pounds per hour of service (lb/h) and parts per million of NO_X at the stack (ppm at stack). Because each regulation type has different levels, each regulation type enters the regression separately.

In addition, I create a dummy variable for boilers affected by either the OTC regulations or the 1998 NO_X SIP call. Here, I distinguish between expectation and enactment of each regulation. In the case of the OTC, the initial memorandum of understanding between member states was signed in 1994. Because boilers in affected states installing new NO_X abatement equipment after 1994 would know that more stringent regulations would soon be enforced, we would expect these plants to be more likely to consider advanced equipment such as SCR. Thus, OTC_Expect equals 1 for boilers in OTC states between 1994 and 1998. In these states,

[29] While most plants do install one of these techniques to comply with regulations, EPA rules allow utilities additional options to comply with federal standards. First, a plant may average the emission rates of two or more boilers. In the data, this most often appears as older vintage boilers being less likely to use any NO_X reduction techniques. Second, plants can apply for less stringent emission standards if the plant can demonstrate that it wouldn't meet the emissions limit using standard NO_X reduction techniques (EIA 1997).

[30] This is important, as it provides variation in the regulations faced by similar boilers in different jurisdictions at a given point in time.

[31] Note that, for each regulation, higher values indicate a *weaker* regulation, as higher values indicate more pollution allowed. Thus, simply including the level of regulation in the regression is insufficient, as a 0 for plants facing no regulation would be interpreted as more stringent than any existing regulation level. Dummy variables control for the effect of *having* one of these regulations, and the levels control for the effect of more stringent regulatory levels *conditional on facing that regulation type*.

the first NO_X reductions were required in 1999, with greater reductions required in phase II, beginning in 2003. OTC_Phase_I and OTC_Phase_II cover these two periods. Similarly, SIP_Phase_I and SIP_Phase_II cover boilers in SIP states between 1999–2002 and in 2003, respectively.[32] In addition, recall that OTC boilers face more stringent regulations during the summer months, beginning in 1999.[33,34]

3.2.3 Boiler Characteristics

Boiler characteristics considered include details about the boiler and the plant owner's finances. Whereas many studies of diffusion include the price of a technology as an explanatory variable, here costs vary by boiler. Boiler characteristics help to determine the cost of NO_X reduction strategies. For example, coals with higher sulfur content reduce the service life of catalysts used in SCR units, making SCR more costly for boilers that use high-sulfur coal. As a result, most SCR units worldwide have been used at boilers burning coal with less than 2% sulfur content (Wu 2002). Costs also increase with boiler size. To control for the type of boiler used, I include a dummy variable for boilers that use tangential firing.[35] I also include dummy variables for the boiler's vintage. Vintage is defined based on the year in which the boiler began service. The vintage dummies control both for the age of the boiler and for any differences in the construction of boilers from a given era that might affect retrofit costs.[36]

Much empirical work on diffusion suggests that firm size is an important influence. Larger firms have better access to credit and are more likely to be able to afford larger, riskier investments. As a measure of the plant owner's finances, I use annual operating revenues of the plant's parent utility. To capture differences across ownership type, I include a dummy variable indicating whether the plant is owned by a regulated utility (plants with financial data from FERC Form 1), is municipal or government-owned (plants with financial data from EIA Form 412), or is owned by an unregulated, privately owned corporation (plants with financial data from Compustat).

4 Estimation

Using the data described above, I proceed with estimation of two hazard functions described by Eqs. (11) and (12). As in Kerr and Newell (2003), I normalize all continuous variables so that a one unit change in the normalized variable is equivalent to a 10% change from

[32] For both the OTC and SIP variables, the Phase I and Phase II dummies are additive. That is, in 2003, both OTC_Phase_I and OTC_Phase_II equal 1 for affected boilers. Thus, the coefficient on the Phase II dummies can be interpreted as the *additional* effect of moving to the second phase of the policy.

[33] The OTC standards only apply between May 1 and September 30. As such, they are not included as the standards reported in the EIA Form 767 database. However, as these (typically) more stringent standards will be relevant for the adoption decision of boilers, I replace the standard reported in the Form 767 database with the OTC standard if the OTC standard is more stringent.

[34] While it was part of the OTC commission, Maryland did not join the agreement to reduce emissions until 2000. As such, OTC_Phase_I equals 0 for Maryland in 1999.

[35] Most US boilers use either tangential-fired or wall-fired boilers. Retrofit costs are higher for tangential-fired boilers (Wu 2002).

[36] The vintage dummy variables are generally defined in 5 year intervals, with exceptions for the youngest and oldest plants, as shown in Tables 2 and 4.

Table 2 Regression results: adoption of combustion modification technology

Variable	Base	Growth	Both techs	Growth and both
Comb. mod. knowledge	0.6448*** (0.1220)	0.6522*** (0.1231)	0.6494** (0.2004)	−0.2443 (0.2594)
Growth CM knowledge		−0.0218 (0.0340)		−0.1598** (0.0531)
NOX post knowledge			−0.0058 (0.2042)	−0.0451 (0.2923)
Growth NOX post knowledge				−0.1307*** (0.0355)
Company experience ($t-1$)	0.0295*** (0.0065)	0.0296*** (0.0066)	0.0295*** (0.0065)	0.0296*** (0.0068)
Industry experience ($t-1$)	−0.0095*** (0.0018)	−0.0101*** (0.0020)	−0.0095*** (0.0020)	−0.0075*** (0.0019)
Has postNOX ($t-1$)	−1.4764** (0.5208)	−1.4697** (0.5212)	−1.4768** (0.5209)	−1.4486** (0.5277)
OTC expect	1.0453*** (0.1416)	1.0607*** (0.1447)	1.0462*** (0.1454)	1.0054*** (0.1430)
OTC phase I	1.2145*** (0.2606)	1.1683*** (0.2667)	1.2143*** (0.2601)	1.1671*** (0.2846)
OTC phase II	−13.4186*** (0.3039)	−12.2237*** (0.3297)	−13.4416*** (0.3026)	−12.7286*** (0.3537)
SIP phase I	0.6254*** (0.1546)	0.5741*** (0.1652)	0.6249*** (0.1516)	0.5704** (0.1833)
SIP phase II	0.0502 (0.3606)	0.1277 (0.3837)	0.0488 (0.3616)	−0.3690 (0.4124)
lb/mmBTU Level	−0.0200*** (0.0049)	−0.0197*** (0.0049)	−0.0200*** (0.0048)	−0.0204*** (0.0050)
Has lb/mmBTU reg	1.6830*** (0.1785)	1.6705*** (0.1790)	1.6826*** (0.1742)	1.7058*** (0.1896)
% Sulfur content of coal	0.0050 (0.0061)	0.0050 (0.0062)	0.0050 (0.0062)	0.0052 (0.0064)
Capacity (MW)	0.0197* (0.0082)	0.0196* (0.0083)	0.0197* (0.0082)	0.0200* (0.0086)
Tangential firing dummy	−0.0706 (0.1144)	−0.0707 (0.1152)	−0.0706 (0.1146)	−0.1012 (0.1247)
Revenue (millions)	0.0019 (0.0038)	0.0018 (0.0038)	0.0019 (0.0038)	0.0021 (0.0040)
Municipal plant	0.1274 (0.2037)	0.1315 (0.2058)	0.1277 (0.2049)	0.1456 (0.2226)
Compustat plant	−0.0578 (0.2389)	−0.0564 (0.2388)	−0.0582 (0.2393)	−0.0654 (0.2472)
Vintage $\leq$ 1960	−0.4176*** (0.1137)	−0.4166*** (0.1138)	−0.4177*** (0.1137)	−0.4128*** (0.1157)
Vintage 1971–1976	0.1784 (0.1476)	0.1792 (0.1478)	0.1785 (0.1478)	0.1727 (0.1500)
Vintage 1977–1980	0.8297** (0.3002)	0.8309** (0.3002)	0.8297** (0.3001)	0.8486** (0.3046)

