Product Market Competition and Upstream Innovation: Theory and Evidence from the US Electricity Market Deregulation*

Paroma Sanyal# & Suman Ghosh##

October, 2008

Abstract

This paper studies the innovation response of upstream technology suppliers when their downstream technology buyers transition from regulation to product market competition. First, we develop a theoretical framework that models this particular organizational structure. Second, we use the US electricity deregulation in the 1990's to test the model. Using patents as a metric for innovation, we identify two channels through which the effects of deregulation are transmitted to innovation: (a) the appropriation effect which has decreased innovation by 19.5 percent after deregulation, and (b) the competition effect which has increased innovation by 10.7 percent after deregulation. Other unobserved effects of deregulation have led to a 14.5 percent decline in innovation. In aggregate we find that electric technology innovation by electric equipment manufacturers (who were the upstream innovators) has experienced a 23 percent decline due to deregulation. In addition, upstream innovation quality and generality have both declined after the introduction of downstream competition.

JEL Code: O30, L51, L94
Key Words: Competition, Innovation, Electricity Deregulation

---

* We thank Nancy Rose and Lawrence White for their comments on an earlier version of the paper. We are also very grateful to Leigh Tesfatsion, David Popp, and Katherine Graddy for their insightful comments on the paper, and to the seminar participants at the 6th International Industrial Organization Conference. We would also like to thank James Bessen for providing the updated COMPUSTAT match for the NBER patent database. The usual disclaimer applies.
# Corresponding Author: Department of Economics & IBS, MS 021, Sachar International Centre, Brandeis University, 415 South Street, Waltham, MA 02454. E-mail- psanyal@brandeis.edu
Department of Economics, Florida Atlantic University, 777 Glades Road, Boca Raton, FL 33431. E-Mail- sghosh@fau.edu

1. Introduction

Starting with Schumpeter (1942), there is a line of research arguing that innovation is best promoted in highly concentrated industries because a monopolist has a stronger incentive and better means to innovate than competitive firms do. On the other hand, there is a "Darwinian" tradition, which argues that the most efficient and most innovative firms survive under competition. This latter argument has been central to the literature called "creative destruction", formalized by several seminal papers, such as Aghion and Howitt (1992, 1996). In the standard set-up of these studies, innovations take place within the firm. Using this as the starting point, the implications of competition on innovation incentives are studied. However, in the long tradition of the literature on competition and innovation, the innovation response of upstream technology suppliers to changing product market competition faced by downstream technology buyers remains understudied. This paper focuses on the effect of competition on innovation in the context of this vertical upstream-downstream industrial organizational structure and differs, therefore, from papers that have considered the effect of competition on innovation incentives in a horizontal set-up.[1]

To study this question, we first develop a theoretical framework to analyze how upstream innovation responds to changing downstream market environment. Next, we test the implications of the model using the deregulation of the US electric utility industry. The technology flow in this industry is from upstream electric equipment manufacturers (EEMs), such as General Electric, who are responsible for innovating and supplying new technology (such as furnaces and

[1] See Scherer and Ross (1990) and Gilbert (2006) for surveys on this topic.

pollution control equipment) to the downstream utilities that do the actual generation, transmission, and distribution of power. Overseen by the Federal Energy Regulatory Commission (FERC) and state regulators, each downstream utility had a service monopoly in a particular geographical region, and their rate of return was regulated. This in turn ensured that electricity prices were fairly stable and not subject to market volatility.

During the early to mid-nineties, the aforementioned regulation paradigm underwent significant changes that were geared towards competitive electricity markets.[2] In 1992, the passing of the Energy Policy Act (EPAct) gave rise to open-access transmission grids for wholesale transactions[3] and formally introduced wholesale competition,[4] thus subjecting incumbent utilities to price uncertainties and entry pressures. After the introduction of the EPAct, consumers such as municipalities could shop for power, putting vertically integrated utilities, which had formerly served all of their needs, at the risk of losing them as customers. This led to major changes in the organizational structure of the electricity industry and altered the incentives and optimization decisions of utilities and all the entities that did business with them. In particular, the EEMs, who supplied the generators, pollution control technologies, and other equipment to the downstream utilities, were directly affected by this change. Thus, the industrial organization of this sector and the transition of the industry from a regulated to a competitive set-up make it ideal for studying innovation behavior in an upstream-downstream set-up.

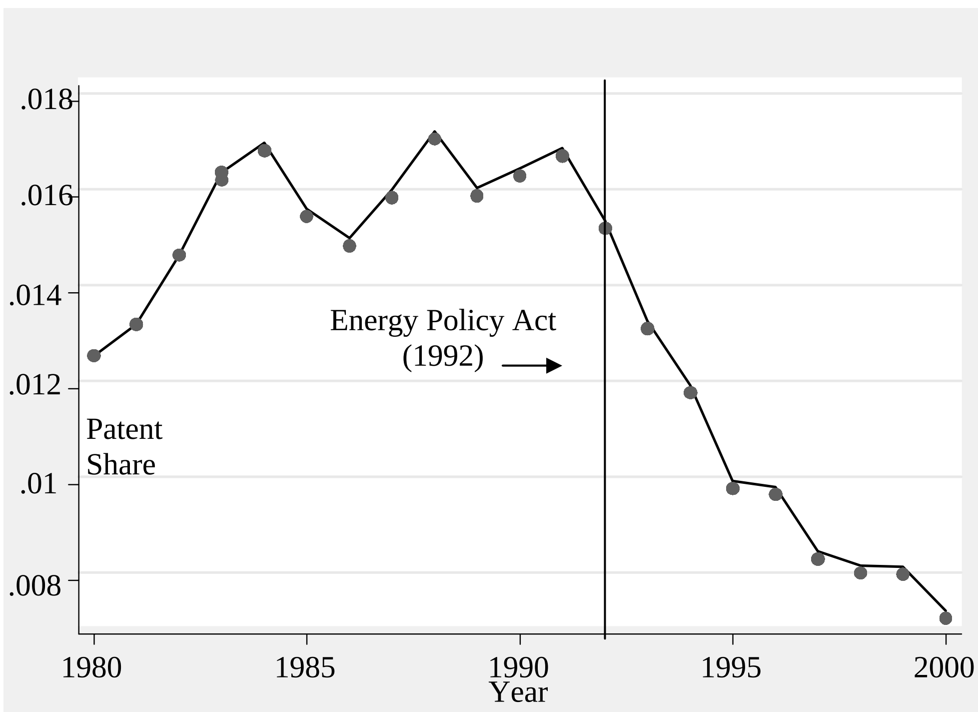
[2] For studies on the electricity deregulation in the US, see Blumstein (1997); Borenstein & Bushnell (1999); Borenstein, Bushnell, and Stoft (2000); Joskow (1997, 1999); Wolak (2004); Puller (2007); and Sanyal and Cohen (2007a,b).

[3] On the wholesale side, FERC took several steps to ensure increased competition. It required utilities to provide a detailed account of their transmission capacities, it expanded the range of services that the utilities were required to provide to wholesale traders, and it made it clear that approval of application for mergers and the IOUs' ability to charge competitive rates were subject to their filing open access transmission tariffs with comparable service provisions.

[4] The competitive threat for utilities comes from the "wholesale" markets where they buy and sell power for resale at retail. Wholesale rates apply to all sales for resale. The Federal Energy Regulatory Commission (FERC) is nominally required to set the rates on a cost-of-service basis; however, in practice it allows the parties involved to choose them.

Our investigation is motivated by the observed changes in innovation behavior of EEMs that are coincident with deregulation and restructuring activity in the electricity market. As Figure 1 below illustrates, with the introduction of the competition that was ushered in by the EPAct (1992), there was a significant drop in the share of electric technology patents granted to EEMs. Even if we ignore the 2000 data due to truncation issues, there is s 52 percent drop in the share of electric technology patenting by EEMs between 1991 and 1999.

