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EXPLORING LINKS BETWEEN INNOVATION AND DIFFUSION: ADOPTION OF NOx CONTROL TECHNOLOGIES AT U.S. 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. Moreover, advances made abroad may affect adoption differently than improvements developed domestically. This paper combines plant-level data on U.S. coal-fired electric power plants with patent data pertaining to NOx pollution control techniques to study these links. I show that technological advances, particularly those made abroad, are important for the adoption of newer post-combustion treatment technologies, but have little effect on the adoption of older combustion modification techniques. Moreover, I provide evidence that adaptive R&D by U.S. firms is necessary before foreign innovations are adopted in the U.S. Expectations of future technological advances delay adoption. Nonetheless, 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.

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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 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 technologies developed at home and abroad, 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

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[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).

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. As such, 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, U.S. 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 U.S. 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. Over

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

time, as NO_X emission rules have been tightened in the U.S., more U.S. plants have adopted post-treatment techniques.

As a result, the study of NO_X abatement technology choices allows us to examine how changes in the available knowledge, developed both at home and abroad, affect the adoption decision. In particular, I ask whether firms take advantage of foreign technologies directly, or must first perform additional research to adopt these technologies to domestic markets. For example, Popp (2006) shows that patents granted in the U.S. for post-combustion treatment by Japanese and German inventors increased when strict NO_X regulations were enacted in those countries in the 1970s and 1980s. Despite the ready availability of these technologies, there is a similar spike in patents from U.S. inventors once U.S. regulations catch up in the 1990s. However, Popp (2006) also shows that these U.S. patents are much more likely to cite earlier foreign patents than are U.S. patents for other air pollution control technologies, even after controlling for differences among the number of foreign and domestic patents available.[4] This suggests that domestic R&D was needed, but that the foreign patents served as an important building block for this R&D. This paper extends that work by asking whether this additional R&D was necessary for adoption to take place.

Another advantage of using the adoption of technology by coal-fired electric power plants is that many 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

[4] Unlike the post-combustion treatment of NO_X, there was significant inventive activity in the U.S. for most new abatement technologies, as other U.S. environmental regulations tended to be as strong, if not stronger, than those in foreign nations.

important here than for other technologies. Thus, 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. Doing so avoids potential multicollinearity problems between the knowledge stocks of previous patents and stocks of previously installed capacity.

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.[5] For long-term problems such as climate change, understanding the potential role that technology will play as part of any policy solution is important. Moreover, since climate change is a global problem, understanding the flow of environmental technologies across nations is important.[6] 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. It also addresses potential links between domestic R&D and knowledge spillovers. For example, both Cohen and Levinthal (1989) and Griffith, Redding, and van Reenen (2003) find positive links between R&D and the ability of firms to absorb knowledge spillovers. However, these papers focus more generally on the ability of firms to absorb knowledge spillovers, rather than on the decision to adopt new technology. Thus, this paper adds to the discussion on the absorptive capacity of R&D by addressing one specific avenue in which knowledge may be absorbed, via the adoption of foreign technologies.

[5] Jaffe, Newell, and Stavins (2003) provide a review.

[6] One paper that addresses this question is Lanjouw and Mody (1996). They find that many environmental patents in developing countries come from foreign inventors, and that those patents that are granted to domestic inventors in developing countries typically represent smaller inventive steps, such as modifying a technique to fit local conditions. However, they look at aggregate patent data, and do not directly address the decision to adopt the technologies in question.

I. NO_X Regulations and Technology

NO_X emissions are produced by the combustion of fossil fuels, when nitrogen contained in the fuel combines with oxygen during the combustion process. 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.

A. Regulations[7]

In the United States, 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, U.S. NO_X regulations have focused on areas where these two problems are primary concerns – California (ozone) and the eastern United States (acid rain). For NO_X, the 1970 CAA established a limit of 0.7 lbs/mmBtu of NO_X for power plants. The 1977 CAA tightened the standard slightly, lowering the limit to 0.5-0.6 lbs/mmBtu.[8] 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), designed to address the regional problem of acid rain in the eastern U.S. The resulting plan, implemented in phases, 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

[7] 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).
[8] 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 U.S. coal-fired electric plants.

allowed trading of NO_X emission permits across plants in the region.[9] The 1998 NO_X SIP Call expanded NO_X reductions to 22 eastern states, and required that emissions reductions be in place by 2004. 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.

In comparison, stringent NO_X regulations have existed elsewhere as far back as the 1970s. Japanese NO_X regulations have been stricter than the U.S. since the 1974 amendments to the Air Pollution Control Law. Those amendments set a standard of 0.5 lbs/mmBtu, making Japan's NO_X standard nearly 30% stricter than the limits in place in the U.S. at the time. These regulations were tightened further in 1987, with a new limit of just 0.33 lbs/mmBtu. Moreover, unlike in the U.S., where older plants are grandfathered from new emission standards, these standards apply to both new and existing plants. Finally, Germany did not set specific limits for NO_X emissions from power plants until June 1, 1983. However, once put in place, its regulations were stricter than either Japan or the U.S, limiting emissions to just 0.16 lbs/mmBtu.

B. 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

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

[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 U.S.. Other boilers are allowed more NO_X emissions.

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 tight NO_X emissions restrictions, such as in Germany and Japan.

The complexity of retrofitting SCR on an existing plant depends on both the level of reduction required and the quality of the coal burned. For example, higher flue gas sulfur and ash loadings make retrofitting more difficult in Germany than Japan (Frey 1995). This also suggests that innovations in one country need not apply to plants elsewhere.

In contrast to post-combustion techniques, combustion modification techniques are less costly, as they do not require add-on equipment. Rather, they involve changing the combustion process to reduce the amount of NO_X formed by combustion. 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 combustion techniques can be combined to achieve greater reductions (Wu 2002, Afonso *et al*. 2000).

II. 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, $R_i(\tau)$, 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* = *CM* or *PT*. The present value of installing technology *j* at time *t* is then:

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

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

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

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

For simplicity, consider first the decision to adopt a technology for which there is no substitute. Adoption is profitable[11] if:

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

[11] 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 could be included as part of the variable *R*. However, regressions including the status of deregulation for the plants included in this paper found that regulatory status did not affect the adoption decision.

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:

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

To derive an expression for y, first define $p(t)$ as the expected change in price over time, $r(t)$ the expected change in regulations over time, and $k(t)$ as the expected change in the knowledge stock over time.[12] Taking derivatives yields

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

From (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

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

This approach, while similar to other models in the adoption literature, differs in that I

[12] 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.

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.[13] In the empirical work that follows, I use instrumental variables to control for the endogenous links between innovation and regulation.[14]

Now, consider a plant that can choose between either of the two technology options. In addition to the profitability and no arbitrage conditions (equations (3) and (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 for both technologies. From equation (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:

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[13] 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.

[14] 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).

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

A. An Econometric Model

Empirical studies of technology adoption have traditionally used one of two approaches. The *epidemic* model of diffusion proposes that information is the primary factor limiting diffusion. Adoption is slow at first, as few people (or firms) know about the technology. However, as more people adopt the technology, knowledge of the technology spreads quickly, leading to a period of rapid adoption. Economists often use the analogy of a contagious disease to describe this period of adoption – the more people "infected" by the technology, the more likely that others will also be "infected". Eventually, few potential adopters remain, as nearly everyone has adopted the technology, so that the rate of adoption levels off again. 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. The second approach to studying diffusion is the *probit* model (David 1969), which focuses on heterogeneity among firms. These models are the basis for the rank effects described above.

Recent work on diffusion use duration models to combine features of both of these earlier methods (e.g. Hannan and McDowell 1984, Rose and Joskow 1990, Karshenas and Stoneman 1993, Kerr and Newell 2003, Snyder *et al*. 2003). These models begin with the hazard function, which can be written as:

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

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 equation (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 learning effects are insignificant. In the results that follow, the exponential distribution is used.[15]

Once the baseline hazard is specified, estimation of equation (9) is completed using duration data techniques.[16] 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

[15] I also estimated models using the Weibull and Gompertz distributions. Both the signs and magnitudes of the knowledge variables change dramatically (and have unrealistic magnitudes) under these specifications, and the models do not always converge, 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. The results for variables other than knowledge are unchanged, and remain unchanged even if the knowledge stocks are omitted. Given that the technologies discussed have been well-known for some time, the assumption that learning effects are small seems reasonable. The key assumption of such a model is that the remaining explanatory variables capture any time-varying incentives to adopt. In similar work, Kerr and Newell (2003) find learning effects to be insignificant for the adoption of isomerization technologies by oil refineries during the U.S. phasedown of leaded gasoline.

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

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-α) 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-α, 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 section III, 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. Finally, since expectations of future knowledge are not observed, I use the current growth rate in knowledge as a proxy.[17]

III. Data

A. Constructing the Knowledge Stocks

The 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 United States. 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

[17] 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.

R&D data, patent counts are available in highly aggregated 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.[18]

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 section I. Relevant patents were identified using the European Classification System (ECLA).[19] Using esp@cenet, the EPO's on-line database, I obtained a list of all patent numbers in relevant technology classes granted in the U.S. since 1920. I construct separate list of patents for combustion modification technologies and post-combustion treatment technologies.[20] Appendix B lists the technology classifications used and their definitions. I merged these patent numbers with additional data from Delphion's on-line database and the U.S. Patent and Trademark Office (USPTO) website to obtain descriptive data on these patents, such as the country of origin and their application date. All patents assigned to U.S. inventors are

[18] 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. Moreover, note that the quality of individual patents vary greatly. Thus, the results of this paper are best interpreted as the average effect of all accumulated knowledge, rather than the effect of any specific invention.

[19] 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.