Table 2 Continued

Variable	Base	Growth	Both techs	Growth and both
Vintage 1981–1985	1.5736* (0.6165)	1.5776* (0.6268)	1.5743* (0.6303)	1.6271* (0.7269)
vintage 1986–1990	0.9780 (0.5001)	0.9521 (0.5040)	0.9755 (0.5043)	0.8888 (0.5578)
Vintage 1991–1995	−0.9272*** (0.1964)	−0.8998*** (0.1983)	−0.9263*** (0.1938)	−0.8087*** (0.2079)
Vintcat 1996+	−0.8979*** (0.2464)	−0.9066*** (0.2519)	−0.8973*** (0.2476)	−1.0507*** (0.2318)
Log likelihood	−1897.153	−1896.927	−1897.152	−1889.533
Joint significance of knowledge vars: χ^2	27.65	28.11	27.66	42.89
$p > \chi^2$	<0.0001	<0.0001	<0.0001	<0.0001

Notes: Standard errors appear below estimates. Some regulatory variables and constant suppressed to save space. Vintage 1961–1970 excluded. $N = 7,469$
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 3 Net effect of technology

	Base (%)	Growth (%)	Both techs (%)	Growth and both (%)
Combustion modification				
Average	47.2	50.5	47.3	40.1
Average 1991–1998	61.1	64.9	61.3	46.2
Average 1999–2003	24.8	27.4	25.0	30.3
Post combustion				
Average 1993–2003	27.6	9.5	49.2	91.9
Average 1993–1998	44.5	8.9	95.4	154.5
Average 1999–2003	7.2	10.3	−6.2	16.7

The table shows the average change in the hazard ratio resulting from changes in the technology variables over time. The values are the average of the additional contribution from new technology each year. The additional contribution is calculated as $[\exp(\beta \times \mathbf{X}(\mathbf{t})]/\exp[\beta \times \mathbf{X}(\mathbf{t} - \mathbf{1}))] - 1$, where $\mathbf{X}(\mathbf{t})$ is a vector of the various technology variables (both levels and growth rates) in each year

its mean value, so as to aid interpretation of the effects on the hazard function.[37] Because the regressions include repeated observations on individual boilers, it is unlikely that the error terms are independently and identically distributed. As such, robust standard errors are calculated using the Huber/White correction, as is standard when estimating hazard models.

Before proceeding, two econometric issues need to be addressed. Most importantly, note that the knowledge stocks are likely endogenous, as domestic patents are influenced by the stringency of US NO_X regulations.[38] To control for this, I use a two-stage procedure. For domestic patents applied for between 1990 and 2003, I regress patent applications on federal NO_X emission standards, dummy variables for various regulatory periods, lagged values of

[37] The normalization first divides each continuous variable by its mean, multiplies by ten, and then takes deviations from the mean by subtracting ten. As in Kerr and Newell (2003), this results in normalized variables that have a mean of zero. Note that because both experience variables are count variables (with many zeros for post combustion technology), they are not normalized in this fashion.

[38] Popp (2006) shows that the same is not true for foreign patents for NO_X control technologies.

Table 4 Regression results: adoption of post-combustion treatment technology

Variable	Base	Growth	Both techs	Growth and both
NOX post knowledge	1.1269 (0.6370)	3.3623** (1.2202)	6.0544 (4.2574)	5.9625 (3.6178)
Growth NOX post knowledge		0.3294* (0.1432)		0.7066* (0.3132)
Comb. mod. knowledge			−1.9263 (1.4837)	1.4661 (2.3655)
Growth CM knowledge				0.6099 (0.3510)
Company experience ($t-1$)	−0.1954 (0.1139)	−0.1929 (0.1141)	−0.1959 (0.1139)	−0.1916 (0.1137)
Industry experience ($t-1$)	−0.0073 (0.0093)	0.0156 (0.0107)	0.0037 (0.0089)	0.0309* (0.0144)
Has combustion modification ($t-1$)	0.1500 (0.2544)	0.1544 (0.2590)	0.1469 (0.2525)	0.1494 (0.2594)
OTC expect	2.1972*** (0.5369)	2.6535*** (0.6524)	2.0140*** (0.5249)	2.2171*** (0.5182)
OTC phase I	3.2997*** (0.5579)	3.0566*** (0.5761)	3.4780*** (0.6678)	3.4512*** (0.7078)
OTC phase II	1.7030** (0.5457)	3.6723** (1.1480)	3.3331* (1.5857)	4.6487* (1.8509)
SIP phase I	1.6201*** (0.3813)	1.3107*** (0.3764)	1.7616*** (0.5074)	1.6980** (0.5300)
SIP phase II	2.0984*** (0.4244)	4.0887*** (1.0990)	3.7424* (1.5680)	5.0805** (1.8300)
lb/mmBTU level	0.0118 (0.0104)	0.0122 (0.0102)	0.0110 (0.0103)	0.0114 (0.0100)
Has lb/mmBTU reg	0.2222 (0.4160)	0.2083 (0.4087)	0.2667 (0.4155)	0.2425 (0.4082)
% Sulfur content of coal	−0.0047 (0.0139)	−0.0049 (0.0140)	−0.0057 (0.0139)	−0.0066 (0.0140)
Capacity (MW)	0.0492*** (0.0143)	0.0493*** (0.0143)	0.0489*** (0.0142)	0.0493*** (0.0141)
Tangential firing dummy	−1.1237*** (0.2507)	−1.1039*** (0.2471)	−1.1163*** (0.2510)	−1.0952*** (0.2480)
Revenue (millions)	0.0136* (0.0066)	0.0122 (0.0065)	0.0125 (0.0067)	0.0107 (0.0066)
Municipal plant	−0.3707 (0.3705)	−0.3544 (0.3695)	−0.3751 (0.3729)	−0.3424 (0.3700)
Compustat plant	−0.9746* (0.4425)	−1.0228* (0.4476)	−1.0167* (0.4459)	−0.9973* (0.4494)
Vintage $\leq$ 1960	0.2364 (0.3160)	0.2323 (0.3151)	0.2200 (0.3166)	0.2162 (0.3151)
Vintage 1971–1976	0.3524 (0.2989)	0.3466 (0.3005)	0.3491 (0.3004)	0.3436 (0.3010)
Vintage 1977–1980	0.2155 (0.3876)	0.1944 (0.3933)	0.1975 (0.3940)	0.1972 (0.3970)