Figure 1
Share of EEM Electric Technology Patents in Total USPTO Patents: 1980 - 2000



This decline is even more puzzling when one observes that the decrease in share is not due to the slower growth of EEM electric patents in comparison to other technologies but, rather, to an absolute drop in the number of electric technology patents granted to EEMs. In Appendix Figures I and II, we compare the total number of EEM electric patents with the number of drug patents obtained by corporations (US and Non-US). We find that after 1992 the total number of

EEM electric patents show a decline while drug patents show an increase. The increase in patents is also shown in other technology classes, such as chemicals and biotech. This paper explores why EEM innovation declined when other technologies boomed.

Common models of innovation and market structure cannot adequately explain the above-mentioned changes because they focus on a horizontal organization structure where innovation takes place within the firm. Therefore, we build a simple theoretical framework that models a vertical organization structure where innovation is done by upstream equipment manufacturers and bought by downstream utilities. After the introduction of the EPAct, wholesale competition was made possible in the downstream market. This affected the upstream firms' innovations in two ways. First, in presence of competitors in the downstream sector, the pricing of the final goods (i.e. electricity price/megawatthour) to consumers changed. This change had an effect on the profits of the incumbent downstream firms (the utilities), which, in turn, affected the innovation incentives of the upstream sector, since they were getting a share of these profits. We call this the "appropriation effect." The second effect is a "competition effect," which is due to the entry of the non-utility generation firms (called independent power producers, or IPPs) in the wholesale market.[5] With the expansion of IPPs, EEMs could increasingly sell their innovation to these firms, and this raised their status quo payoff and provided an added incentive to innovate. The existence of this outside option implied that the price that they received for their innovations from the downstream firms increased as a result of their bargaining power increase. We model the above phenomenon with the two above-

[5]Public Utility Regulatory Policy Act (PURPA) (1978) required utilities to purchase power from local non-utility generators at "avoided cost" prices. This encouraged the growth of independent power producers (IPPs). However, they could not sell their power to wider markets, which limited competition. When the EPAct allowed FERC to issue wheeling orders, the IPPs began competing with the utilities for large customers such as municipalities.

mentioned effects, which will lead us to verify the channel through which innovation incentives were affected post-deregulation.

Using patents as a metric for innovation, we find that for both the equipment manufacturers and the particular electric equipment patent classes, the amount of innovation declined after the EPAct (1992), which started the deregulation process in the US power industry. Thus, competition in the downstream generation sector adversely affected the innovation behavior of EEMs. We also find that the appropriation effect dominates the competition effect – the former leading to a 19.5 percent decline in innovation after deregulation, while the latter leads to a 10.7 percent increase in innovation during the same time frame. The introduction of the EPAct alone decreased innovation by another 14.5 percent. In aggregate, electric technology innovation by EEMs declined by 23 percent after deregulation. In addition, "quality," as it is measured by citations, has been adversely affected and has declined by 38.5 percent, while 'generality' has decreased by 51 percent since the establishment of the EPAct.

Before proceeding, we briefly review the works that are most closely related to our study. As mentioned before, the existing literature has analyzed in considerable detail how the horizontal structure of an industry- the number of firms, in particular- affects incentives for process innovation.[6] Conversely, the literature has devoted much less attention to the corresponding issue of how the vertical structure of an industry affects innovation. A recent strand of the literature considers such vertical structures as they pertain to the impact of vertical integration on innovation incentives.[7] For our purpose, we rule out the possibility of such vertical integration because in the regulated electricity industry, the owners of the upstream and downstream firms had totally different core activities, which prevented such incentives. Finally,

[6] See, for example, Arrow (1962); Loury (1979); and, more recently, Aghion, et al. (2005) on this.
[7] Choi et.al (2003); Buehler, et al. (2006); Brocas (2003); and Buehler, et al. (2004) are some papers that delve into such issues.

there is related literature that studies the effect of product market competition on managerial incentives.[8] Aghion, Dewatripont, and Rey (1999) is similar in spirit to that literature, but they consider the effects of competition and the threat of liquidation on innovation and growth in an endogenous growth model. More recently, Raith (2003) shows that changes in competition affect incentives if these changes lead to higher firm-level output, and Karuna (2007) shows that particular industry characteristics play a major role in influencing incentives.

Our paper adds to the innovation-competition literature in two ways. First, to the best of our knowledge, this is one of the few papers that develops a theoretical framework to model upstream-downstream innovation behavior. The results have implications for all industries with a similar organizational structure. Second, empirically testing the model with novel data furthers our understanding of how downstream product market competition influences the innovation behavior of upstream technology suppliers.

The rest of this paper is comprised of five sections and is organized as follows: Section 2 develops a brief theoretical framework that helps in understanding the mechanisms at work. Section 3 describes the data and empirical methodology, and Section 4 discusses the results. The last section concludes.

2. Theoretical Underpinnings

In this section we model the innovation behavior of the EEMs under two different scenarios. Since our main objective is to study the impact on upstream innovations due to competition in the downstream sector, we consider just one upstream firm and vary the

[8] Schmidt (1997); Hart (1983); Hermalin (1992, 1994); and Scharfstein (1998) are some papers in this vein.

downstream competition. First, we consider the case before deregulation by modeling the downstream firm as a monopoly since we know that the downstream firms were allowed to maintain a geographic monopoly by the government. Next, we consider the post-deregulation phase, where there was competition in the downstream sector. As in Schmidt (1997), to keep the model as general as possible, the market game in the downstream market post-deregulation is not modeled explicitly. Instead, it is assumed that there is a unique equilibrium in the market game, yielding a reduced-form gross profit function, which we shall introduce. Also, in our model we abstract away from the "make or buy" decision as the downstream utilities did not engage in any significant innovation activity in the electric equipment area as evident from the lack of patents obtained by these utilities during the sample period.

2.1. Pre-deregulation Scenario

We first consider the regulation scenario in which the government maintained a monopoly in the downstream retail sector. The upstream firm sells the innovation I , $I \in [0, \bar{I}]$, which it makes at a cost of $g(I)$. The innovation cost increases with I , $g' > 0,$ at an increasing rate, $g'' > 0.$ Also $g(0) = g'(0) = 0$ and $\lim_{I \to \bar{I}} g(I) = \infty.$ Correspondingly, the marginal cost for a downstream firm is $c(I), c'(I) < 0, c''(I) > 0.$ Note that as the upstream firm invests more, the marginal cost of the downstream firm decreases, which is precisely how we model the role of new innovations. The reduced form profit function of the downstream firm is:

$$\pi = \pi(c(I)), \phi). \tag{1}$$

The parameter $\phi \in R$ measures the "degree of competition" in the market. It may depend on the number of potential competitors, on whether competition is in prices or quantities, or on the degree to which products are differentiated. We assume ϕ to be a continuous variable. The profit function is continuously differentiable in $c(I)$ and ϕ and satisfies the following: $\partial\pi(c(I)),\phi)/\partial c(I) < 0$; $\partial\pi(c(I)),\phi)/\partial\phi < 0$. The above assumptions imply that both costs and the degree of competition are inversely related to profits.[9] We also assume that the cross partials $\pi_{12}, \pi_{21} < 0$, where the subscripts 1 and 2 stand for the first and second arguments in the profit function respectively.

The timing of the game is as follows. First the upstream firm decides on its innovation level. The downstream firm buys the innovation from the upstream firm at price, which is determined by Nash bargaining. The bargaining process is discussed more explicitly later. Finally, the downstream firm sells the final product to the consumers. After we have considered the regulated regime, we will then consider the restructured regime, where there is entry of new firms in the downstream retail sector.