[20] The database can be found at http://ep.espacenet.com/search97cgi/s97is.dll?Action=FormGen&Template=ep/en/home.hts

considered domestic, and all others are considered foreign patents. Figure 1 shows U.S. and foreign patent applications for each technology. Of particular importance, note that 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.

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 U.S. upon grant until 2001, no public record exists of unsuccessful U.S. patent applications. Thus, the data only include patent applications that were subsequently granted. Since many recent applications have yet to be granted, data for later year are scaled to avoid truncation problems.[21]

Using these patent data, I create separate stocks of knowledge for combustion modification and post-combustion technologies. Within each field, I create separate stocks of foreign and domestic patents. 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. Defining *s* as the number of years before the current year, the stock of knowledge at time *t* for technology *j* is written as:

$$K_{j,t} = \sum_{s=0}^{\infty} e^{-\beta_1(s)}(1-e^{-\beta_2(s+1)})PAT_{j,t-s} \ . \tag{11}$$

[21] 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. This scaling is only significant for patents from 2001 and 2002. However, as we will see below, these patents receive little weight in the knowledge stocks, as their diffusion process is just beginning.

The rate of diffusion is multiplied by *s*+1 so that diffusion is not constrained to be zero in the current period. To check whether domestic R&D is needed before adopting foreign technologies, I also create a stock of patents that interacts domestic patents with foreign knowledge:

(12) $$K_{j,t}^{INT} = \sum_{s=0}^{\infty} e^{-\beta_1(s)}(1-e^{-\beta_2(s+1)})PAT_{j,t-s}^{US} \cdot K_{j,t-s-1}^{F} .$$

The base results presented below use a decay rate of 0.1, and a rate of diffusion of 0.25 for each stock calculation.[22] 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).

B. 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 SNCR). In addition to plant characteristics, several studies of diffusion suggest that financial

[22] 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 A presents sensitivity analysis with respect to the rates of decay and diffusion.

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 1990-2002.

Table 1 provides descriptive data for the variables used in the regressions. Two dummy variables indicate whether a boiler has either combustion modification or post-combustion treatment technologies to reduce NO_X emissions. Figure 2 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 percent in 1990 to 76 percent in 2002. In comparison, no post-combustion treatment technologies were adopted 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, fewer than 10 percent of boilers use post-combustion treatment. Usage of post-combustion technologies is greatest in OTC states, where 23 percent of boilers use the technology by 2002. However, there is some adoption of post-combustion technologies in other states, with 5 percent using post-combustion techniques in SIP states, and 2 percent in states that are neither OTC or SIP states.[23]

Descriptive data for the knowledge stocks shows how the value of the stocks faced by any firm varies throughout the sample period (1990-2002). 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. Of greater importance is that foreign stocks are, on average, larger than domestic stocks for post-combustion treatment, but smaller than domestic stocks for combustion modification. Figure 3 presents the trends in these stocks over time. Finally, to control for expectations of future knowledge stocks, I include a variable for the growth rate of each stock, defined as $(K_t - K_{t\text{-}1})/K_{t\text{-}1}$. Average growth rates range from 2.8 to 7.7 percent, depending on the technology and source of the innovation.

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.

[23] Note that 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).

Note that boilers may face regulations at federal, state, and local levels. Form 767 includes the level of the most stringent of these regulations.[24] 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. Most common are regulations specifying a maximum level of NO_X emissions per million Btus of fuel burned (lbs/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/hour) 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. In both cases, such boilers face the expectations of tighter regulations in the future. Thus, boilers facing the need to install new abatement equipment now might invest in better equipment in anticipation of forthcoming stringent regulations. In addition, recall that OTC boilers face more stringent regulations during the summer months, beginning in 1999.[25,26]

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 two percent sulfur content (Wu 2002). Costs also increase with boiler size. To control for the type of

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

[25] 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.

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

boiler used, I include a dummy variable for boilers that use tangential firing.[27] 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.[28]

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. After deregulation, ownership of some plants shifts to unregulated entities. To control for this, I create a dummy variable equal to one if the plant owner's information comes from the Compustat database, which is the only database to include unregulated entities. Because the other databases specifically report operating revenues for electricity generation, while the Compustat database includes revenues from all sources of diversified companies, the scale of revenues is different for plants in the Compustat database. Thus, I also interact the Compustat dummy with revenues. Finally, since the exponential distribution of the hazard assumes no other learning, it is important to control for any other learning that may take place. An 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 as the total number of boilers owned by a utility using each technology in the previous year.

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

[28] The vintage dummy variables are generally defined in five year intervals, with exceptions for the youngest and oldest plants, as shown in Tables 2, 3, 5, & 6.

IV. Estimation

Using the data described above, I proceed with estimation of the hazard function. I estimate separate equations for adoption of each technology. To begin, define the following variables. $\mathbf{C_i}$ is a vector of time-invariant boiler characteristics, $\mathbf{X_i(t)}$ is a vector of time-varying boiler characteristics, $d_{i,r}(t)$ is a dummy variable equal to one if a boiler has regulation type r at time (t), $R_{i,r}(t)$ is the level of regulation type r faced by plant i at time t. $OTC_i(t)$ and $SIP_i(t)$ are dummy variables equal to one if the boiler is affected by OTC or SIP regulations. $K(t)$ represents the respective knowledge stocks for each technology, and $k(t)$ is the growth in each knowledge stock. The index s below represents the source of knowledge: domestic or foreign. $HASCM_i(t\text{-}1)$ and $HASPT_i(t\text{-}1)$ are dummy variables equal to one if the boiler used the other technology option 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).[29] Using these variables, the two hazard functions are:

(13) $$h_{i,CM}(t) = f\{\mathbf{C_i}, \mathbf{X_i(t)}, d_{i,r}(t)R_{i,r}(t), d_r(t), OTC_i(t), SIP_i(t), K^S{}_{CM}(t), k^S{}_{CM}(t), K^S{}_{PT}(t), k^S{}_{PT}(t), HASPT_{ii}(t\text{-}1)\}$$

(14) $$h_{i,PT}(t) = f\{\mathbf{C_i}, \mathbf{X_i(t)}, d_{i,r}(t)R_{i,r}(t), d_r(t), OTC_i(t), SIP_i(t), K^S{}_{PT}(t), k^S{}_{PT}(t), K^S{}_{CM}(t), k^S{}_{CM}(t), HASCM_{ii}(t\text{-}1)\}$$

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 ten percent change from its mean value, so as to aid interpretation of the effects on the hazard function.[30] Because the regressions include repeated observations on individual boilers, it is unlikely that the error terms are independently and

[29] 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).

[30] The normalization first divides each continuous variable by its mean, multiplies by 10, and then takes deviations from the mean by subtracting 10. As in Kerr and Newell (2003), this results in normalized variables that have a mean of 0. Note that because company experience is a count variable (with many zeros for post combustion technology), it is not normalized in this fashion.

identically distributed. As such, robust standard errors are calculated using the Huber/White correction.

Before proceeding, two econometric issues need to be addressed. Most importantly, note that the domestic knowledge stocks are likely endogenous, as they are influenced by the stringency of U.S. NO_X regulations.[31] To control for this, I use a two-stage procedure. For patents applied for between 1990 and 2002, I regress patent applications on federal NO_X emission standards, a dummy for the years in which OTC regulations are in force, lagged values of the foreign knowledge stock, and a time trend. I then use the predicted values in place of actual patent counts from 1990-2002 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 U.S. 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:

$$L(\boldsymbol{\beta}) = f(t;\mathbf{X},\boldsymbol{\beta})^{\alpha}(1-F(t;\mathbf{X},\boldsymbol{\beta}))^{1-\alpha}F(0;\mathbf{X},\boldsymbol{\beta})^{\gamma} \tag{15}$$

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.[32]

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

[32] 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 equation (10) is used for post-combustion technology.

A. Adoption of Combustion Modification Techniques

Tables 2 and 3 present 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 stocks. In column 2, I consider expectations by adding the growth of combustion modification technology knowledge. Columns 3 and 4 consider the interaction between domestic and foreign knowledge, as defined by equation (12), both with and without the growth variables.

The results suggest that available knowledge has just a small effect on the adoption of combustion modification techniques. In all cases, a likelihood ratio test of the joint significance of the knowledge variables rejects the null hypothesis that these coefficients are zero. However, the magnitude of the effect of knowledge is small. In the base model, both domestic and foreign technologies have a statistically significant effect on adoption. However, these effects tend to offset each other, so that the net effect of technology is near zero. While a 10 percent increase in the stock of domestic knowledge raises the hazard rate by 51 percent, a 10 percent increase in the stock of foreign knowledge lowers the hazard rate by 43 percent. As expected, expectations of future technology advances, proxied by the growth rates of knowledge, negatively influence adoption, although the effect is only significant for domestic knowledge, and only at the ten percent level. The interaction terms (columns 3 & 4) are significantly positive, and the net effect of both domestic knowledge is positive.