Table 4 Continued

Variable	Base	Growth	Both techs	Growth and both
Vintage 1981–1985	−0.1842 (0.5495)	−0.2026 (0.5468)	−0.1963 (0.5529)	−0.2018 (0.5513)
vintage 1986–1990	−0.3245 (0.7914)	−0.3454 (0.7929)	−0.3389 (0.7941)	−0.3511 (0.7984)
Vintage 1991–1995	0.2449 (0.7034)	0.2335 (0.6889)	0.2368 (0.6880)	0.2361 (0.6686)
Vintcat 1996+	1.8156** (0.6812)	1.5845* (0.6898)	1.7297** (0.6614)	1.6849* (0.7237)
Log likelihood	−121.716	−117.258	−119.005	−112.850
Joint significance of knowledge vars: χ^2	9.12	18.03	14.57	26.85
$p > \chi^2$	0.0025	< 0.0001	0.0007	< 0.0001

Notes: Standard errors appear below estimates. Some regulatory variables & constant suppressed to save space. Vintage 1961–1970 excluded. $N = 12,995$
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

a knowledge stock using only foreign patents, and a time trend.[39] I then use the predicted values in place of domestic patent counts from 1990–2003 when constructing the stocks.

Second, note that some boilers adopted combustion modification techniques before the first year of data availability. In fact, the first boiler to install combustion modification techniques in the US did so in 1974. Thus, the likelihood function must control for boilers that adopt early (that is, that do not survive until 1990; Cox and Oakes 1985). This adds an additional term to the likelihood function used to estimate the hazard function for combustion modification:

$$L(\boldsymbol{\beta}) = f(t; \mathbf{X}, \boldsymbol{\beta})^{\alpha}(1 - F(t; \mathbf{X}, \boldsymbol{\beta}))^{1-\alpha} F(0; \mathbf{X}, \boldsymbol{\beta})^{\gamma} \tag{14}$$

Here, α equals 1 for boilers that adopt in year t, conditional on not adopting before. γ equals 1 for boilers that adopted combustion modification technologies before 1990, and 0 otherwise. Boilers that did not adopt before 1990 contribute to the likelihood function in each year prior to adoption via 1 - α, and during the year of adoption through α. Boilers that did adopt prior to 1990 contribute through γ. After a boiler adopts, it is dropped from the data.[40]

4.1 Adoption of Combustion Modification Techniques

Table 2 presents regression results for combustion modification technology. The tables present estimated coefficients from the maximum likelihood regression. To interpret these coefficients, note that the effect of the hazard ratio for each coefficient is calculated as exp(β). Table 2 begins with a naïve model, which assumes myopic adoption decisions and ignores the availability of competing technology. This model, presented in column 1, ignores knowledge stocks for post-combustion technology and growth in either technology's knowledge

[39] The regulatory dummy variables are Post_CAA (1990–1992), OTC_Expect (1994–1998), OTC (1999–2002), and SIP_II (2003). The R^2 of the patent regression is 0.84 for post-combustion patents and 0.65 for combustion modification patents.

[40] The term $F(0; \mathbf{X}, \boldsymbol{\beta})^{\gamma}$ is not needed for post-combustion technology, as the first adoption occurs in 1993. Thus, the likelihood function described in Eq. (10) is used for post-combustion technology.

stocks. In the naïve model, the stock of combustion modification knowledge has a significant positive effect. A 10% increase in this knowledge stock increases the likelihood of adoption by 91%.[41] In column 2, I consider expectations by adding the growth of combustion modification technology knowledge. Expectations of future technology advances, proxied by the growth rates of knowledge, negatively influence adoption, although the effect is insignificant. The coefficient on the level of the knowledge stock remains virtually unchanged. This is also the case in column 3, which adds the level of competing post combustion technology to the naïve model. The sign on the competing technology is negative, as expected, but is insignificant. Finally, column 4 includes expectations of both technologies. In this complete model, the effect of expectations is significantly negative for both technologies. Plant-owners are more likely to wait to adopt when the technology is advancing rapidly. However, the effect of the levels of knowledge is now insignificant.

To help put these results in perspective, it is useful to consider the combined effect of increases in knowledge during this time frame. Table 3 shows such calculations. The table presents the average increase in the adoption probability resulting from new knowledge in each year for both combustion modification and post combustion technologies.[42] For combustion modification technologies, note that the average net impact of knowledge ranges from a 40.1 to 50.5% increase in the likelihood of adoption. The effect of knowledge is greater at the beginning of the decade, when patenting counts for this technology were highest.

Turing to other variables, the results are as expected. Moreover, the results for other variables are consistent across specifications. By far the most important predictor of adoption is regulatory stringency. Being subject to OTC regulations increases the likelihood of adoption by a factor of three. Expectations of future regulations also matter, as both the OTC_Expect and SIP_PhaseI variables have significant positive effects. However, once the NO_X budget trading program begins (SIP_PhaseII), boilers in SIP states are not more likely to install combustion modification. As the next section shows, the NO_X Budget Trading Program made these plants more likely to choose post-combustion techniques. Similarly, the presence of lb/mmBTU regulation increases adoption by a factor of five.[43] Note also the negative sign for regulatory levels—adoption is more likely when *fewer* emissions are allowed. However, this effect is small. A 10% more stringent than average regulation (e.g. 10% fewer emissions allowed) never increases the likelihood of adoption by more than 2%. That the simple presence of regulation is more important than the level occurs because combustion modification is of less use when regulations are very stringent. Thus, tighter regulations need not induce additional adoption.