First let us consider the scenario in which the downstream firms do not buy the innovations from the upstream firms. Let $\pi^*((c(0)),\phi_M))$ denote the profit in that case, where ϕ_M denotes the fact that the market structure of the downstream firm is that of a monopoly and $c(0)$ denotes the marginal cost corresponding to no innovation being bought from the upstream firm. Now suppose there is an innovation I, which is bought from the upstream firm. Let $\bar{\pi}((c(I)),\phi_M))$ denote the corresponding profits.

Lemma : $\bar{\pi}((c(I)),\phi_M)) > \pi^*((c(0)),\phi_M))$.

[9] Schmidt (1997) has a similar formulation of the market game with the reduced form profit function and makes similar assumptions to the ones we have made.

This follows directly from the fact that $\partial\pi(c(I)),\phi)/\partial c(I) < 0$ and $c'(I) < 0$. The above lemma implies that the profit that the downstream firm makes with the innovation is higher than the profit that the firm makes without buying the innovation from the upstream firm.

We denote the increase in profits brought about by the innovation by $\prod(I)$, where $\prod(I) = \overline{\pi}((c(I)),\phi_M)) - \pi^*((c(0)),\phi_M))$. This is shared between the upstream and the downstream firm. We use the axiomatic Nash Bargaining solution to determine the price, which is, in turn, determined by the outside options of the parties.[10] According to the "outside options principle," the parties' outside option only affects negotiations if its value exceeds the payoff that the parties would realize when negotiating without having such an option. Once the value of the outside option exceeds half of the bargaining pie, the outside option fully determines the party's share.[11] In this case, we say that the outside option "binds." Hence, we need to determine the outside option or the disagreement points of the individual parties concerned. For the upstream firm, the disagreement value is zero since there is only one downstream firm to which it can sell its innovation. On the other hand, the disagreement value of the downstream firm is the profit that it gets by not buying the innovation, which is $\pi^*((c(0)),\phi_M))$. For what follows, we assume that the outside option binds. Thus, by applying the standard outcome of Nash Bargaining over $\prod(I)$ with outside options $\pi^*((c(0)),\phi_M))$ and zero gives the outcomes,

$$W_U(I) = [\prod(I) + (0 - \pi^*)]$$

where, $W_U(I)$ represents the share of the $\prod(I)$ to the upstream firm. The upstream firm chooses I to maximize the net benefit from its investment in innovation. Let us denote I^* such that I^* is the solution to the problem

---

[10] In the parlance of bargaining theory, we use the well-known "outside option principle." See Binmore, Rubinstein, and Wolinsky (1986) for a classic reference on this.

[11] Binmore, et al. derive this from a non-cooperative model with alternating offers and impatient players.

$$Max_I \frac{1}{2}[\prod(I) + (0 - \pi^*)] - g(I)\,. \qquad (2)$$

After some minor simplification, the FOC is given by: $\bar{\pi}'((c(I^*), \phi_M) = g'(I^*)$. (3)

2.2. Post-deregulation Scenario

Now we consider the scenario post-deregulation. Taking the framework used above as our base model, we need to establish the distinguishing features of the new regime. First, the disagreement points will be different for both the upstream and downstream firms. Because there was previously only one downstream firm, the disagreement payoff for the upstream firm was zero. Now there are other firms that could potentially use the innovations of the upstream firm in case there is a bargaining failure with the primary downstream firm. Also, since there is more competition in the downstream retail sector, the increased profits that the use of the innovation will bring will also change. Below $\prod^C$ denotes the incremental profit, which the downstream firm derives as a result of the innovation, and $\pi^1(I)$ denotes the outside option for the innovation of the upstream firm.[12] $\pi^1(I)$ has the usual assumptions of concavity. Hence, we can rewrite (2) as:

$$Max_I [\prod^C(I) + (\pi^1(I) - \pi^*)] - g(I) \qquad (4)$$

Let us denote I^{**} such that I^{**} is the solution to the above problem. Basically, $\prod^C$ has the same interpretation as $\prod$ before, but now the market structure in the downstream firms is that of competition, as compared to the monopoly it was before.

[12] π^1 is typically less than the profit generated by the primary downstream firm using the innovation because of the discount factor if bargaining breaks down in a typical bargaining game. What is important, though, is that it is greater than zero and is a function of the level of investment.

After some minor simplification, the FOC gives: $\overline{\pi^C}'((c(I^{**}),\phi_C) + \pi^1{}'(I^{**}) = g'(I^{**})$.   (5)

Next, we compare the innovation investments pre- and post-deregulation in the following proposition.

Proposition: For all I, such that $I \in [0,\bar{I}]$, if $\bar{\pi}_{12} < \pi^1{}'$ then $I^{**} > I^*$, otherwise $I^{**} < I^*$ where I^* and I^{**} are the pre- and post-deregulation innovation levels respectively and are derived from equations (3) and (5).

Proof: In Appendix 1.

The Proposition above sums up the main issue that we want to investigate in our paper. We interpret the left hand side of the inequality ($\bar{\pi}_{12} < \pi^1{}'$) as the "appropriation effect," which is the difference in marginal profits of each downstream firm due to the upstream innovation pre- and post-deregulation. The term $\bar{\pi}_{12}$ captures this. The right hand side is the "competition effect." Thus, there are two opposing forces at work here. Post-deregulation, the value added due to the innovation decreases because of the competition downstream. This, in turn, negatively affects the innovation incentive for the upstream firm. But there is an added element that increases innovation incentive for the upstream firm. After deregulation, the upstream firm can possibly cater to other competitor downstream firms ($\pi^1(I)$). Thus, whether innovation will actually increase or decrease depends on the magnitude of the opposing forces. Another way to think about this is in terms of bargaining parlance. Basically, the total pie, which is the marginal increase in profits brought about by innovation, decreases in the post-deregulation scenario, but the bargaining power of the upstream firms increase. So, in a sense, they get a larger share of a smaller pie. Now, whether the absolute value of innovations increases or decreases as a result depends upon the magnitude of each effect. The proposition noted above gives the conditions under which either outcome can happen. We now take up this question in our empirical section.

3. Data

3.1. Data Sources

Our primary interest is to investigate how downstream competition affects upstream innovation. Using patents as a metric of innovation, we empirically model how the magnitude and nature of innovation by EEMs changes from the regulated to the competitive regime. The number of patents, or patent characteristics (such as quality), (Y_{it}) is modeled as a function of a deregulation dummy ($D_{treatment}$), a dummy ($D_{treated}$) for the group that is being affected by deregulation (i.e., electricity patent classes or the EEMs), firm or patent class characteristics ($Char_{it}$), the appropriation effect (A_t), the competition effect (C_t), and macro controls (M_t).

$$Y_{it} = \left(D_{treatment}, D_{treated}, Char_{it}, A_t, C_t, M_t\right) \tag{6}$$

Thus, the primary categories of data that this paper relies on are: 1) information on patents, 2) variables measuring the appropriation and competition effects, and 3) firm level data on financial and other firm characteristics. The patent data is from the National Bureau of Economic Research (NBER) “Patent Citations Database.”[13] This data contains exhaustive information on all patents granted in the US from 1980 to 2002. These comprise application and grant years, geographical distribution of these patents, technology classifications, number of claims per patent, backward and forward citations (i.e., citations to and from a patent),[14]

[13] The updated data is provided by Prof. Browyn Hall.
[14] US citation only.

standardized assignee names, and assignee codes that help in tracking assignees across years. In addition, for publicly traded companies, it matches the unique CUSIP identifier from the COMPUSTAT[15] database with assignee numbers.