Table 3 presents results that consider the availability of both technologies. Here, however, one adjustment must be made. When including both foreign and domestic stocks of each technology, multicollinearity is a problem. Thus, in Table 3, only a combined stock, including both foreign and domestic patents, is used for each technology. Column 1 repeats the naïve model with just the one knowledge stock. Here, knowledge has almost no effect on adoption, as the coefficient is insignificant, and the increase in the hazard rate from a ten percent increase in knowledge is just 1 percent. Adding expectations to the model in column 2, we get the surprising result that expectations of future technological gains increase the hazard rate. In addition, the level of knowledge now has a significant positive effect, with a ten percent increase raising the probability of adoption by 12 percent. Column 3 considers stocks of both combustion modification and post-combustion treatment. Here, the signs are the reverse of expectations: increased knowledge for the *competing* technology encourages more adoption, while increased combustion modification knowledge decreases adoption. However, the results of column 4 suggest these unexpected results come from a misspecified model. Most importantly, once both technologies and expectations are considered, both the level and growth of the competing NO_X technology have a negative effect on adoption. In contrast, the level of combustion modification knowledge has no effect on adoption. This suggests that combustion modification serves as a "default" technology for firms that must adopt pollution control technology. Once better alternatives are available, the likelihood of adopting combustion modification falls.[33]

To help put these results in perspective, it is useful to consider the combined effect of increases in knowledge during this time frame. Table 4 shows such calculations. The table presents the average increase in the adoption probability resulting from new knowledge in each

[33]However, it is still the case that expectations of future growth in combustion modification technology increase adoption. Since the level of technology itself does not affect adoption, this may suggest that expectations capture expectations of other variables that might influence adoption.

year for both combustion modification and post combustion technologies.[34] For combustion modification technologies, note that the average net impact of knowledge ranges from just a 0.07% increase to a 3.26% decrease in the likelihood of adoption. In some models, particularly those without the competing technology, knowledge does have a larger impact in the beginning of the sample, at which time patent counts for these technologies 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. Boilers subject to OTC or SIP regulations are twice as likely to adopt combustion modification technology. Similarly, the presence of lb/mmBTU regulation increases adoption by a factor of six.[35] Note also the negative sign for regulatory levels – adoption is more likely when fewer emissions are allowed. However, this effect is small. A ten percent more stringent than average regulation never increases the likelihood of adoption by more than two percent. That the simple presence of regulation is more important than the level is important 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 seventy percent 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 four percent. As for other

[34] The calculation is the average of $\exp(\mathbf{X(t)}'\beta) - \exp(\mathbf{X(t\text{-}1)}'\beta)$, 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.
[35] Results for other types of regulations are similar. Because these affect fewer boilers, they are omitted from the table to conserve space.

characteristics, boiler size, sulfur content of coal, and the vintage dummies are significant. Larger boilers are more likely to adopt combustion modification techniques. In addition, the probability of adoption generally rises in later vintage years, although it is smallest for boilers established sine 1996. 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 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 option until conditions are more favorably financially.

B. Adoption of Post-Combustion Treatment

Tables 5 and 6 present the results of estimation for post-combustion treatment technologies. Once again, Table 5 ignores the availability of competing technology, but considers both foreign and domestic sources of knowledge separately. Here, some interesting patterns emerge. Domestic knowledge is insignificant in each model presented in Table 5, and foreign knowledge is only significant in columns 2 and 4. However, except in column 1, the joint effect of all knowledge variables is significant (although only at 7 percent in column 3). In column 3, note that interaction term is strongly significant, and that the net effect of domestic knowledge is positive in this model. Recall that NO_X post-combustion techniques were first developed and installed abroad. These results suggest that developments made abroad are important to potential U.S. adopters, but that domestic R&D is necessary to adapt foreign innovations to the U.S. market. This is consistent with results in Popp (2006), which shows that U.S. post-combustion patents are much more likely to cite foreign patents than other U.S. pollution control patents, suggesting that these post-combustion patents primarily serve to build upon foreign innovations. While similar results are also found in the more complete model in column 4, multicollinearity is a problem. Although the net effect of knowledge is not much greater for this model (as shown in Table 4), the magnitude of the individual coefficients varies widely.

Table 6 presents results for a single knowledge stock for each of the two competing technologies. Results are generally as expected, although the results are not as statically significant as the combustion modification results, as the lower adoption rates result in less variation in the data. Note also that the joint effect of knowledge is less significant when using the combined knowledge stock, suggesting that the capturing the variation in the timing of foreign and domestic knowledge, as in Table 5, is important. Referring to the likelihood ratio tests at the bottom of Table 6, the joint effect of all knowledge variables is significant at the 10 percent level in columns 1, 2, and 4.[36] The combined post-combustion stock increases adoption, with a 10 percent increase from average levels increasing adoption by 60 percent. Moreover, expectations of technological advances (column 2) delay adoption. As before, the sign on the competing knowledge stock in column 3 is reverse of expectations, although insignificant. However, this problem disappears in the completely specified model in column 4, which considers both technological alternatives and expectations. Here, advances in post-combustion

[36] That the t-statistic on knowledge in column 1 suggests that the knowledge variable is significant at the five percent level, while the likelihood ratio test suggests that it is only significant at the 10 percent level, results from the robustness correction of the standard errors. Because the knowledge variables change over time, but not across boilers, the robustness correction provides slightly overoptimistic standard errors for the knowledge variables. In contrast, the log-likelihood statistics, and hence the likelihood ratio tests, are not affected by the robustness correction.

technology increase adoption, and advances in combustion modification technology decrease adoption. Expected advances in either technology delay adoption, although the effect is insignificant.

Finally, note that, compared to combustion modification techniques, knowledge plays a more important role for post combustion techniques, as shown in Table 4. In the naïve models (column 1 in each table), technological progress increases adoption by 9 percent each year. This percentage increases to over 20% in the more complete models.[37] In contrast, new knowledge only increased combustion modification adoption rates by less than one percent per year. The importance of technological progress for the newer post-combustion technology, but not for the more established combustion modification techniques, suggest that a competing technology must evolve sufficiently before plants will choose it over a well-established technology.[38]

Turning to other variables, note that once again the coefficients on other variables are consistent across models. There are, however, several differences between technologies. 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

[37] While the percentage is even higher in the models including growth rates for foreign and domestic knowledge, large changes in the magnitudes of key parameters in these models suggest multicollinearlity problems.

[38] Lissoni (2000) provides a theoretical model supporting such a conclusion. His paper presents both a theoretical model and a case study of electronic color pre-press printing equipment that firms may choose older “intermediate” technologies if new cutting edge technologies do not provide sufficient advantages.

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.

Note that by far the most important of the regulatory variables are the dummy variables indicating boilers covered by OTC regulations. Boilers affected by OTC regulations are 25-40 times more likely to install post-combustion treatment, and boilers subject to the NO_X SIP call are generally about six times more likely to install post-combustion treatment. This reflects both the increased stringency required in OTC states beginning in 1999, and expectations of future, more stringent regulations, as OTC rules specified that NO_X standards would be further tightened in 2003, and the NO_X SIP call included stringent regulations beginning in 2004. As a result of the strong effect of these variables, the effect of other regulations is insignificant.[39,40]

Finally, I consider the effect of other boiler characteristics. Company experience is significant in half of the specifications. Additional experience with post combustion technology within the parent utility increases the likelihood of adoption by 22 to 36%. Interestingly, the vintage effects are non-linear. While the oldest boilers are less likely to adopt, the boilers most likely to adopt post combustion technique are those brought on line during the 1970s or 1990s. While the increase in the 1990s is likely attributable to technological change, it is more likely that the increase for boilers from the 1970s stems from the lack of emissions equipment that would have been in place on these boilers. As such, they may need more advanced technologies to come into compliance with new NO_X regulations. Unlike combustion modification, boilers

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[39] 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.

[40] Other regulatory variables do have significant effects if the OTC and SIP dummy variables are dropped from the model. Results available from the author by request.

that use tangential firing are less likely to adopt post-combustion treatment. Because of the large installation costs of post-combustion treatment, the financial strength of plant owners is also important. A 10 percent increase in revenue increases the hazard rate by about 4 percent.[41] 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.

V. 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. As in previous work on the adoption of environmental technologies, I find that regulations are the driving force behind adoption. This paper extends the existing literature on adoption by considering competing technologies and by considering the role of available knowledge in the adoption decision.

Of the two technologies considered, combustion modification is cheaper and more well-established in the U.S. However, it is not as effective as reducing emissions as post-combustion treatment. Because U.S. NO_X regulations only recently caught up with countries such as Japan and Germany, combustion modification has been the technique of choice in the U.S. In comparison, much early innovation on post-combustion treatment was completed in Japan and Germany. I find that, even after controlling for increased regulatory stringency over time,

[41] The negative interaction with the Compustat dummy simply controls for larger revenue levels of these plant owners, who are large, diversified energy corporations, rather than dedicated electric utilities.

advances in post-combustion technology lead to increased likelihood of adoption. Moreover, while advances from abroad are important, domestic R&D to adapt foreign innovations is required. There is some evidence that expectations of future advances slow adoption, although not all expectation variables are statistically significant. In comparison, because combustion modification serves as a "default" technology, the state of its available knowledge has little effect on adoption of combustion modification techniques.

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 suggests two limitations to the ability of technological change to act as a panacea. First, note 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 problems, this suggests that diffusion of environmental technology is not independent from the problem of diffusion of environmental regulations themselves.[42] Second, it suggests that technologies developed in one country may not diffuse to additional countries without additional R&D to adopt the innovation to local conditions. As this comes with opportunity costs, models that ignore this cost may overstate the benefits of new technologies.

[42] One caveat is that, for climate change, emission reductions currently focus on reducing combustion of fossil fuels, rather than cleaning emissions from a smokestack. As such, incentives for diffusion of these technologies exist via savings in energy costs.