Turning to boiler characteristics, boilers that already have post-combustion treatment are nearly 80% less likely to adopt combustion modification. This is not surprising, as post-combustion treatment is both more effective and more expensive. Plants are unlikely to invest in such technology if it is insufficient to meet regulatory hurdles. Company experience is important. For each additional existing boiler with a combustion modification unit operated by the utility, the likelihood of adoption at a different boiler increases by 3%. In contrast, industry experience is less important. Each additional boiler using combustion modification reduces the probability of adoption next year, but by just 1%. As for other characteristics, only boiler size and the vintage dummies are significant. Larger boilers are more likely to

41 Recall that knowledge is normalized so that a one-unit change in the variable represents a 10% increase in knowledge. As a result, the 91% increase is simply calculated as $\exp(\beta)$.

42 The calculation is the average of $(\exp(\mathbf{X(t)}'\beta)/\exp(\mathbf{X(t-1)}'\beta)) - 1$, where $\mathbf{X}$ is a vector of the relevant technology variables in each model (including the growth rates), and β is the vector of coefficients.

43 Results for other types of regulations are similar. Because these affect fewer boilers, they are omitted from the table to conserve space.

adopt combustion modification techniques, although the magnitude of this increase is no higher than 2% for a 10% increase in size. In addition, the probability of adoption rises in newer vintage years until passage of the 1990 Clean Air Act. Since then, new boilers have been less likely to install combustion modification techniques. As shown in the next section, these very new boilers make less use of combustion modification because they instead install post combustion techniques, which are state of the art at the time these newest boilers are built. Of particular importance is that all financial and ownership variables are insignificant. As I discuss with the results for post-combustion techniques, it is unlikely that this result occurs because many utilities operate in regulated markets, but rather because it is regulatory pressure that provides the initial impetus for adoption. Once faced with regulation, plants do not have the option to delay installation until conditions are more favorably financially.

4.2 Adoption of Post-combustion Treatment

Table 4 presents estimation results estimation for post-combustion treatment technologies. Estimates are generally as expected, although the results are not as statistically significant as the combustion modification results, as the lower adoption rates of post-combustion technology result in less variation in the data. As before, the level of the knowledge stock increases adoption. However, this is only significant in the equation including technology growth (column 2). Unlike before, expectations of technological advances increase adoption. In the model including competing technologies, signs are as expected, but both coefficients are insignificant. Finally, in the completely specified model in column 4, which considers both technological alternatives and expectations, most knowledge variables are insignificant. Note however, that in both columns 3 and 4, although the individual knowledge variables are insignificant, I cannot reject the null hypothesis that the knowledge coefficients are jointly significant. Moreover, there is greater variation in the magnitude of the effects of knowledge, including implausibly high values on the level of knowledge coefficients in columns 3 and 4. Both results are evidence of multicollinearlity. Given that fewer plants ever choose to adopt post-combustion technology, identifying the effect of multiple knowledge stocks appears to be asking too much of the data.

Referring back to Table 3, the net effect of technology on post-combustion adoption tends to be smaller than for combustion modification. However, because of the imprecise coefficient estimates, there is more variation in the overall effect. Focusing on the OTC era (1999–2003), we see that technological advances have half the influence on adoption of post-combustion, compared to combustion modification, techniques. It may be that advances in combustion modification techniques are more important because they were needed to keep the technology viable as more stringent regulations take effect. However, additional years of data would be needed to conclude this with confidence.

By far the most important influence on adoption of post-combustion techniques are environmental regulations. Stricter regulations make plant operators more willing to pay the greater fixed cost of post-combustion techniques. In OTC states, simply knowing that future regulations would be in place makes adoption of post-combustion techniques seven to fourteen times more likely. Recall that federal standards for boilers were tightened in 1995. While those standards alone were not enough to justify post-combustion technology, plants that know they will soon need to comply with even stricter regulations are more likely to install advanced abatement equipment. The likelihood of adoption increases further once the OTC plan takes effect in 1999, and further still when regulations are strengthened in 2003. Similarly, in the SIP states, adoption increases upon announcement of the program, and further still on the planned start of the NO_X Budget Trading Program in 2003. As a result of the strong effect of these variables, the effect of other regulations is insignificant.[44]

Still, even in OTC states, 2/3 of all boilers use combustion modification. Thus, it is useful to consider what other factors influence adoption of post-combustion techniques. First, whether a boiler has or does not have existing combustion modification technologies has no effect on the adoption of post-combustion control. Indeed, post-combustion techniques can be paired with combustion modification techniques to increase effectiveness, which may be necessary to meet strict emissions standards. Moreover, the costs of SCR systems are lower when combined with combustion modification, as less catalyst is needed if the remaining NO_X concentrations to be removed are lower (Wu 2002). Thus, boilers that had previously installed combustion modification (perhaps to comply with earlier, less stringent regulations) may still choose to add a post-combustion device as regulations become stronger. This result suggests an important lesson for new technologies: to avoid lock-in when developing a new, otherwise superior technology, it may be helpful to work *with* existing technologies, rather than simply serving as a substitute.

As in the case of combustion modification, larger boilers are more likely to adopt post-combustion techniques. Unlike combustion modification, neither company nor industry experience is significant. Most post-combustion adoptions take place within a few years at the end of the sample, leaving little time for learning. Additional years of adoption data will be needed to see if the no-learning effect holds over time. Regarding vintage, the boilers most likely to adopt post combustion technique are those brought on line since 1996. New boilers facing strict NO_X regulations could install post-combustion equipment during initial construction, rather than face a more expensive retrofit. Unlike combustion modification, boilers that use tangential firing are less likely to adopt post-combustion treatment, as they have higher retrofit costs. Because of the large installation costs of post-combustion treatment, the financial strength of plant owners is somewhat important. A 10% increase in revenue increases the hazard rate by about 1.2%, although only significant at the 10% level in columns 2–4. In comparison, recall that adoption of combustion modification techniques was not sensitive to revenue. Financial strength gives firms the option to invest in *better* technology, but all regulated firms must invest in some technology. This is similar to results in Rose and Joskow (1990), who find that firm size is more important for the adoption of more advanced supercritical boilers than more conventional units. Finally, ownership does matter, as non-regulated utilities (the Compustat plants) are less likely to adopt post-combustion techniques. This is consistent with the concern that such companies will be less able to pass the costs of advanced techniques on to consumers.

4.3 Differences Across Regulatory Regimes

Because the regionally imposed regulatory regimes play such a large role, Tables 5 and 6 compare results for the base regression model for boilers in each of the three regulatory-state types (OTC, SIP, or other states).[45] In both cases, the major differences are between other states and those facing either OTC or SIP regulations. For combustion modification, both

[44] Once again, results for other types of regulations are omitted to save space, as these affect few plants. The one exception to insignificant results is a strong negative effect on "has lb/hour reg," which is driven by the few boilers (just 17, representing 157 observations) that have such regulations. Only one boiler adopts post combustion technology while facing such regulations, and it is also affected by the NO_X SIP call when it does.