We then identify the *treated* group either as electric technology patent classes or as firms that can be categorized as EEMs. First, we identify the electric technology patent classes using the US patent office class descriptions. This yields 40 electric technology-related patent classes. Second, to classify firms as EEMs, we use the Energy Information Administration's (EIA) Form 767, which identifies the largest equipment manufacturers in the power industry. These manufacturers fall into three main categories: boiler manufacturers, flue gas de-sulfurization unit manufacturers, and manufacturers of low nitrogen oxide control burners. It is important to note that there is considerable overlap between the groups. In all three categories, there are 89 EEMs identified by the EIA. General Electric, Babcock, and Wilcox are some of the larger manufacturers in this group. A detailed list of the equipment manufacturers is provided in the Supplementary Appendix Table I.

In order to obtain the patents granted to each EEM, we matched the list mentioned above with the standardized patent assignee names from the NBER database. In a majority of cases, several patent assignee names appear to belong to the same firm. When an EEM is a publicly traded company, such as GE, the match between multiple patent assignees and a parent firm is relatively easy. The CUSIP and assignee match from the NBER database[16] allow us to identify all assignees that belong to a single parent. However, not all the subsidiaries of GE, for example, are engaged in electric technology innovation. Therefore, we exclude obvious mismatches, such as the National Broadcasting Corporation. Of the remaining subsidiaries, we cross reference our

[15] The COMPUSTAT database contains financial data on all publicly traded companies in the US.
[16] Updated COMPUSTAT-assignee match is provided by James Bessen.

list with multiple industry sources, such as Hoovers, industry publications, and the company websites, to observe whether the subsidiary is engaged in the electric technology sector. We only keep those GE subsidiaries that are directly involved in the electricity sector, and the patents granted to these remaining subsidiaries are classified under GE. However, when the company is not publicly traded and no CUSIP match exists in the NBER database, the match between patent assignee and a parent EEM is not straight forward. Often there are multiple similar assignee names. In such cases, we use the industry sources mentioned above to match the assignee to the EEM identified in the EIA report. After this exercise, if we are still uncertain about the exact match, we retain all the similar assignee names and classify them under one EEM[17]. Lastly, we match the sample of EEMs from EIA Form 767 to COMPUSTAT data that contains firm financial characteristics such as profits and assets.

From the data we find that, out of the 89 equipment manufacturers identified by the EIA, approximately 55 percent patented in the U.S. during our sample period. In addition, these firms most frequently patented in US patent class 110 (Furnaces).[18] Matching the EEM list to COMPUSTAT leaves us with 15 firms. For all our samples, if a patent assignee or firm does not patent in a given year, we set the number of patents to zero in that year. We do not drop the observation.

[17] As a robustness check we have excluded these companies from the sample and there is no significant difference to the estimation results.

[18] Placement of an original patent into Class 110 requires the following minimum structure or steps for operating such structure: (1) means or a step to either convey or support solid combustible material during combustion, (2) means or a step to supply either directly or indirectly a noncombustible fluid to the solid combustible material, and (3) means or a step to enclose or control the combustion reaction.

3.2. Variable Construction

Dependent Variables

Our primary dependent variables fall into two categories: measures of patenting activity and citation-based patent characteristics. In Table 2, to measure patenting activity, we construct patent shares by patent class and by patent assignee. This patent share variable is constructed by dividing the number of patents granted in each patent class, or to each assignee, by all patents granted in the US.[19] In Tables 3, where we focus on EEMs in particular, we use patent counts as the dependent variable. For Table 4, we use the citation-based measures to construct two main patent characteristics: patent "quality" and "generality." The number of citations received per patent is often used as a measure of patent quality. This form of measurement is based on the idea that patents that make significant contributions will have more citations, i.e., a greater number other patents will cite these patents, than those that embody minor innovations (Jaffe et al. 1993, 2000). However, the raw number of citations that a patent receives can be misleading. A patent may receive more citations simply because there are more patents in a given field in the following years, or it may come from a field where it is customary to cite frequently. To solve this, we purge the citations of the year and field effects as suggested by Hall, et al. (2001). We then create demeaned average and total citation measures, and citation stocks[20] by patent class and year and by firm and year. The generality measure was developed by Trajtenberg, Jaffe, and Henderson (1997) and is based on citations received by individual patents. Generality implies

[19] For robustness, we have constructed alternative patent share measures, where the numerator is number of patents granted in each patent class or to an assignee (same as above), and the denominator is USPTO patents granted to all corporations, or granted to US corporations.
[20]We use the declining balance formula outlined in Hall et all. (2005) to create the citation stocks, and use a 15 percent depreciation rate.

that patents from a variety of other classes cite this particular patent, i.e., it has a significant impact on a wide variety of fields.[21]

Variables Capturing the Effects of Deregulation

To test the predictions from the theoretical framework, we first need to identify deregulation dummies, electricity technology classes, and the EEMs who supplied technology to downstream utilities. We construct two restructuring dummies that identify the two major law changes that ushered in competition in the electricity market. The *deregulation dummy* is 1 after the passage of the EPAct in 1992. Using the theory model, the two channels through which downstream competition may affect upstream innovation behavior are the appropriation effect and the competition effect. The *appropriation effect* captures the difference in profits for the utilities in the pre- and post-restructuring periods. We use the average profit (return on assets) of all downstream utilities to characterize this effect. The *competition effect* measures the impact of new entry on EEM innovation. Ideally, we want to obtain the number of entrants to the generation sector in each year and their generation capacity. However, this data is difficult to obtain, so we use the share of generation by non-utilities as a proxy for competition. We assume that if utilities are losing market share, this must be due to non-utilities entering the market.

We then construct dummies that identify the electricity patent classes and the EEMs. Form EIA 767 contains exhaustive data on EEMs, including their names and the particular type of technology they supply. The NBER patent data also includes company names and unique assignee numbers for each of those companies. The *EEM dummy* is 1 if the company was identified as an EEM in Form EIA 767. Supplementary appendix tables I and II provide the

[21] Generality = $1-\sum_{j=1}^{J}\left(\frac{n_{ij}}{n_i}\right)^2$ where n_i is the number of forward citations to a patent and n_{ij} is the number of citations received from patents in class j. A detailed discussion about this variable can be found in Hall, Jaffe, and Trajtenberg (2001).

details. To identify core electricity technology classes, we cross reference the US Patent Office electricity technology classes[22] with those in which the EEMs patent. The *electricity patent class dummy* is 1 if it is a electricity-related patent class and there is EEM patenting activity in that class. This yields 50 patent classes.

Innovation Inputs

We use lagged patent characteristics to capture the innovation environment of a firm or patent class. When explaining the number of patents in a patent class obtained by a firm, we use *lagged quality stock*, *lagged average generality*, and the *average number of claims* as input measures. The idea is that past patents serve as knowledge inputs for current patents, so the quality of input, as measured by past citations, matters. For example, if a firm has had a very high quality patent portfolio in the past, it has a better base of knowledge to build on than another firm with low quality patents. We construct past citation stocks[23] to measure innovation input quality. Therefore, the former will have more inventions than the latter. The generality variable should affect the number of patents in the same way.

The average number of claims is used as a proxy for patent breadth (Guellec et al., 2006) – the more claims a patent makes, the more things it "claims" to do, giving it a bigger breadth. The effect of this variable on patents in unclear. If past patents have a greater breadth, then numerous potential applications may have already been covered. This phenomenon may lead to a lower number of current patents. Conversely, if breadth serves as a proxy for quality, we may find the reverse effect. When we use the patent characteristics as the explanatory variables, we include the *lagged patent stock*[24] as an additional control. We hypothesize that a firm that has a

[22] Source table: http://www.uspto.gov/web/offices/ac/ido/oeip/taf/stelec.pdf
[23] As mentioned previously, we use the declining balance formula outlined in Hall et all. (2005) to create the citation stocks, and use a 15 percent depreciation rate.
[24] We use a 15 percent depreciation rate to create patent stocks following Hall et. al (2005)

high patent stock also has a greater number of inputs at its disposal and is, therefore, more likely to come up with better inventions.