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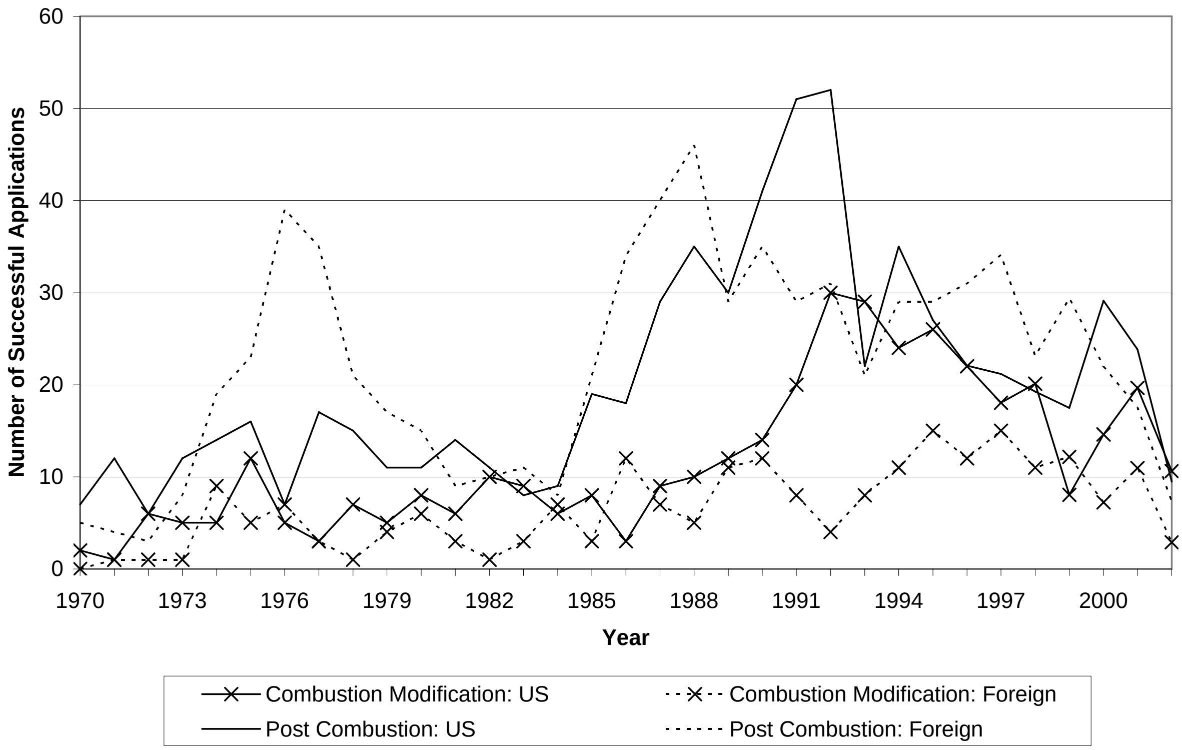
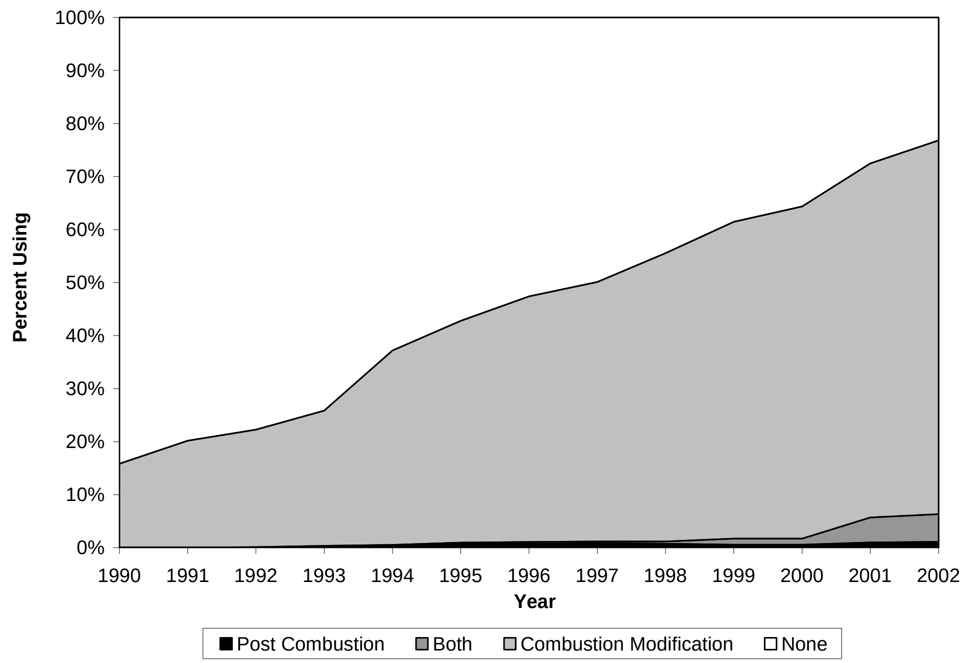
Figure 1 – NO_X Pollution Control Patents by Year



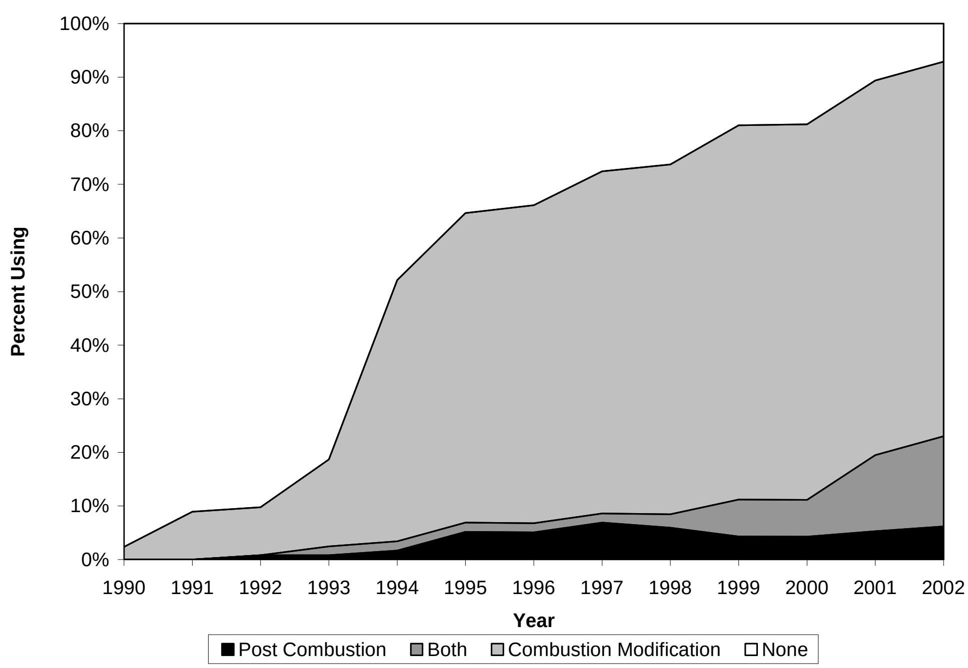
The figure shows all patents granted in the U.S. for each of the two NO_X pollution control technologies. Patents are sorted by their year of application, and only successfully granted patent applications are included. The data for recent years are scaled to account for applications not yet processed, as described in footnote 21.