[45] Two modifications are necessary to estimate the model on these smaller subsamples. First, while vintage dummies are still included in these regressions, fewer groupings, each including more years, are used, as no boilers appear in some regulatory regimes for some of the vintage groups used in the full sample. Second, the model for other states does not converge unless industry experience is dropped from the regression. There are

Table 5 Adoption of combustion modification by regulation type

Variable	All	OTC states	SIP states	Other states
Comb. mod. knowledge	0.6448***	1.0013***	0.8131***	−0.1253
	(0.1220)	(0.2743)	(0.1313)	(0.0772)
Company experience ($t-1$)	0.0295***	−0.2358***	0.0294***	0.1073**
	(0.0065)	(0.0709)	(0.0074)	(0.0406)
Industry experience ($t-1$)	−0.0095***	−0.0637***	−0.0186***	
	(0.0018)	(0.0150)	(0.0035)	
Has postNOX ($t-1$)	−1.4764**	−1.6638**	−12.8583***	−1.1520
	(0.5208)	(0.6049)	(0.3180)	(0.6150)
OTC expect	1.0453***	1.4599***		
	(0.1416)	(0.3818)		
OTC phase I	1.2145***	1.1719		
	(0.2606)	(0.5993)		
OTC phase II	−13.4186***	−13.8443***		
	(0.3039)	(0.3555)		
SIP phase I	0.6254***		0.5976**	
	(0.1546)		(0.2097)	
SIP phase II	0.0502		0.1448	
	(0.3606)		(0.3808)	
lb/mmBTU level	−0.0200***	−0.0325**	−0.0169**	0.0133
	(0.0049)	(0.0114)	(0.0059)	(0.0280)
Has lb/mmBTU reg	1.6830***	2.3846***	1.5814***	1.0014
	(0.1785)	(0.3813)	(0.2275)	(0.6389)
% Sulfur content of coal	0.0050	−0.0134	0.0104	−0.0123
	(0.0061)	(0.0335)	(0.0074)	(0.0118)
Capacity (MW)	0.0197*	0.0145	0.0139	0.0538**
	(0.0082)	(0.0141)	(0.0083)	(0.0186)
Tangential firing dummy	−0.0706	0.0555	−0.1977	−0.2883
	(0.1144)	(0.2096)	(0.1218)	(0.3817)
Revenues (millions)	0.0019	0.0199*	0.0043	−0.0264*
	(0.0038)	(0.0101)	(0.0046)	(0.0124)
Municipal plant	0.1274		−0.0237	−0.0780
	(0.2037)		(0.2182)	(0.3899)
Compustat plant	−0.0578	−0.6924*	0.2028	1.4295
	(0.2389)	(0.3292)	(0.3174)	(0.8295)
Number of obs.	7469	878	4189	2402
Log likelihood	−1897.153	−236.886	−1082.593	−541.532

Notes: Standard errors appear below estimates. Some regulatory variables, vintage dummies and constant suppressed to save space
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

the presence and level of a lb/mmBTU regulation increases the likelihood of adoption in OTC and SIP states, but not in other states. Capacity is only significant for other states.[46]

Footnote 45 continued
only 4 years in which plants in other states adopt post-combustion technology, making it difficult to separately identify the effect of multiple variables that vary only across time. To test robustness of the results, I also ran models for SIP and OTC states that excluded industry experience. Removing this variable biases estimates of the knowledge stock downward. No other parameter estimates change when removing industry experience.

[46] While knowledge is insignificant for other states, this may be a result of having to drop industry experience from the regression, as removing that variable from the OTC or SIP state regressions biases the coefficient on knowledge downward.

Table 6 Adoption of post-combustion treatment by regulation type

Variable	All	OTC states	SIP states	Other states
NOX post knowledge	1.1269 (0.6370)	1.6964 (0.8755)	6.1085 (3.8762)	3.9712* (1.5861)
Company experience ($t-1$)	−0.1954 (0.1139)	−0.0693 (0.1735)	−0.2129 (0.1582)	−18.5470*** (1.1526)
Industry experience ($t-1$)	−0.0073 (0.0093)	−0.0206 (0.0525)	−0.0483 (0.0262)	
Has combustion modification ($t-1$)	0.1500 (0.2544)	−1.0140* (0.4608)	0.6803 (0.3878)	4.2985*** (0.8857)
OTC expect	2.1972*** (0.5369)	−2.2204 (1.6273)		
OTC phase I	3.2997*** (0.5579)	−0.3378 (1.8998)		
OTC phase II	1.7030** (0.5457)	1.8285* (0.8489)		
SIP phase I	1.6201*** (0.3813)		0.0098 (1.0727)	
SIP phase II	2.0984*** (0.4244)		3.3417*** (0.9391)	
lb/mmBTU level	0.0118 (0.0104)	0.0244 (0.0205)	0.0136 (0.0128)	−0.7026*** (0.1123)
Has lb/mmBTU reg	0.2222 (0.4160)	0.7754 (1.0623)	0.0910 (0.5037)	22.6523*** (1.6919)
% Sulfur content of coal	−0.0047 (0.0139)	−0.0310 (0.0525)	0.0176 (0.0161)	0.0071 (0.0770)
Capacity (MW)	0.0492*** (0.0143)	0.0290 (0.0179)	0.0430** (0.0135)	0.1974* (0.0996)
Tangential firing dummy	−1.1237*** (0.2507)	−0.6593* (0.3205)	−1.5761*** (0.4124)	−1.6308 (0.8382)
Revenues (millions)	0.0136* (0.0066)	−0.0027 (0.0119)	0.0229** (0.0083)	0.1924*** (0.0495)
Municipal plant	−0.3707 (0.3705)		−0.3821 (0.5194)	1.0528 (1.2163)
Compustat plant	−0.9746* (0.4425)	−1.2773** (0.4643)	−0.8447 (0.6488)	−30.5212*** (1.5088)
Number of obs.	12995	1534	6729	4732
Log likelihood	−121.716	−30.917	−37.511	−4.800

Notes: Standard errors appear below estimates. Some regulatory variables, vintage dummies and constant suppressed to save space
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

More interesting changes are found for post-combustion treatment. Here, while knowledge is insignificant for OTC or SIP states, it has a strong positive effect in other states.[47] Moreover, this difference is not merely an artifact of dropping industry experience from the other state regression, as removing that variable from the OTC or SIP state regressions biases the estimate of knowledge downward. Also of note is that the effect of lb/mmBTU regulations is only

[47] However, these changes should be treated as exploratory, rather than the final word, as only 8 plants in other states choose post-combustion technology. Additional adoptions would be needed to obtain more robust results.

significant in other states. Thus, regulatory pressure is still needed to encourage adoption of post-combustion treatment. In combination, these two results suggest that improvements to a technology developed primarily to comply with stringent regulations elsewhere can lead to diffusion of the technology even to areas with weaker environmental regulation, assuming some regulatory incentives are in place.[48] Interestingly, in other states, post-combustion treatment is much more likely to be installed when a boiler already has combustion modification techniques in place. Recall that installing these technologies in tandem lowers the operating costs of post-combustion treatment. Boilers not facing the very stringent OTC or SIP regulations appear particularly sensitive to these costs. Finally, note that the effects of revenues and private ownership are much stronger in other states. In these states where regulatory forces play less of a role encouraging adoption of post-combustion treatment, strong finances and an ability to pass costs on to consumers are necessary for boilers to willingly adopt post-combustion treatment technologies.