Firm Characteristics

In Table 2, where our sample is all EEMs, we use several firm-level variables to account for the nature of the firm. EEMs produce three main types of products: boiler manufacturers, flue gas desulfurization manufacturers, and low nitrogen-oxide control burners. We construct two dummies based on the type of products. The *multiproduct firm dummy* is value 1 if an EEM produces more than one type of product. It is possible that such a firm will produce a greater number of innovations since its activities span a greater product space. In addition, we also include a separate *dummy for EEMs that produce burners or desulfurization unit*s. The Clean Air Act Amendments (CAAA) of 1992 targeted older generation plants in need of updating their pollution control technologies. The two primary technologies that could be adopted to meet the CAAA requirements were low NOx burners and desulfurization units. Thus, this dummy captures the effect the CAAA may have had on these specific EEMs. In addition, we create a *large EEM dummy* that captures whether the EEM is publicly traded in the US or not. This variable serves as a proxy for firm size and R&D because we lack data for these variables. Last, we include a *US firm dummy* that captures whether the EEM is headquartered in the US, since our sample includes both domestic and foreign EEMS.

Macro Environment

In all specifications, we include three main macro controls: the *number of boilers affected by the CAAAs*, a *measure of R&D*, and *GDP*. The CAAA forced utilities to undertake pollution control measures, and, thus, it is conceivable that as more boilers have to be in compliance, demand for new technology will increase. We hypothesize that this increased downstream demand will have a positive effect on upstream innovation. This data is from the EIA Clean Air Act Database. The GDP variable captures the overall health of the economy and controls for macro fluctuations; it is obtained from the Bureau of Economic Analysis. The R&D variables are obtained from the National Science Foundation data on Science and Technology Indicators and from the EIA. We use two alternate measures of R&D. In Tables 2 and 5, we use the total *R&D expenditure stock* in the US to capture the overall research spending in the economy. In Table 3, since our sample is restricted to EEMs, we use *total energy R&D expenditure* (federal and company). All dollar figures are in real terms (2000 dollars), and all time-varying explanatory variables are lagged by 2 years.

4. Empirical Methodology and Results

4.1. Deregulation and Electricity Innovation

We begin by estimating a simple difference-in-difference model to see whether the regime change after deregulation had a significant impact on the innovation behavior of the upstream EEMs. This ensures that deregulation was indeed responsible for the decline in the quantity and quality of innovation in the electric equipment manufacturing sector and that this was not just a secular downward trend that had little to do with the deregulation policies.

$$Y_{it} = \alpha + \beta D_{treatment} + \phi D_{treated} + \theta(D_{treament} * D_{treated}) + \phi t + \sum_{J=1}^{j} \theta_J Z_{it}^{j} + v_i + \varepsilon_{it} \qquad (7)$$

In the equation above, Y_{it} is the percentage of patents[25] for a given patent class or firm in a given application year, t is a time trend and Z^j are other control variables. $D_{treatment}$ is the deregulation dummy (lagged by 2 years), and $D_{treated}$ captures the treated group, which is either electric

[25] Percentage of patents per patent class = (Number of patents granted in a patent class *i* in year *t*/Total number of utility patents granted by the USPTO)*100. The year refers to application year.

equipment patent classes (compared to all other patent classes) or the EEMs (compared to a random sample of US manufacturing firms). θ is the difference-in-difference coefficient. If deregulation was responsible for a significant negative impact on the innovation behavior, we expect θ to have a negative sign.

Since the dependent variable is in percentage, we cannot use a panel data fixed effects model; the predictions from this model will not be bounded between zero and hundred, as is required by the nature of the dependent variable. Instead, we estimate a panel tobit model[26] (Wooldridge, 2001). This model accounts for the left-censoring of the data at 0 and for the right censoring at 100. We present the results in Table 2. However, we have conducted using several robustness checks using a random effect GLS model with robust and clustered standard errors and a first order autocorrelated model, and the results are stable across all specifications.

From Table 2, the interaction term between the treated group and the treatment dummy is the coefficient of interest. As outlined earlier, a negative and significant coefficient implies that deregulation has adversely affected the outcome being studied. In column 1, the sample consists of patents granted to corporations in all patent classes between 1980 and 2000. The dependent variable is the number of patents granted in each patent class in a given year.[27] The treated groups are the electric equipment patent classes. First, we find that the passage of the EPAct has had no influence on patenting. Second, electric equipment classes have a higher number of

---

[26] We assume that the random effects, v_i, are normally distributed with zero mean and constant variance σ^2_v, i.e. N(0, σ^2_v). Thus we have: $\Pr(y_i \mid x_i) = \int_{-\infty}^{+\infty} \frac{e^{-v_i^2/\sigma_v^2}}{\sqrt{2\pi\sigma_v}} \left(\prod_{t=1}^{n_i} F(x_{it}\beta + v_i) \right) dv_i$

where: $$F(\Delta_{it}) = \begin{cases} (-1/\sqrt{2\pi\sigma_\varepsilon})e^{-(y_{it}-\Delta_{it})^2 /)2\sigma_\varepsilon^2)} & \text{if } y_{it} \text{ is non-censored,} \quad \Phi\left(\frac{y_{it}-\Delta_{it}}{\sigma_\varepsilon}\right) \quad \text{if } y_{it} \text{ is left-censored} \\ 1-\Phi\left(\frac{y_{it}-\Delta_{it}}{\sigma_\varepsilon}\right) & \text{if } y_{it} \text{ is right-censored} \end{cases}$$

This model is estimated in Stata by Gauss-Hermite quadrature.

[27] All counts are by application year, i.e., out of all the patents applied for in year t, the number that were granted.

patents when compared to non-electric equipment classes, holding all else constant. But the difference-in-difference coefficient (-0.074) is negative and significant at the 1 percent level, implying that the introduction of competition in the power sector has had an adverse impact on patenting in the electric equipment patent classes when compared with other patent classes.

We find the same pattern from column 2, where we test whether the EEMs were adversely affected compared to other groups within the electric equipment patent classes. We find that, all else equal, the passage of the EPAct has had no impact on patenting in electric equipment classes, and the percentage of EEM patents is higher when compared to other assignees in the electric equipment technology classes. As before, the difference-in-difference coefficient is negative and significant (-0.009), implying that patenting by EEMs declined following the EPAct. Before investigating the channels through which such declines occurred, we briefly discuss how the other variables affected patenting.

As discussed earlier, we control for measures of input quality in these regressions. Previous patents are often used as inputs in current patents, and the properties of past knowledge will influence the amount of innovation that is generated today (Popp, 2002, 2006). First, we control for the average stock of patent "quality" in past years[28] in a given class. Apriori, it is difficult to anticipate the direction of impact. One could argue that better quality inputs may increase current innovation. However, the reverse may be true as well – if a class already has patents of very high quality, the patent space may be crowded, and it may be difficult to come up with patentable innovations. From Table 2, we find support for the former hypothesis. We find that a 1 percent increase in patent quality stock increases the percentage of patents in each class (on average) by 0.001 percent (column 1). We also control for the average generality of a patent

[28] We lag the patent class characteristics by 2 years since these are used as measures of past knowledge and input quality, and since the diffusion of knowledge is not instantaneous, current patents would build on patents that had been granted a couple of years earlier.

class in a given year. Higher average generality implies that patents in this class influence knowledge in a wide range of fields, so it may be easier to build on these patents and come up with patentable inventions in such a fertile field. The number of claims, which measures the breadth of the class, also has a positive impact on patenting implying that greater patent breath in the past encourages current innovation. We also find that as the number of boilers affected by the Clean Air Act Amendments increases, it encourages innovation in general. However, electric technology classes and EEMs show decreased innovation after CAAA. This result is counterintuitive since the CAAA should have increased innovation by these particular groups. We suspect that instead to picking up the effect of the CAAA, this result reflects the effect of further restructuring activity around 1996, when the second phase of boilers had to be brought under compliance. Lastly, lagged R&D stock has a positive impact on overall patenting, and income levels have no additional impact.