Figure 2 – Percentage of Boilers Adopting NO_X Pollution Control Technologies

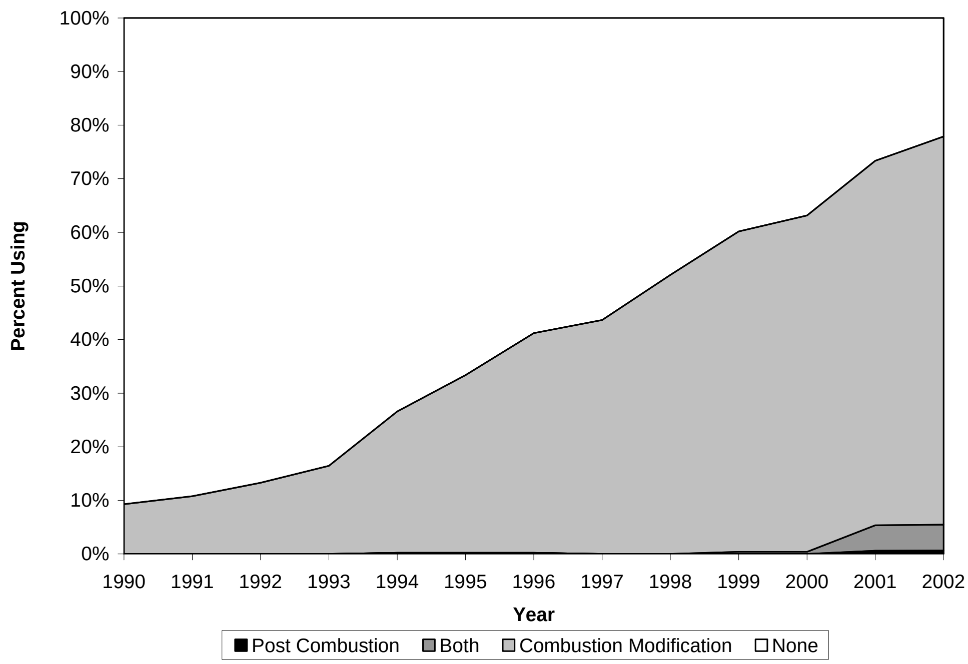
A. Overall



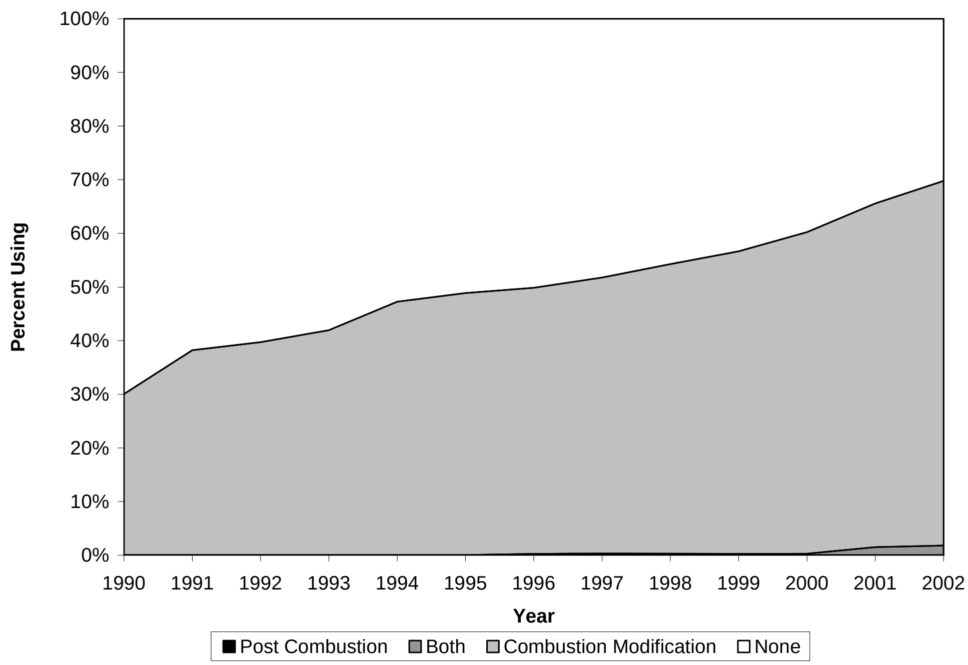
B. OTC States



C. NO_X SIP Call States

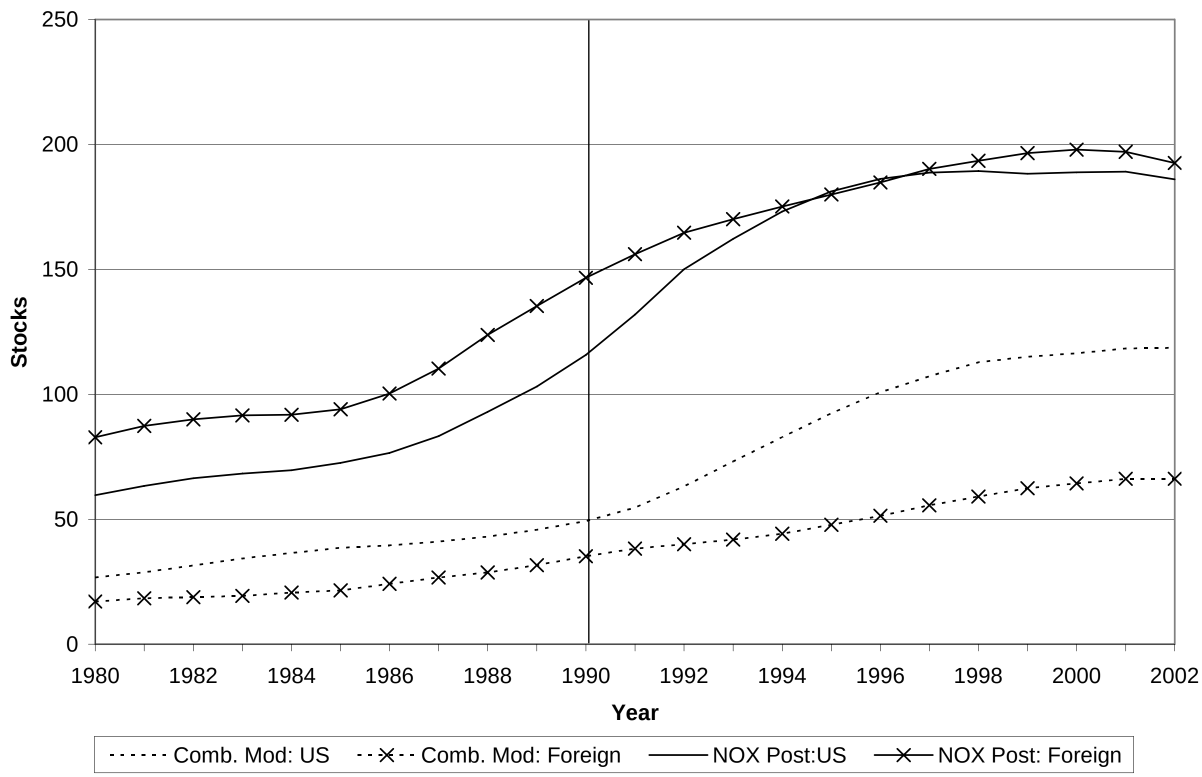


D. Other States



The figures show the percentage of boilers who have adopted each NO_X control technology by the year on the *x*-axis.

Figure 3 – Knowledge Stocks Over Time



The figure shows how each knowledge stock varies over time. Note that the foreign knowledge stock is generally greater than domestic knowledge for post combustion technologies, but that the domestic stock is greater for combustion modification. Also, note that both domestic stocks increase soon after passage of the 1990 Clean Air Act.

Table 1 – Descriptive Data

variable	N	mean	sd	min	median	max
Dependent Variables:						
Has Comb. Mod.	12295	0.449	0.497	0	0	1
Has Post Comb. Treatment	12295	0.016	0.124	0	0	1
*Knowledge Stocks:**						
Comb. Mod: US	13	92.651	25.439	49.295	100.755	118.615
Comb. Mod: Foreign	13	51.736	11.257	35.191	51.418	66.191
Post Comb. Treatment: US	13	171.587	24.566	115.820	185.996	189.365
Post Comb. Treatment: For.	13	180.386	16.816	146.605	184.770	197.889
Growth US CM Stock	13	0.077	0.055	0.002	0.077	0.159
Growth For CM Stock	13	0.059	0.030	-0.001	0.057	0.114
Growth US PCT Stock	13	0.048	0.056	-0.016	0.027	0.139
Growth For PCT Stock	13	0.028	0.028	-0.023	0.027	0.083
Regulations:						
OTC Dummy	12295	0.037	0.190	0	0	1
Has lb/mmBTU reg	12295	0.498	0.500	0	0	1
lb/mmBTU level**	6122	0.665	0.394	0.045	0.57	6.600
Has lb/hour reg	12295	0.007	0.084	0	0	1
lb/hour level**	88	1928.114	1520.604	235	1360	5920
Has ppm reg	12295	0.005	0.070	0	0	1
ppm at stack level**	61	0.476	0.089	0.32	0.500	0.76
Boiler Characteristics:						
Company Experience: CM	12295	5.762	8.205	0	3	55
Company Experience: PCT	12295	0.082	0.4269	0	0	5
% sulfur content of coal	12295	1.224	0.906	0	0.933	13.353
Capacity (MW)	12295	1957.375	31144.090	8	200	790400
Tangential Firing dummy	12295	0.424	0.494	0	0	1
Revenues (millions)	12295	2519.964	3095.176	13.03074	1619.978	40137.520
Compustat dummy	12295	0.043	0.203	0	0	1
Revenues * Compustat**	531	10320.950	9001.590	442.6078	8862.334	40137.52
Age of boiler	12295	31.764	12.133	0	33	69

* -- descriptive statistics from knowledge stocks faced by any firm in a given year (1990-2002)
** -- statistics for positive values only

Table 2 – Regression Results: Adoption of Combustion Modification Technology

Variable	Base	Growth	Interact	Growth & Int.
Comb. Mod. Knowledge: US	0.4096	0.6643	-0.0089	-0.5258
	4.5830	4.1917	-0.0730	-1.9438
Comb. Mod. Knowledge: Foreign	-0.5695	-1.1486	-1.5920	-1.8472
	-4.4718	-3.2337	-6.2699	-4.3172
Growth US CM Knowledge		-0.0893		0.0550
		-1.7247		0.9392
Growth Foreign CM Knowledge		-0.0173		0.0588
		-1.3729		3.0128
Comb. Mod. Knowledge: Interact			0.7325	1.2623
			4.7361	5.3052
Company Experience (t-1)	0.0408	0.0411	0.0408	0.0411
	6.9444	6.6891	6.6060	6.4188
has PostNOX(t-1)	-1.2013	-1.2180	-1.2117	-1.2229
	-2.1338	-2.1537	-2.0838	-2.1046
OTC dummy	0.8528	0.8349	0.8021	0.8598
	3.3419	3.1477	2.9949	3.1650
SIP dummy	0.4781	0.4539	0.4098	0.4706
	2.7404	2.4120	2.2339	2.4278
lb/mmBTU level	-0.0202	-0.0204	-0.0210	-0.0215
	-4.2011	-3.9515	-4.2663	-4.0186
Has lb/mmBTU reg	1.7822	1.7948	1.8110	1.8207
	9.5591	8.8450	9.3435	8.5721
% sulfur content of coal	0.0111	0.0113	0.0108	0.0105
	1.9547	1.9327	1.8839	1.7886
Capacity (MW)	0.0006	0.0006	0.0006	0.0006
	5.8629	5.8487	5.8568	5.8807
Tangential Firing dummy	-0.0337	-0.0510	-0.0451	-0.0429
	-0.2875	-0.3925	-0.3688	-0.3187
Revenues (millions)	-0.0098	-0.0096	-0.0091	-0.0095
	-1.2951	-1.2337	-1.1691	-1.2034
Revenues*Compustat	0.0026	0.0026	0.0025	0.0026
	2.0611	1.9945	1.9440	1.9708
Vintage <= 1960	-0.5310	-0.5342	-0.5481	-0.5525
	-5.7140	-5.7356	-5.8457	-5.8731
Vintage 1971-1976	0.4016	0.4035	0.3904	0.3975
	3.3609	3.3584	3.2376	3.2735
Vintage 1977-1980	0.9810	0.9997	0.9869	0.9663
	3.2368	3.2558	3.2364	3.1710
Vintage 1981-1985	1.6069	1.7109	1.6380	1.7141
	2.6272	2.1805	2.4540	2.0488
Vintage 1986-1990	0.8698	0.6815	0.7819	0.5969
	1.9208	1.2917	1.6318	1.0994
Vintage 1991-1995	-1.0291	-0.9836	-1.0319	-1.1139
	-4.9005	-4.2959	-4.2936	-4.1860
Vintage 1996+	-1.1672	-1.2917	-1.4474	-1.4059
	-6.1624	-6.3678	-6.1302	-6.0066
Constant	-3.4647	-3.4591	-3.4477	-3.4745
	-27.9746	-25.6712	-27.2047	-24.5222
Log likelihood	-1888.967	-1885.596	-1880.559	-1876.263
Joint significance of knowledge vars: χ^2	24.00	30.74	40.81	49.41
Prob > χ^2	<0.0001	<0.0001	<0.0001	<0.0001

NOTES: T-stats appear below estimates. Continuous variables normalized as described in footnote 30. *N*=7,279.