5 Conclusions

This paper examines the adoption of two separate NO_X pollution control technologies by boilers at coal-fired power plants: combustion modification and post-combustion treatment of emissions. Of the two technologies considered, combustion modification is cheaper and more well-established in the US. However, it is not as effective as reducing emissions as post-combustion treatment. Because US NO_X regulations only recently caught up with the requirements in Japan and Europe, combustion modification has been the technique of choice in the US. Over time, as new regulations lowered allowable NO_X emissions, particularly in the northeast, boilers began to adopt post combustion techniques. As in previous work on the adoption of environmental technologies, I find that regulations are the driving force behind this adoption decision.

This paper extends the existing literature on adoption by considering competing technologies and by considering the role of available knowledge in the adoption decision. For combustion modification technologies, most of the predictions of the theoretical model hold. Advances in available knowledge increase the likelihood of adoption. Adoption is slower when these advances occur more quickly, suggesting firms benefit from postponing adoption and waiting for improved technologies. However, this effect is only significant in the model with competing technologies. For post combustion technologies, the results are less satisfying, as the limited number of adoptions, which mostly occur in recent years, makes identifying the effect of knowledge on adoption difficult. Further research using the adoption model in the paper with other data sets, particularly those where environmental regulation is not the driving force, is needed to corroborate these results.

While the results linking adoption and technological progress should be of interest to a wide range of economists, the paper also offers additional lessons specific to the field of environmental economics. In particular, while much attention has been recently paid to links between environmental policy and technological change, this study shows that even when a more advanced technology is available, it will not diffuse without regulatory incentives to do so. For those concerned with environmental problems in developing countries, this

[48] While the results also suggest that expectations of regulation (e.g. OTC_Expect and SIP_Phase I) are no longer important, this change in results is harder to interpret, as the base case for comparison of the dummy variables has changed. In the overall regression, the base case is *all plants* prior to 1994, and plants facing no regulation after 1994. In contrast, here the comparison is only among plants in the same region.

suggests that diffusion of environmental technology is not independent from the problem of diffusion of environmental regulations themselves.[49] Focusing on adoption of the more advanced post-combustion techniques, note that the ability to work with existing technologies appears important, as does the financial strength of adopting firms. Regulators will want to keep such issues in mind when designing policy to encourage adoption of new environmental technologies.

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Appendix 1: Knowledge Stock Sensitivity Analysis

In this appendix, I examine the sensitivity of the regression results to changes in the rates of decay and diffusion used to calculate the knowledge stock. I focus on interpretation of the knowledge variables, as there are no significant changes to the parameters of other variables when the rates of decay and diffusion are changed. In addition to the base rates of decay = 0.1 and diffusion = 0.25, I consider three alternative sets of decay and diffusion rates. To aid in interpreting these rates, I also note the number of years it takes for a patent to have its maximum effect on the stock under each set of assumptions. For comparison, patents have their maximum effect after 4 years using the base rates.

- decay = 0.25, diffuse = 0.5 (peak = 1 year)
- decay = 0.05, diffuse = 0.5 (peak = 4 years)
- decay = 0.05, diffuse = 0.1 (peak = 10 years)

Tables 7 and 8 present the estimates for the knowledge stock coefficients for each of the model specifications. Note that there are few changes in sign or significance of individual parameters. One notable change is that in the base model for post combustion technology (Table 8), the level of the knowledge stock has a significant effect when using a lower decay rate. The two models with slower decay also have higher log-likelihood values. However, slower decay and/or diffusion of the post-combustion techniques occurs because the US adopted stringent NO_X regulations more slowly than other countries. The base case decay and diffusion are chosen to be consistent with other studies in the literature of knowledge flows. As regulatory differences appear to be the main influence on adoption, there is no theoretical reason to *a priori* impose slower rates of decay and diffusion on the spread of knowledge *itself*. Thus, one question is whether the true decay rates can be separately identified from things such as policy changes that influence adoption.

[49] One caveat is that, for reducing carbon emissions for climate change, emission reduction strategies currently focus on reducing combustion of fossil fuels, rather than cleaning emissions from a smokestack. As such, private incentives for diffusion of energy efficiency technologies exist via savings in energy costs, and may partially diffuse without regulatory impetus.

Table 7 Parameter sensitivity: adoption of combustion modification technology

Variable	Base	Growth	Both techs	Growth and both
Decay = 0.1, diffuse = 0.25				
Comb. mod. knowledge	0.6448*** (0.1220)	0.6522*** (0.1231)	0.6494** (0.2004)	−0.2443 (0.2594)
Growth CM knowledge		−0.0218 (0.0340)		−0.1598** (0.0531)
NOX post knowledge			−0.0058 (0.2042)	−0.0451 (0.2923)
Growth NOX post knowledge				−0.1307*** (0.0355)
log likelihood	−1897.153	−1896.927	−1897.152	−1889.533
Decay = 0.25, diffuse = 0.5 (peak = 1)				
Comb. mod. knowledge	0.1607** (0.0588)	0.2044** (0.0633)	0.1842* (0.0719)	0.0399 (0.0998)
Growth CM knowledge		0.0205 (0.0107)		−0.0017 (0.0145)
NOX post knowledge			−0.0744 (0.1385)	−0.1320 (0.1544)
Growth NOX post knowledge				−0.0027** (0.0010)
Log likelihood	−1906.882	−1905.254	−1906.661	−1902.557
Decay = 0.05, diffuse = 0.5 (peak = 4)				
Comb. mod. knowledge	0.8252*** (0.1355)	0.8312*** (0.1361)	0.7603** (0.2325)	0.3419 (0.3190)
Growth CM knowledge		0.0128 (0.0359)		−0.0656 (0.0581)
NOX post knowledge			0.0864 (0.2510)	−0.0684 (0.3222)
Growth NOX post knowledge				−0.0729 (0.0439)
Log likelihood	−1893.749	−1893.687	−1893.671	−1892.418
Decay = 0.05, diffuse = 0.10 (peak = 10)				
Comb. mod. knowledge	1.0629*** (0.1813)	1.2201*** (0.1675)	0.6265* (0.2518)	−0.5307 (0.5865)
Growth CM knowledge		0.1454** (0.0541)		−0.3350 (0.1831)
NOX post knowledge			0.6455** (0.2338)	0.8772 (0.5211)
Growth NOX post knowledge				−0.3830* (0.1793)
Log likelihood	−1890.263	−1886.181	−1885.865	−1880.291