4.2. Channels of Influence

Next, we focus solely on the EEMs and estimate a richer model that incorporates the appropriation and entry effects and illustrates the channels through which downstream deregulation impacted upstream innovation. Our sample consists of all EEMs,[29] and we estimate the effect of deregulation on the innovation activity of these firms by focusing on the number of patents granted to each EEM. Since these patent counts are non-negative integer numbers, we cannot use the usual least squares approach.[30] In addition, these counts have a disproportionate

[29] Supplementary Appendix Table 1b provides a list of these companies along with their assignee codes (from the NBER Database) and patenting rank.

[30] Using OLS will yield some negative predicted values. But since the dependent variable is non-negative, the predicted values should also be non-negative for all explanatory variables. If all values of the dependent variable were strictly positive, we could have used a log transformation. However, since some of the values are zero, we prefer using a count data model.

number of zeros[31] since many of the smaller EEMs do not patent every year, and some EEMs never patent during our sample period. The data-generating process for the zero outcomes may be qualitatively different from the process that generates the positive outcomes. Therefore, we estimate the above equation using a zero-modified negative binomial model.[32] The log-likelihood function for the model has two distinct parts--one that models the zero outcomes and another that is used for the positive counts.

In the first stage, the zero outcomes are modeled as a binary probability model (logit specification in our case) that describes the probability of observing a zero or positive outcome. It is shown by equation 8 below.

$$\Pr ob(Z = 1 \mid X) = \frac{e^{x'\beta}}{1 + e^{x'\beta}} \tag{8}$$

where: Z is the dependent variable and is either 1 or 0 depending on whether the EEM has at least one patent in the given application year. The vector explanatory variables (X) include lagged patent stock, lagged average quality of past patent portfolio, a dummy denoting whether the EEM is a large firm, a dummy for multiproduct firm, a dummy denoting a US or foreign firm, lagged energy R&D expenditure and GDP in the US (in real 2000$), and year fixed effects.[33]

The patent counts are then modeled using a negative binomial function[34] with robust standard errors that are clustered by firm. This specification is given by equation 9 below.

---

[31] About 55 percent of the dependent variable has zero value.

[32] See "Econometric Analysis" (Fifth Edition, Prentice Hall) by W. H. Greene for a discussion of the model.

[33] From the estimation results, we find that EEMs that have more past patents and greater quality past patents are more likely to innovate in the current period. Being in a multiproduct firm or large firm increases the likelihood of getting a patent; however, the coefficients are not significant. US firms are less likely to patent. R&D and GDP have negligible impact.

[34] Exclusion restrictions for the model imply that there must be at least one variable that is included in the logit model that is not included in the negative binomial part. The multiproduct firm dummy and the lagged patent stock serve as exclusion restrictions.

$$Y_{it} = \alpha + \beta D_{treatment} + \chi A_t + \delta C_t + \phi_i (D_{treatment} * A_t) + \varphi_i (D_{treatment} * C_t) + \sum_{P=1}^{p} \gamma_P Char_{it} + \sum_{M=1}^{2} \delta_M Macro_t + \varepsilon_{it} \quad (9)$$

where: Y_{it}, the number of granted patents for each EEM in a given application year t, is regressed on the deregulation dummy ($D_{treatment}$), the appropriation and competition effects (A_t and C_t respectively), and two interaction terms. The interaction terms between the treatment dummy and the appropriation and competition effects, show how these latter variables affect innovation behavior after deregulation. $Char_{it}$ denote a set of firm specific controls, such as patent characteristics for each EEM, capturing the quality of previous knowledge that the firm can build on and the type of firm (i.e. boiler manufacturers, flue gas desulfurization manufacturers, low nitrogen-oxide control burners, or a combination). $Macro_t$ denotes the macro controls. In Table 3, columns 1a and 1b, the sample consists of all EEMs, irrespective of whether they have a patent or not. In columns 2a and 2b, we restrict the sample to EEMs that have at least one patent during our sample period, 1980-2000. Columns 1a and 2a report the semi-elasticities while 1b and 2b report the aggregate elasticities (or semi-elasticities for dummy variables) after taking into account the interaction terms. The results are similar in sign and significance across the two samples, and we will discuss the results in column 1a and b.

First, we find that, after factoring in the direction and magnitude of the appropriation and competition interactions, deregulation alone has led to a 14.5 percent decline in patenting by EEMs. We also find that both the appropriation effect and the competition effect are significant after the passage of the EPAct, but not before. Before the EPAct, the regulated electric industry did not behave like a profit maximizer, so the adoption of new technology was not governed by cost-minimization concerns. Thus, the appropriation effect is not important in explaining upstream innovation in the regulated era. After the introduction of the EPAct, this effect determines, in part, the innovation response of EEMs. From the theoretical model we know that if the profitability from adopting a new technology declines, as captured by the difference in pre- and post-EPAct profits of downstream utilities, then upstream innovations will decline. We find that a 1 percent decline in downstream profits decreases upstream innovation by approximately 6.5 percent post-EPAct. From Table 1B we observe that for our sample period, profits have declined on average, by 3 percent after deregulation. Thus the appropriation effect is responsible for a 19.5 percent decrease in innovation.

The competition effect, which captures how the status quo payoff of EEMs before and after restructuring affects innovation, is not significant before the EPAct. This is expected because prior to 1992, there were very few new generating companies that were entering the downstream generation market. This changed in a significant way after restructuring, and keeping with the theoretical model, we find that the innovation increases when EEMs have greater outside opportunities to sell their product as new companies enter the downstream market. Empirically, we find that a 1 percent increase in competition, as captured by the non-utility generation share, increases innovation by approximately 1.6 percent following the introduction of the EPAct. From Table 1B we observe that for our sample period, competition has increased on average, by 6.68 percent after deregulation. Thus the appropriation effect is responsible for a 10.7 percent increase in innovation.

In addition, we find that the quality of innovation inputs matter (Popp, 2002, 2006). Firms that produced higher quality patents in the past had a higher number of current patents. A 1 percent increase in the patent quality stock increased current patents between 0.18 to .31 percent. In addition, companies whose past patent portfolios were more general also showed an increase in current patenting. The breadth of the past patent portfolio did not affect current innovation. To account for the effect of the CAAA of 1992, we included the interaction of the number of boilers affected by the CAAA each year and the dummy for firms that produced the low NOx burners and desulfurization units. Consistent with earlier literature (Popp, 2003), we find that the CAAA had a positive impact on innovation for these particular EEMs. Last, we find that the size of the EEM has no impact on patenting, while U.S. based EEMs are less innovative than their foreign counterparts. The R&D and GDP variables are not significant in any specification.

4.3. Patent Characteristics

Guided by the finding from our theoretical framework, we have focused solely on the magnitude of innovations in the above specifications. However, we believe that studying the effect of regulatory changes on patent characteristics is an important empirical question, since patent numbers do not allow us to draw conclusions about the changing nature of innovation. For example, Firm A has 25 patents with an average of 10 citations per patent before deregulation. The firm has 15 patents, each with an average of 5 citations, after deregulation. Firm B also has 25 patents before deregulation and 15 patents after. However, it has 5 citations per patent on average pre-deregulation and 3 citations per patent on average after deregulation. If we focus solely on the number of patents, the effect of deregulation is the same for both firms. Clearly, this is not the case. Pre-deregulation, Firm A is producing innovations of greater quality than Firm B. However, after deregulation, Firm A suffers a greater quality decline than does Firm B.