Table 3 – Regression Results: Adoption of Combustion Modification Technology

Variable	Base	Growth	Both Techs	Growth & Both
Comb. Mod. Knowledge: All	-0.0077	0.1133	-0.2214	-0.0394
	-0.2847	2.6425	-2.8191	-0.2524
Growth All CM Knowledge		0.0770		0.1446
		3.2866		3.8508
NOX Post Knowledge: All			0.4344	-0.5491
			2.8124	-2.1217
Growth All NOX Post Knowledge				-0.1236
				-5.5213
Company Experience (t-1)	0.0416	0.0410	0.0410	0.0401
	7.0323	7.0609	7.0185	6.6859
has PostNOX(t-1)	-1.1132	-1.1631	-1.1457	-1.2083
	-1.9053	-2.0553	-2.0010	-2.0874
OTC dummy	0.5330	0.7579	0.6832	0.9092
	2.1469	3.0125	2.7401	3.4214
SIP dummy	0.1036	0.3687	0.2823	0.5086
	0.6871	2.1772	1.7692	2.7819
lb/mmBTU level	-0.0166	-0.0187	-0.0184	-0.0201
	-3.4308	-3.9255	-3.9265	-4.2778
Has lb/mmBTU reg	1.6485	1.7224	1.7180	1.7644
	8.7122	9.3333	9.4373	9.6295
% sulfur content of coal	0.0115	0.0111	0.0114	0.0099
	2.0920	1.9939	2.0534	1.7808
Capacity (MW)	0.0005	0.0005	0.0005	0.0005
	5.6991	5.8064	5.7802	5.8364
Tangential Firing dummy	-0.0020	-0.0123	-0.0147	-0.0160
	-0.0176	-0.1076	-0.1299	-0.1392
Revenues (millions)	-0.0108	-0.0105	-0.0102	-0.0096
	-1.4289	-1.4058	-1.3566	-1.2746
Revenues*Compustat	0.0027	0.0027	0.0026	0.0026
	2.1449	2.1552	2.0790	2.0375
Vintage <= 1960	-0.5402	-0.5318	-0.5341	-0.5536
	-5.7974	-5.7250	-5.7418	-5.8957
Vintage 1961-1970				
Vintage 1971-1976	0.3882	0.3990	0.3937	0.3881
	3.2330	3.3350	3.2982	3.2260
Vintage 1977-1980	0.9199	0.9418	0.9509	0.9396
	3.1120	3.1639	3.1761	3.1629
Vintage 1981-1985	1.5123	1.5477	1.5164	1.5504
	2.5419	2.6777	2.6852	2.6336
Vintage 1986-1990	0.7064	0.8332	0.9202	0.8531
	1.5718	1.9095	2.1216	1.9183
Vintage 1991-1995	-0.9351	-1.0305	-0.9850	-1.1009
	-5.8910	-5.5895	-5.6499	-4.9297
Vintage 1996+	-1.4088	-1.1379	-1.2531	-1.3104
	-6.1898	-5.6552	-6.2932	-5.5177
Constant	-3.3070	-3.4154	-3.3864	-3.4489
	-28.4693	-28.2248	-29.3264	-28.1562
Log likelihood	-1900.912	-1894.845	-1896.453	-1884.824
Joint significance of knowledge vars: χ^2	0.110	12.240	9.030	32.280
Prob > χ^2	0.742	0.002	0.011	<0.0001

NOTES: T-stats appear below estimates. Continuous variables normalized as described in footnote 30. *N*=7,279.

Table 4 – Net Effect of Technology

	Foreign and Domestic Own Technology				*All Knowledge Both Technologies*			
Combustion Mod.	Base	Growth	Interact	Growth & Int.	Base	Growth	Both Techs	Growth & Both
average	-2.20%	-3.26%	0.07%	-2.63%	-0.45%	-2.40%	-0.68%	-0.11%
average 91-96	9.55%	10.93%	11.19%	8.02%	-0.61%	3.75%	4.86%	2.06%
average 97-02	-13.95%	-17.45%	-11.05%	-13.28%	-0.29%	-8.55%	-6.22%	-2.28%
Post Combustion								
average	9.45%	41.32%	20.93%	28.71%	9.37%	18.44%	12.97%	20.04%
average 91-96	15.06%	29.14%	14.66%	88.88%	16.42%	14.10%	12.72%	23.50%
average 97-02	3.84%	53.51%	27.19%	-31.46%	2.32%	22.78%	13.22%	16.58%

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(β***X(t)**) - exp(β***X(t-1)**), where **X(t)** is a vector of the various technology variables (both levels and growth rates) in each year.

Table 5 – Regression Results: Adoption of Post-Combustion Treatment Technology

Variable	Base	Growth	Interact	Growth & Int.
NOX Post Knowledge: US	0.1213	1.7399	-0.3040	-2.7514
	0.1544	1.1090	-0.3507	-1.6374
NOX Post Knowledge: Foreign	0.4007	2.6933	-0.7028	-11.2648
	0.3194	1.8039	-0.6236	-2.2966
Growth US NOX Post Knowledge		0.5243		1.4660
		2.7261		2.8260
Growth Foreign NOX Post Knowledge		-0.2985		0.1337
		-2.8811		0.9594
NOX Post Knowledge: Interact			0.6465	12.1964
			2.5820	2.5844
Company Experience(t-1)	0.3081	0.2652	0.2063	0.2977
	2.0563	1.7503	1.4035	1.9595
has Combustion Modification(t-1)	-0.1338	-0.1737	-0.1795	-0.2238
	-0.4379	-0.5593	-0.5795	-0.7543
OTC dummy	3.4979	3.2113	3.3610	3.3431
	6.2325	5.6324	6.1558	5.5336
SIP dummy	1.7633	1.3883	1.5295	1.4860
	3.9713	3.1871	3.5851	3.1375
lb/mmBTU level	0.0186	0.0186	0.0192	0.0188
	1.3914	1.4947	1.5837	1.4778
Has lb/mmBTU reg	-0.3609	-0.3950	-0.4463	-0.3879
	-0.7105	-0.7918	-0.9055	-0.7967
% sulfur content of coal	0.0050	0.0049	0.0032	0.0050
	0.3500	0.3263	0.2120	0.3414
Capacity (MW)	-0.0016	-0.0015	-0.0015	-0.0015
	-3.2721	-3.2369	-3.2874	-3.1985
Tangential Firing dummy	-1.2216	-1.2131	-1.2143	-1.1922
	-3.5366	-3.5172	-3.5315	-3.4549
Revenues (millions)	0.0352	0.0371	0.0370	0.0357
	1.9309	2.0310	2.0213	1.9702
Revenues*Compustat	-0.0051	-0.0058	-0.0055	-0.0059
	-1.6124	-1.7479	-1.6731	-1.7483
Vintage <= 1960	-0.5029	-0.5275	-0.5215	-0.5554
	-1.3465	-1.3959	-1.3802	-1.4660
Vintage 1961-1970				
Vintage 1971-1976	1.0845	1.0801	1.0791	1.0779
	2.9386	2.9562	2.9441	2.9513
Vintage 1977-1980	1.2026	1.1923	1.2055	1.2073
	2.5591	2.5127	2.5453	2.5348
Vintage 1981-1985	0.5610	0.5415	0.5738	0.5570
	0.8464	0.8124	0.8619	0.8418
Vintage 1986-1990	0.1339	0.1283	0.1404	0.1434
	0.1303	0.1240	0.1352	0.1387
Vintage 1991-1995	0.8111	0.8339	0.8466	0.7434
	0.9193	0.9935	0.9583	0.9172
Vintage 1996+	2.5061	2.0918	2.1123	2.0236
	3.2205	2.3897	2.4010	2.6437
Constant	-6.2196	-6.8264	-6.1478	-6.6928
	-14.6788	-11.1542	-14.6501	-12.8244
Log likelihood	-130.213	-122.952	-128.298	-117.881
Joint significance of knowledge vars: χ^2	3.30	17.83	7.13	27.97
Prob > χ^2	0.1917	0.0013	0.0678	<0.0001

NOTES: T-stats appear below estimates. Continuous variables normalized as described in footnote 30. N=12,156.