Notes: Standard errors appear below estimates
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 8 Parameter sensitivity: adoption of post combustion treatment technology

Variable	Base	Growth	Both techs	Growth and both
Decay = 0.1, diffuse = 0.25				
NOX post knowledge	1.1269 (0.6370)	3.3623** (1.2202)	6.0544 (4.2574)	5.9625 (3.6178)
Growth NOX post knowledge		0.3294* (0.1432)		0.7066* (0.3132)
Comb. mod. knowledge			−1.9263 (1.4837)	1.4661 (2.3655)
Growth CM knowledge				0.6099 (0.3510)
Log likelihood	−121.716	−117.258	−119.005	−112.850
Decay = 0.25, diffuse = 0.5 (peak = 1)				
NOX post knowledge	0.9637 (0.7646)	0.9684 (0.7893)	0.9881 (0.7444)	0.8528 (0.9109)
Growth NOX post knowledge		−0.0012 (0.0024)		0.0052 (0.0102)
Comb. mod. knowledge			0.0193 (0.0913)	0.6649 (0.6487)
Growth CM knowledge				0.0937 (0.0519)
Log likelihood	−124.931	−124.864	−124.925	−122.990
Decay = 0.05, diffuse = 0.5 (peak = 4)				
NOX post knowledge	1.1551* (0.5242)	2.2213** (0.6860)	9.2125** (2.9809)	5.9181 (3.4126)
Growth NOX post knowledge		0.3146* (0.1337)		0.6075* (0.2829)
Comb. mod. knowledge			−4.2280** (1.5099)	0.3018 (2.8292)
Growth CM knowledge				0.8467** (0.3221)
Log likelihood	−119.169	−115.801	−109.255	−101.659
Decay = 0.05, diffuse = 0.10 (peak = 10)				
NOX post knowledge	0.7678* (0.3269)	3.6932*** (0.9246)	−1.7792 (1.1817)	−0.1404 (3.9731)
Growth NOX post knowledge		1.4859*** (0.4046)		3.6106*** (0.9271)
Comb. mod. knowledge			1.6894 (0.9087)	8.5695* (4.2487)
Growth CM knowledge				3.3801** (1.2073)
Log likelihood	−119.132	−110.106	−118.146	−102.283

Notes: Standard errors appear below estimates
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 9 Joint significance of knowledge variables: sensitivity analysis

	Base	Growth	Both techs	Growth and both
Combustion mod.				
Decay = 0.1, diffuse = 0.25				
LR χ^2	27.65	28.11	27.66	42.89
$p > \chi^2$	<0.0001	<0.0001	<0.0001	<0.0001
Decay = 0.25, diffuse = 0.5				
LR χ^2	8.20	11.45	8.64	16.85
$p > \chi^2$	0.0042	0.0033	0.0133	0.0022
Decay = 0.05, diffuse = 0.5				
LR χ^2	34.46	34.59	34.62	37.13
$p > \chi^2$	<0.0001	<0.0001	<0.0001	<0.0001
Decay = 0.05, diffuse = 0.10				
LR χ^2	41.43	49.60	50.23	61.38
$p > \chi^2$	<0.0001	<0.0001	<0.0001	<0.0001
Post combustion				
Decay = 0.1, diffuse = 0.25				
LR χ^2	9.12	18.03	14.57	26.85
$p > \chi^2$	0.0025	<0.0001	0.0007	<0.0001
Decay = 0.25, diffuse = 0.5				
LR χ^2	2.69	2.82	2.70	6.57
$p > \chi^2$	0.1012	0.2442	0.2597	0.1606
Decay = 0.05, diffuse = 0.5				
LR χ^2	14.21	20.95	34.04	49.23
$p > \chi^2$	0.0002	<0.0001	<0.0001	<0.0001
Decay = 0.05, diffuse = 0.10				
LR χ^2	14.28	32.33	16.25	47.98
$p > \chi^2$	0.0002	<0.0001	0.0003	<0.0001

Table 10 Net effect of technology: sensitivity analysis

	Base (%)	Growth (%)	Both techs (%)	Growth and both (%)
Combustion mod.				
Decay = 0.1, diffuse = 0.25				
Average	47.2	50.5	47.3	40.1
Average 1991–1998	61.1	64.9	61.3	46.2
Average 1999–2003	24.8	27.4	25.0	30.3
Decay = 0.25, diffuse = 0.5				
Average	7.3	6.2	8.8	14.6
Average 1991–1998	12.5	9.3	13.6	15.3
Average 1999–2003	−0.8	1.3	0.9	13.6
Decay = 0.05, diffuse = 0.5				
Average	67.1	66.3	65.3	47.2

Table 10 continued

	Base (%)	Growth (%)	Both techs (%)	Growth and both (%)
Combustion mod.				
Average 1991–1998	82.1	81.1	80.5	57.6
Average 1999–2003	43.0	42.6	41.1	30.5
Decay = 0.05, diffuse = 0.10				
Average	109.4	121.0	111.6	86.2
Average 1991–1998	113.4	132.1	123.4	96.6
Average 1999–2003	103.1	103.1	92.7	69.6
Post combustion				
Decay = 0.1, diffuse = 0.25				
Average 1993–2003	27.6	9.5	49.2	91.9
Average 1993–1998	44.5	8.9	95.4	154.5
Average 1999–2003	7.2	10.3	−6.2	16.7
Decay = 0.25, diffuse = 0.5				
Average 1993–2003	−14.3	−10.9	−14.0	−4.1
Average 1993–98	−14.2	−9.2	−13.3	−0.9
Average 1999–2003	−14.4	−13.0	−14.8	−7.9
Decay = 0.05, diffuse = 0.5				
Average 1993–2003	39.5	21.0	45.6	154.9
Average 1993–1998	52.7	14.1	43.6	180.2
Average 1998–2003	23.6	29.4	47.9	124.4
Decay = 0.05, diffuse = 0.10				
Average 1993–2003	42.5	31.1	51.4	403.0
Average 1993–1998	50.5	2.6	42.9	645.6
Average 1999–2003	32.8	65.3	61.6	111.8

Table 9 presents the tests for joint significance of the knowledge variables. For combustion modification, these results are also unchanged across the various assumptions of decay and diffusion. For the post combustion technologies, the knowledge stocks become insignificant when assuming rapid decay and diffusion.