In addition, with the introduction of competition in the downstream power sector, EEMs may face greater pressure to shorten their innovation cycle, and this would adversely affect both the quality and generality of their innovations. They would build on narrow previous knowledge and not explore other fields. This may lead to a decline in the average quality, and generality would also decline since these patents would embody very narrow technology. To capture this quality variation, we use characteristics such as quality and generality using the difference-in-difference model outlined in equation (7).

We use two metrics to measure patent quality: the average and the aggregate adjusted quality of a firm's patent portfolio[35], since neither one by themselves may be sufficient to capture true innovation quality. In an environment where EEMs are getting fewer patents than in previous years, total citations to a firm's portfolio of patents may fall simply because the number of patents obtained by the EEM is declining, or because there are fewer citing patents in the electric technology class. Thus a decline in total number of citations may not be a true indicator of quality decline. Mean quality however, may be a better metric. This would fall if and only if the rate of decline in citations is greater than the rate of decline in the number of patents. Hence we use both measures to assess the effect of deregulation on patent quality of EEMs.

Quality, as explained earlier, is measured by the number of backward citations received by a patent (a count variable), purging these of technology and year effects and using the means and stocks of these variables (by firm) make them continuous. The adjusted generality measure is a continuous variable for the same reason. When measured in levels all the above variables are bounded by zero on the lower end of the distribution. Hence a panel tobit model that accounts for the truncation would be appropriate. However, this does not allow one to correct errors for

[35] Average adjusted quality is measured by the mean number of citations (purged of year and field effects) that each firm/assignee receives. Aggregate adjusted quality is the total number of citations (purged of year and field effects) that each firm/assignee receives. When we purge the citations of year and field effects, this in essence controls for technology and year fixed effects.

clustering and heteroscedasticity. Therefore we use a random effects GLS model[36] with clustered and robust standard errors when estimating the average quality and generality specifications. We have conducted using several robustness checks using a random effect tobit model and a censored normal, and the results are stable across all specifications. For the aggregate quality equation there is a strong autocorrelation component in the data and correcting the errors for AR(1) is necessary, and hence we use a linear AR(1) panel data model in this case.

Results are presented in Table 4 where the sample consists of electric equipment patent classes only. The unit of observation is the patent assignee, the treated groups are the EEMs (electric equipment manufacturers), and the control group is a random sample of 2000 firms[37] that patent in the electric equipment classes but are not EEMs. The dependent variables are the average (adjusted) quality, aggregate (adjusted) quality, and average (adjusted) generality by patent assignee. Columns 1 and 2 present results for patent quality. From both columns we find that the difference-in-difference coefficient is strongly negative and significant implying that deregulation has led to a decline in patent quality for EEMs. For example, after deregulation EEM average adjusted patent quality declines by 38.55 percent while aggregate adjusted quality declines by 23.76 percent. On average EEM patent quality is higher than other patents in the electric technology category. From column 3 we find that, again, the difference-in-difference coefficient is negative and significant, implying that after deregulation patents generated by EEMs became less general compared to that of other firms, alluding to the fact that equipment manufacturers may be concentrating on a narrow set of innovations. Deregulation has led to a 50.93 percent decline in average generality, although EEM patent generality is higher compared to the control group.

[36] The error can be disaggregated into two components: v_i - the random disturbance that varies by firm but not over time ($v_i \sim N(0, \sigma^2_v)$), and ε_{it} - is the idiosyncratic error component ($\varepsilon_{it} \sim N(0, \sigma^2_\varepsilon)$).
[37] We selected a random sample of 2000 firms for tractability.

We also find that past patent stock has a positive effect on the quality and generality of current patents, i.e., firms that have a bigger portfolio of past patents tend to produce better quality and more general patents in the current period. The breadth of the patent portfolio also has a positive impact on both average quality and average generality. In addition, firms with more ‘general’ and broader past patent portfolios have greater average quality. Also firms with better quality of past patents produce more general innovation, and firms whose innovation spans a greater technological area tend to produce more quality patents. Our control for the CAAA is negative and significant, implying that after the CAAA, average patent quality and generality has suffered. In addition, in columns 1 and 2, the interaction between the EEM dummy and the CAAA term is negative and significant implying that EEM patent quality suffered after CAAA. However, we do not believe that this is the effect of the CAAA. Rather as argued earlier, this may be the effect of the accelerated deregulation policies pursued by states after 1996 that coincided with the second compliance phase of the CAAA. As before, aggregate R&D stock appears to have a negative effect on quality and we believe that this may be picking up some secular trend in the data. Last improving economic environment (as captured by the GDP variable) has a positive effect on average patent quality. The main finding of Table 4 is the significant negative impact that deregulation has had on patent quality and generality.

5. Conclusion

Deregulation has dramatically changed the landscape of the US electric utility industry by introducing competition in the generation sector. Product market competition from non-utilities (such as the independent power producers) has made utilities more conscious of their bottom line. This shift has impacted their technology buying behavior, which has, in turn, affected EEM innovation. This paper models the effect of such downstream competition on upstream innovation behavior in situations where the technology buyer and seller are not vertically integrated. The theoretical model outlines the conditions under which competition may induce greater innovation or dampen it. The empirical section uses this model to explain why electric equipment innovation suffered after deregulation.

The theoretical model outlines two opposing effects of deregulation: the appropriation effect and the competition effect. The appropriation effect measures the difference in marginal profits of each downstream firm due to the upstream innovation. Post-deregulation, the value added (to utilities) due to new technology adoption decreases because of the competition faced by utilities. This decline in value added decreases the demand for new technology, which, in turn, negatively affects the innovation incentive for the upstream firms. However, the competition effect increases innovation. Greater downstream competition and increased participation of non-utilities in the wholesale market increases the EEM customer base, positively affecting innovation. The relative strength of these two effects determines the overall effect of downstream product market competition on upstream innovation.

The empirical results show that for the electricity industry, competition in the downstream sector has adversely affected the innovation behavior of EEMs. First, using difference-in-difference models, we show that the introduction of competition in the power sector has had an adverse impact on patenting in the electric equipment patent classes when compared with other patent classes. In addition, patenting by EEMs declined after the passage of the EPAct when compared to other firms in the electric equipment technology sector. Next, we use the theoretical model to understand the channels through which such a decline has occurred. We find that deregulation alone has led to a 14.5 percent decline in patenting by EEMs. We also find that both the appropriation effect and the competition effect are significant after the introduction of the EPAct, but not before. Following the passage of the EPAct, the appropriation effect has led to a 19.5 percent decline in innovation which has been partly offset by an increase of 10.7 percent due to the competition effect. In addition, the innovation environment of a firm matters, and the quality of innovation inputs affect current patenting. The CAAA has had a positive impact on innovation for firms that manufacture low NOx burners and gas desulfurization units, and large firms have higher patents. Last, we find that US EEMs have lower patents when compared to their foreign counterparts. We take the empirical model further by investigating the impact of deregulation on innovation characteristics. We find that average quality, aggregate quality and average generality has declined by 38.5, 23.7 and 50.9 percent respectively after deregulation. Thus the introduction of downstream competition has degraded the quality of upstream innovation and has made them more specific and less general.

This paper contributes to the innovation-competition literature by developing a theoretical framework to model upstream-downstream innovation behavior and by testing the predictions of the model with novel data. The results have implications for all industries with a similar organizational structure and may help in furthering our understanding of innovation incentives in complex markets.