Table 6 – Regression Results: Adoption of Post-Combustion Treatment Technology

Variable	Base	Growth	Both Techs	Growth & Both
NOX Post Knowledge: All	0.4700	0.0406	0.0047	1.8246
	2.2933	0.1741	0.0092	2.0200
Growth All NOX Post Knowledge		-0.0580		-0.1163
		-2.1647		-1.5820
Comb. Mod. Knowledge: All			0.2340	-1.2361
			0.7986	-1.9557
Growth All CM Knowledge				-0.1230
				-0.8607
Company Experience(t-1)	0.3054	0.2188	0.2731	0.2064
	2.0646	1.4853	1.7950	1.4016
has Combustion Modification(t-1)	-0.1362	-0.1697	-0.1433	-0.1920
	-0.4530	-0.5535	-0.4753	-0.6238
OTC dummy	3.5375	3.4162	3.3787	3.6468
	6.7688	6.5627	6.7268	6.0146
SIP dummy	1.8036	1.6024	1.6079	1.8286
	5.1506	4.6732	4.2442	3.5953
lb/mmBTU level	0.0185	0.0190	0.0191	0.0183
	1.3630	1.5202	1.4768	1.4006
Has lb/mmBTU reg	-0.3551	-0.4282	-0.4033	-0.3884
	-0.7057	-0.8727	-0.8002	-0.7498
% sulfur content of coal	0.0049	0.0033	0.0046	0.0027
	0.3369	0.2143	0.3072	0.1786
Capacity (MW)	-0.0016	-0.0015	-0.0015	-0.0016
	-3.2718	-3.2900	-3.2852	-3.2814
Tangential Firing dummy	-1.2227	-1.2161	-1.2172	-1.2205
	-3.5455	-3.5376	-3.5262	-3.5370
Revenues (millions)	0.0352	0.0367	0.0357	0.0373
	1.9197	1.9914	1.9329	2.0102
Revenues*Compustat	-0.0051	-0.0054	-0.0052	-0.0055
	-1.6114	-1.6563	-1.6177	-1.6693
Vintage <= 1960	-0.5036	-0.5182	-0.5080	-0.5270
	-1.3499	-1.3764	-1.3553	-1.4022
Vintage 1961-1970				
Vintage 1971-1976	1.0848	1.0795	1.0810	1.0814
	2.9328	2.9391	2.9446	2.9349
Vintage 1977-1980	1.2036	1.2054	1.2009	1.2150
	2.5431	2.5283	2.5413	2.5454
Vintage 1981-1985	0.5632	0.5733	0.5606	0.5901
	0.8439	0.8543	0.8403	0.8829
Vintage 1986-1990	0.1359	0.1401	0.1297	0.1584
	0.1321	0.1349	0.1256	0.1524
Vintage 1991-1995	0.8099	0.8409	0.8266	0.8372
	0.9170	0.9507	0.9378	0.9490
Vintage 1996+	2.5190	2.2038	2.3381	2.2821
	3.2309	2.5423	2.8097	2.6867
Constant	-6.2319	-6.1673	-6.1702	-6.3297
	-13.9225	-13.9722	-14.3213	-15.0211
Log likelihood	-130.224	-128.907	-129.877	-127.962
Joint significance of knowledge vars: χ^2	3.28	5.92	3.98	7.81
Prob > χ^2	0.0700	0.0519	0.1370	0.0990

NOTES: T-stats appear below estimates. Continuous variables normalized as described in footnote 30. *N*=12,156.

Appendix A – 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 A1 – A4 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. Most of the changes that do occur are in the model including growth rates of both foreign and domestic knowledge stocks. As noted in footnote 37, the results suggest that multicollinearity is a problem for this specification. Other than that, only the model assuming fast diffusion differs much from the base results.

Table A5 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 alternative assumptions about decay and diffusion increase the joint significance of the knowledge variables. This result is particularly striking for the slowest diffusion assumption. However, slower diffusion of the post-combustion techniques occurs because the U.S. 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*.

To better interpret the differences, Table A6 reproduces the net technology effects shown in Table 5 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. One, as discussed before, is in the model including growth rates for both domestic and foreign technology. A second is in the model using only the overall technology level for NO_X post combustion. Here, the average net effect of technology ranges from 2.5% with rapid diffusion to 19.0% with slow diffusion. However, these differences are smaller in the more complete models for this technology, with a range of 11.5%-26.2% in the most complete model.

Table A1 – Parameter Sensitivity: Adoption of Combustion Modification Technology

Variable	Base	Growth	Interact	Growth & Int.
Decay = 0.1, Diffuse = 0.25				
Comb. Mod. Knowledge: US	0.4096	0.6643	-0.0089	-0.5258
	4.5830	4.1917	-0.0730	-1.9438
Comb. Mod. Knowledge: Foreign	-0.5695	-1.1486	-1.5920	-1.8472
	-4.4718	-3.2337	-6.2699	-4.3172
Growth US CM Knowledge		-0.0893		0.0550
		-1.7247		0.9392
Growth Foreign CM Knowledge		-0.0173		0.0588
		-1.3729		3.0128
Comb. Mod. Knowledge: Interact			0.7325	1.2623
			4.7361	5.3052
Decay = 0.25, Diffuse = 0.5				
Comb. Mod. Knowledge: US	0.1584	0.0848	0.1360	-0.6059
	4.3701	2.2499	1.5415	-3.3001
Comb. Mod. Knowledge: Foreign	-0.2305	-0.4813	-0.2499	-0.8124
	-4.5367	-5.5204	-2.9064	-6.7789
Growth US CM Knowledge		-0.0401		0.0116
		-3.5451		0.6620
Growth Foreign CM Knowledge		0.0192		0.0302
		5.4349		6.6773
Comb. Mod. Knowledge: Interact			0.0251	0.8371
			0.2789	3.8551
Decay = 0.05, Diffuse = 0.5				
Comb. Mod. Knowledge: US	0.4467	0.5973	0.0045	-0.3887
	4.6168	4.3013	0.0309	-1.5586
Comb. Mod. Knowledge: Foreign	-0.5781	-0.9378	-1.6023	-1.9445
	-4.7434	-3.5383	-5.5096	-5.7183
Growth US CM Knowledge		-0.0773		0.0325
		-1.6804		0.6329
Growth Foreign CM Knowledge		0.0015		0.0618
		0.0947		3.0401
Comb. Mod. Knowledge: Interact			0.7601	1.2237
			3.9150	4.8677
Decay = 0.05, Diffuse = 0.10 (peak = 10)				
Comb. Mod. Knowledge: US	0.7989	1.5793	1.0946	0.7232
	3.4632	2.6671	4.0552	1.1377
Comb. Mod. Knowledge: Foreign	-0.9660	-2.0503	-2.3449	-3.3775
	-3.5200	-2.5750	-3.3869	-3.8777
Growth US CM Knowledge		-0.0826		0.1856
		-1.0548		1.7666
Growth Foreign CM Knowledge		-0.1372		-0.0441
		-2.1434		-0.6430
Comb. Mod. Knowledge: Interact			0.4943	1.2564
			2.1970	3.7259

NOTES: T-stats appear below estimates.

Table A2 – Parameter Sensitivity: Adoption of Combustion Modification Technology

Variable	Base	Growth	Both Techs	Growth & Both
Decay = 0.1, Diffuse = 0.25				
Comb. Mod. Knowledge: All	-0.0077	0.1133	-0.2214	-0.0394
	-0.2847	2.6425	-2.8191	-0.2524
Growth All CM Knowledge		0.0770		0.1446
		3.2866		3.8508
NOX Post Knowledge: All			0.4344	-0.5491
			2.8124	-2.1217
Growth All NOX Post Knowledge				-0.1236
				-5.5213
Decay = 0.25, Diffuse = 0.5				
NOX Post Knowledge: All	0.0160	0.1314	0.0043	0.0462
	0.6025	3.5164	0.1564	0.8520
Growth All NOX Post Knowledge		0.0275		0.0514
		4.2532		5.6282
Comb. Mod. Knowledge: All			0.1418	-0.0752
			1.9058	-0.7717
Growth All CM Knowledge				-0.0003
				-4.5481
Decay = 0.05, Diffuse = 0.5				
NOX Post Knowledge: All	-0.0093	0.1598	-0.3397	0.0606
	-0.4001	3.3429	-2.9427	0.3365
Growth All NOX Post Knowledge		0.1141		0.1385
		4.0065		3.7688
Comb. Mod. Knowledge: All			0.5915	-0.6115
			2.9141	-1.9342
Growth All CM Knowledge				-0.1485
				-4.0844
Decay = 0.05, Diffuse = 0.10				
NOX Post Knowledge: All	-0.0152	0.0794	-0.4933	-0.8599
	-0.7041	2.1241	-3.2704	-2.3277
Growth All NOX Post Knowledge		0.1401		0.0586
		3.1082		0.6332
Comb. Mod. Knowledge: All			0.6679	-0.6636
			3.2032	-1.4144
Growth All CM Knowledge				-0.8332
				-5.4745

NOTES: T-stats appear below estimates.