To better interpret the differences, Table 10 reproduces the net technology effects shown in Table 3 of the main text for each of the decay and diffusion assumptions. Comparing the magnitude of the net effects is important, as the magnitude of the coefficients vary in part because the magnitude of the stocks themselves varies as the rates of decay and diffusion are changed. Here, we see a few cases where the effect of knowledge varies. Most notable, technology has less of an effect in the model with rapid decay and diffusion. Knowledge has more of an effect in the models with a slow decay rate.

Appendix 2: Patent Classifications Used for Each Control Technology

European Classifications for Pollution Control Patents

See Table 11.

Table 11 Nitrogen dioxide pollution control

Combustion modification	
F23C 6/04B	MECHANICAL ENGINEERING; LIGHTING; HEATING; WEAPONS; BLASTING ENGINES OR PUMPS/COMBUSTION APPARATUS; COMBUSTION PROCESSES/COMBUSTION APPARATUS USING FLUENT FUEL/combustion apparatus characterised by the combination of two or more combustion chambers/in series connection/[N: with staged combustion in a single enclosure]
F23C 6/04B1	MECHANICAL ENGINEERING; LIGHTING; HEATING; WEAPONS; BLASTING ENGINES OR PUMPS/COMBUSTION APPARATUS; COMBUSTION PROCESSES/COMBUSTION APPARATUS USING FLUENT FUEL/combustion apparatus characterised by the combination of two or more combustion chambers/in series connection/[N: with staged combustion in a single enclosure]/[N: with fuel supply in stages]
F23C 9	MECHANICAL ENGINEERING; LIGHTING; HEATING; WEAPONS; BLASTING ENGINES OR PUMPS/COMBUSTION APPARATUS; COMBUSTION PROCESSES/COMBUSTION APPARATUS USING FLUENT FUEL/combustion apparatus with arrangements for recycling or recirculating combustion products or flue gases
Post-combustion	
B01D 53/56	PERFORMING OPERATIONS; TRANSPORTING/PHYSICAL OR CHEMICAL PROCESSES OR APPARATUS IN GENERAL/SEPARATION/separation of gases or vapours; recovering vapours of volatile solvents from gases; chemical or biological purification of waste gases, e.g. engine exhaust gases, smoke, fumes, flue gases, aerosols/chemical or biological purification of waste gases/removing components of defined structure/nitrogen compounds/nitrogen oxides
B01D 53/56D	PERFORMING OPERATIONS; TRANSPORTING/PHYSICAL OR CHEMICAL PROCESSES OR APPARATUS IN GENERAL/SEPARATION/separation of gases or vapours; recovering vapours of volatile solvents from gases; chemical or biological purification of waste gases, e.g. engine exhaust gases, smoke, fumes, flue gases, aerosols/chemical or biological purification of waste gases/removing components of defined structure/nitrogen compounds/nitrogen oxides/[N: by treating the gases with solids]
B01D 53/60	PERFORMING OPERATIONS; TRANSPORTING/PHYSICAL OR CHEMICAL PROCESSES OR APPARATUS IN GENERAL/SEPARATION/separation of gases or vapours; recovering vapours of volatile solvents from gases; chemical or biological purification of waste gases, e.g. engine exhaust gases, smoke, fumes, flue gases, aerosols/chemical or biological purification of waste gases/removing components of defined structure/simultaneously removing sulfur oxides and nitrogen oxides
B01D 53/86F2	PERFORMING OPERATIONS; TRANSPORTING/PHYSICAL OR CHEMICAL PROCESSES OR APPARATUS IN GENERAL/SEPARATION/separation of gases or vapours; recovering vapours of volatile solvents from gases; chemical or biological purification of waste gases, e.g. engine exhaust gases, smoke, fumes, flue gases, aerosols/chemical or biological purification of waste gases/general processes for purification of waste gases; apparatus or devices specially adapted therefore/catalytic processes/ [N: removing nitrogen compounds]/[N: nitrogen oxides]/
B01D 53/86F2C	PERFORMING OPERATIONS; TRANSPORTING/PHYSICAL OR CHEMICAL PROCESSES OR APPARATUS IN GENERAL/SEPARATION/separation of gases or vapours; recovering vapours of volatile solvents from gases; chemical or biological purification of waste gases, e.g. engine exhaust gases, smoke, fumes, flue gases, aerosols/chemical or biological purification of waste gases/general processes for purification of waste gases; apparatus or devices specially adapted therefore/catalytic processes/ [N: removing nitrogen compounds]/[N: Nitrogen oxides]/[N: processes characterised by a specific catalyst]

Table 11 continued

B01D 53/86F2D	PERFORMING OPERATIONS; TRANSPORTING/PHYSICAL OR CHEMICAL PROCESSES OR APPARATUS IN GENERAL/SEPARATION/separation of gases or vapours; recovering vapours of volatile solvents from gases; chemical or biological purification of waste gases, e.g. engine exhaust gases, smoke, fumes, flue gases, aerosols/chemical or biological purification of waste gases/general processes for purification of waste gases; apparatus or devices specially adapted therefore/catalytic processes/ [N: removing nitrogen compounds]/[N: nitrogen oxides [N: processes characterised by a specific device]
B01D 53/86G	PERFORMING OPERATIONS; TRANSPORTING/PHYSICAL OR CHEMICAL PROCESSES OR APPARATUS IN GENERAL/SEPARATION/separation of gases or vapours; recovering vapours of volatile solvents from gases; chemical or biological purification of waste gases, e.g. engine exhaust gases, smoke, fumes, flue gases, aerosols/chemical or biological purification of waste gases/General processes for purification of waste gases; apparatus or devices specially adapted therefore/catalytic processes/ [N: simultaneously removing sulfur oxides and nitrogen oxides]
B01J 29/06D2E	PERFORMING OPERATIONS; TRANSPORTING/PHYSICAL OR CHEMICAL PROCESSES OR APPARATUS IN GENERAL/CHEMICAL OR PHYSICAL PROCESSES, e.g. CATALYSIS, COLLOID CHEMISTRY; THEIR RELEVANT APPARATUS/catalysts comprising molecular sieves/having base-exchange properties, e.g. crystalline zeolites/crystalline aluminosilicate zeolites; Isomorphous compounds thereof/[N: containing metallic elements added to the zeolite]/[N: containing iron group metals, noble metals or copper]/[N: iron group metals or copper]

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