Table A3 – Parameter Sensitivity: Adoption of Post Combustion Treatment Technology

Variable	Base	Growth	Interact	Growth & Int.
Decay = 0.1, Diffuse = 0.25				
NOX Post Knowledge: US	0.1213	1.7399	-0.3040	-2.7514
	0.1544	1.1090	-0.3507	-1.6374
NOX Post Knowledge: Foreign	0.4007	2.6933	-0.7028	-11.2648
	0.3194	1.8039	-0.6236	-2.2966
Growth US NOX Post Knowledge		0.5243		1.4660
		2.7261		2.8260
Growth Foreign NOX Post Knowledge		-0.2985		0.1337
		-2.8811		0.9594
NOX Post Knowledge: Interact			0.6465	12.1964
			2.5820	2.5844
Decay = 0.25, Diffuse = 0.5				
NOX Post Knowledge: US	0.4614	0.4240	-1.0520	-6.3287
	1.6911	1.4183	-1.1753	-2.0715
NOX Post Knowledge: Foreign	-0.7721	-0.1038	-0.9341	-4.2932
	-3.4581	-0.1571	-3.2068	-1.9448
Growth US NOX Post Knowledge		-0.0058		0.0422
		-1.4224		1.9075
Growth Foreign NOX Post Knowledge		0.0075		-0.0245
		0.7165		-1.1778
NOX Post Knowledge: Interact			1.5568	7.0101
			1.7490	2.2116
Decay = 0.05, Diffuse = 0.5				
NOX Post Knowledge: US	0.6771	5.0620	0.0875	1.7010
	0.7774	2.1702	0.0986	1.0829
NOX Post Knowledge: Foreign	-0.2041	-0.9501	-1.4396	-14.1589
	-0.1792	-0.6356	-1.2778	-2.6024
Growth US NOX Post Knowledge		0.7417		1.4567
		2.9442		2.8115
Growth Foreign NOX Post Knowledge		-0.2694		0.3628
		-2.9805		1.6174
NOX Post Knowledge: Interact			0.7892	10.3545
			2.7455	2.4988
Decay = 0.05, Diffuse = 0.10				
NOX Post Knowledge: US	-2.2509	6.5756	-2.5364	20.9624
	-1.0889	1.3247	-0.9021	2.7855
NOX Post Knowledge: Foreign	3.1254	1.9021	3.7930	-26.9161
	1.2136	0.4729	0.8491	-2.2536
Growth US NOX Post Knowledge		3.5710		6.6223
		2.9524		2.9990
Growth Foreign NOX Post Knowledge		-0.5089		1.5331
		-2.0662		1.9097
NOX Post Knowledge: Interact			-0.1314	10.1576
			-0.2635	2.3429

NOTES: T-stats appear below estimates.

Table A4 – Parameter Sensitivity: Adoption of Post Combustion Treatment Technology

Variable	Base	Growth	Both Techs	Growth & Both
Decay = 0.1, Diffuse = 0.25				
NOX Post Knowledge: All	0.4700	0.0406	0.0047	1.8246
	2.2933	0.1741	0.0092	2.0200
Growth All NOX Post Knowledge		-0.0580		-0.1163
		-2.1647		-1.5820
Comb. Mod. Knowledge: All			0.2340	-1.2361
			0.7986	-1.9557
Growth All CM Knowledge				-0.1230
				-0.8607
Decay = 0.25, Diffuse = 0.5				
NOX Post Knowledge: All	-0.2270	0.3846	-0.2854	0.5948
	-1.2782	1.2452	-1.3189	1.5420
Growth All NOX Post Knowledge		-0.0004		-0.0006
		-2.8677		-3.3041
Comb. Mod. Knowledge: All			0.0760	-0.1714
			0.7865	-0.8644
Growth All CM Knowledge				0.0229
				0.6418
Decay = 0.05, Diffuse = 0.5				
NOX Post Knowledge: All	0.5476	0.1612	1.4325	4.7510
	2.2916	0.4882	1.6780	1.6422
Growth All NOX Post Knowledge		-0.0641		-0.2458
		-1.4831		-1.5402
Comb. Mod. Knowledge: All			-0.4431	-2.8908
			-0.9392	-1.8296
Growth All CM Knowledge				-0.1036
				-0.7243
Decay = 0.05, Diffuse = 0.10				
NOX Post Knowledge: All	0.3664	0.5204	0.5033	3.6675
	2.4366	1.0013	0.7065	2.1027
Growth All NOX Post Knowledge		0.0630		0.0755
		0.3145		0.1899
Comb. Mod. Knowledge: All			-0.0889	-2.6208
			-0.1771	-1.6119
Growth All CM Knowledge				-0.5898
				-1.6156

NOTES: T-stats appear below estimates.

Table A5 – Joint Significance of Knowledge Variables: Sensitivity Analysis

	Foreign and Domestic Own Technology				*All Knowledge Both Technologies*			
Combustion Mod.	Base	Growth	Interact	Growth & Int.	Base	Growth	Both Techs	Growth & Both
Decay = 0.1, Diffuse = 0.25								
LR chi2	24.00	30.74	40.81	49.41	0.11	12.24	9.03	32.28
Prob > chi2	<0.0001	<0.0001	<0.0001	<0.0001	0.7419	0.0022	0.011	<0.0001
Decay = 0.25, Diffuse = 0.5								
LR chi2	22.67	53.92	22.75	68.98	0.36	19.59	4.10	40.91
Prob > chi2	<0.0001	<0.0001	<0.0001	<0.0001	0.5464	0.0001	0.1289	<0.0001
Decay = 0.05, Diffuse = 0.5								
LR chi2	22.98	27.1	37.56	49.81	0.16	16.48	8.89	32.98
Prob > chi2	<0.0001	<0.0001	<0.0001	<0.0001	0.689	0.0003	0.0117	<0.0001
Decay = 0.05, Diffuse = 0.10								
LR chi2	13.05	18.91	17.78	32.32	0.5	10.32	11.08	41.13
Prob > chi2	0.0015	0.0008	0.0005	<0.0001	0.4806	0.0057	0.0039	<0.0001
Post Combustion								
Decay = 0.1, Diffuse = 0.25								
LR chi2	3.30	17.83	7.13	27.97	3.28	5.92	3.98	7.81
Prob > chi2	0.1917	0.0013	0.0678	<0.0001	0.07	0.0519	0.137	0.099
Decay = 0.25, Diffuse = 0.5								
LR chi2	6.49	8.24	10.19	14.04	1.27	6.93	1.59	9.16
Prob > chi2	0.039	0.0832	0.017	0.0154	0.2606	0.0313	0.451	0.0572
Decay = 0.05, Diffuse = 0.5								
LR chi2	5.73	18.82	8.63	28.41	5.53	6.41	6.13	11.49
Prob > chi2	0.0569	0.0009	0.0346	<0.0001	0.0186	0.0406	0.0466	0.0216
Decay = 0.05, Diffuse = 0.10								
LR chi2	8.03	26.38	8.07	33.55	6.34	6.38	6.35	8.14
Prob > chi2	0.018	<0.0001	0.0446	<0.0001	0.0118	0.0412	0.0417	0.0866

Table A6 – Net Effect of Technology: Sensitivity Analysis

	Foreign and Domestic Own Technology				*All Knowledge Both Technologies*			
Combustion Mod.	Base	Growth	Interact	Growth & Int.	Base	Growth	Both Techs	Growth & Both
Decay = 0.1, Diffuse = 0.25								
average	-2.20%	-3.26%	0.07%	-2.63%	-0.45%	-2.40%	-0.68%	-0.11%
average 91-96	9.55%	10.93%	11.19%	8.02%	-0.61%	3.75%	4.86%	2.06%
average 97-02	-13.95%	-17.45%	-11.05%	-13.28%	-0.29%	-8.55%	-6.22%	-2.28%
Decay = 0.25, Diffuse = 0.5								
average	0.7%	-5.6%	1.1%	-3.3%	0.5%	-5.1%	-0.8%	-2.3%
average 91-96	8.7%	2.5%	8.6%	-2.4%	1.4%	0.4%	3.4%	-0.3%
average 97-02	-7.3%	-13.6%	-6.4%	-4.1%	-0.4%	-10.6%	-5.1%	-4.3%
Decay = 0.05, Diffuse = 0.5								
average	-1.6%	-3.5%	0.9%	-2.5%	-0.6%	-2.8%	-0.3%	-0.6%
average 91-96	9.7%	10.3%	11.1%	8.0%	-0.7%	3.5%	4.6%	2.4%
average 97-02	-13.0%	-17.2%	-9.2%	-13.1%	-0.4%	-9.1%	-5.2%	-3.6%
Decay = 0.05, Diffuse = 0.10								
average	-3.0%	-1.4%	-4.1%	-0.6%	-1.1%	-2.0%	-1.1%	-1.9%
average 91-96	5.3%	8.9%	4.1%	9.7%	-1.1%	4.3%	5.6%	0.5%
average 97-02	-11.2%	-11.7%	-12.4%	-11.0%	-1.0%	-8.4%	-7.8%	-4.3%
Post Combustion								
Decay = 0.1, Diffuse = 0.25								
average	9.45%	41.32%	20.93%	28.71%	9.37%	18.44%	12.97%	20.04%
average 91-96	15.06%	29.14%	14.66%	88.88%	16.42%	14.10%	12.72%	23.50%
average 97-02	3.84%	53.51%	27.19%	-31.46%	2.32%	22.78%	13.22%	16.58%
Decay = 0.25, Diffuse = 0.5								
average	8.6%	15.5%	20.6%	24.4%	2.5%	17.0%	6.2%	11.5%
average 91-96	14.9%	23.7%	33.9%	34.3%	-5.2%	23.0%	0.5%	20.0%
average 97-02	2.2%	7.3%	7.3%	14.5%	10.1%	11.0%	11.9%	3.1%
Decay = 0.05, Diffuse = 0.5								
average	15.4%	40.8%	23.1%	29.9%	15.4%	19.4%	13.4%	26.2%
average 91-96	22.1%	40.7%	20.0%	86.2%	17.0%	15.5%	22.1%	41.1%
average 97-02	8.7%	41.0%	26.2%	-26.4%	13.9%	23.3%	4.7%	11.3%
Decay = 0.05, Diffuse = 0.10								
average	21.7%	66.8%	21.5%	43.9%	19.0%	18.6%	18.8%	19.9%
average 91-96	2.2%	55.8%	2.0%	278.9%	13.4%	14.1%	14.4%	16.4%
average 97-02	41.3%	77.9%	41.0%	-191.0%	24.6%	23.2%	23.1%	23.4%

Appendix B – Patent Classifications Used for Each Control Technology

European Classifications for Pollution Control Patents

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]
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]