References

Aghion, Phillipe & Peter Howitt, (1996) – "Research and Development in the Growth Process", ***Journal of Economic Growth,*** *1:49-73.*

Aghion, Phillipe & Peter Howitt, (1992) – "A Model of Growth Through Creative Destruction", ***Econometrica,*** *60: 323-351.*

Aghion, Philippe & Dewatripont, Mathias & Rey, Patrick, (1999)- "Competition, Financial Discipline and Growth," ***Review of Economic Studies****, 66(4): 825-52.*

Aghion, Phillipe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt, (2005) – "Cpmpetition and Innovation: An Inverted-U Relationship," ***Quarterly Journal of Economics****, 117 (2): 701-728.*

Arrow, Kenneth (1962) – "Economic Welfare and the Allocation of Resources for Invention," ***The Rate and Direction of Inventive Activity*** (Princeton, NJ; Princeton University Press); 609-625.

Binmore, Ken, Ariel Rubinstein and Asher Wolinsky, (1986) – "The Nash Bargaining Solution in Economic Modeling", ***Rand Journal of Economics****, 17: 176-188.*

Blumstein, Carl (1997) - "What is Public Interest R&D", *Energy Views, POWER Notes Newsletter, Fall. University of California Energy Institute*, Berkeley.

Borenstein, Severin & Bushnell, James (1999) - "An Empirical Analysis of the Potential for Market Power in California's Electricity Market", ***Journal of Industrial Economics*** *47(3):285-323.*

Borenstein Severin, James Bushnell, and Steven Stoft. (2000)- "The Competitive Effects of Transmission Capacity in a Deregulated Electricity Industry", ***Rand Journal of Economics****, 31, No. 2: 294-325.*

Brocas, Isabelle, (2003)- "Vertical Integration and the Incentives to Innovate", ***International Journal of Industrial Organization****, 21 (4): 457-488.*

Buehler, Stefan, Armin Schmutzler and Men-Andri Benz (2004)- "Infrastructure Quality in Deregulated Industries: Is there an Underinvestment Problem?" ***International Journal of Industrial Organization****, 22(2): 253-267.*

Buehler, Stefan, Dennis Gartner and Daniel Halbheer, (2006)- "Deregulating Network Industries: Dealing with Price-Quality Tradeoffs," ***Journal of Regulatory Economics****, 30 (1): 99-115.*

Choi, Jay Pil, Gwanghoon Lee and Christodoulos Stefanadis, (2003)- "The Effects of Integration on R&D Incentives in Systems Markets," ***Netnomics****, 5(1): 21-32.*

Cohen, L. R. & Sanyal. P. (2007a) – "R&D Choice in Restructured Industries: In-house v/s Collaborative Research in the US Electricity Industry", *Working Paper, Brandeis University.*

Gilbert, Richard, (2006)- "Looking for Mr Schumpeter: Where are we in the Competition-Innovation Debate?," in ***Innovation Policy and the Economy***, Adam Jaffe, Josh Lerner and Scott Stern (eds), Cambridge, MA: National Bureau of Economic Research.

Guellec, Dominique, van Pottelsberghe de la Potterie, Bruno and van Zeebroeck, Nicolas (2006) - "Claiming More: The Increased Voluminosity of Patent Applications and its Determinants". *CEPR Discussion Paper No. 5971*

Hall, Bronwyn H.; Jaffe, Adam B. & Trajtenberg, Manuel (2005) - "Market Value and Patent Citations," ***Rand Journal of Economics,*** *36, 16-38.*

Hall, Bronwyn H.; Jaffe, Adam B. & Trajtenberg, Manuel (2001) – "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools", *NBER Working Papers 8498, National Bureau of Economic Research, Inc.*

Hart, Oliver (1983) - The Market as an Incentive Mechanism", ***Bell Journal of Economics***, *14, 366-382.*

Hermalin Benjamin (1992) – "The Effects of Competition on Executive Behavior", ***Rand Journal of Economics***, *23, 350-365.*

Hermalin Benjamin (1994) – "Heterogeneity in Organizational Form: Why Otherwise Identical Firms Choose Different Incentives for their Managers", ***Rand Journal of Economics***, *25, 518-537.*

Jaffe, Adam B., Trajtenberg, Manuel and Fogarty, Michael S. (2000) – "The Meaning of Patent Citations: Report on the NBER/Case-Western Reserve Survey of Patentees" *NBER Working Paper No. W7631*

__________; Peterson, Steven R.; Portney, Paul R. and Stavins, Robert N. (1995) - "Environmental Regulation and the Competitiveness of US Manufacturing: What Does the Evidence Tell Us", ***Journal of Economic Literature****, 33(1): 132 – 163.*

___________; Trajtenberg, Manuel; and Henderson, Rebecca (1993) – "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations" ***The Quarterly Journal of Economics,*** *108(3), pp. 577-598*

Joskow, Paul (1999) - "Deregulation and Regulatory Reform in the US Electric Power Sector". *Discussion draft for Brookings AEI Conference on Deregulation in Network Industries.*

______ (1997) - "Restructuring, Competition, and Regulatory Reform in the US Electric Sector", ***Journal of Economic Perspectives****, 11(3): 119-138.*

Karuna, Christo (2007) – "Industry Product Market Competition and Managerial Incentives", ***Journal of Accounting and Economics***, *43: 275-297.*

Loury, Glenn, (1979) - "Market Structure and Innovation," ***Quarterly Journal of Economics***, *93(3): 395-410.*

Popp, David (2006) "They Don't Invent Them Like They Used To: An Examination of Energy Patent Citations Over Time," ***Economics of Innovation and New Technology***, *15(8): 753-776.*

________ (2003) "Pollution Control Innovations and the Clean Air Act of 1990", ***Journal of Policy Analysis and Management***, *22(4): 641-660.*

_________ (2002) "Induced Innovation and Energy Prices," ***American Economic Review***, *92(1): 160-180.*

Puller, Steven (2007) – "Pricing and Firm Conduct in California's Deregulated Electricity Market", ***Review of Economics and Statistics***, *89(1): 75-87*.

Raith, Michael (2003)- "Competition, Risk and Managerial Incentives", ***American Economic Review***, 9*3 (4): 1425-1436.*

Sanyal, Paroma & Cohen, Linda R. (2007b) **–** "Powering Progress: Restructuring, Competition, and R&D in the U.S. Electric Utility Industry", ***The Energy Journal,*** *Forthcoming.*

Scharfstein, David. (1988) – "Product Market Competition and Managerial Slack", ***Rand Journal of Economics***, *19, 147-155.*

Scherer, F.M. and D. Ross. (1990) **–** ***Industrial Market Structure and Economic Performance***, *3rd Edition (Boston: Houghton Mifflin Company)*

Schmidt, Klaus M. (1997) **–** "Managerial Incentives and Product Market Competition", ***Review of Economic Studies***, *64, 191-213.*

Schumpeter, Joseph. (1942) **–** ***Capitalism, Socialism and Democracy.*** (*London: Alan and Unwin).*

Trajtenberg, Manuel; Jaffe, Adam B. & Henderson, Rebecca (1997) **–** "University Versus Corporate Patents: A Window on the Business of Invention", ***Economics of Innovation and New Technology***, *5(1): 19-50.*

Wolak, Frank A. (2004) - "Market Design and Price Behavior in Restructured Electricity Markets: An International Comparison", in ***The California Electricity Crisis: What, Why and What's Next****.* Springer US: 75-83.

Woolbridge, (2002) - ***Econometric Analysis of Cross Section and Panel Data***. Cambridge MA, MIT Press.

APPENDIX 1

From (3) we know that $\overline{\pi}'((c(I^*),\phi_M) = g'(I^*)$

and from (5) $\overline{\pi^C}'((c(I^{**}),\phi_C) + \pi^1{}'(I^{**}) = g'(I^{**})$.

We need to prove that $\overline{\pi}_{12} < \pi^1{}'$ then $I^{**} > I^*$.

Suppose Not. Then it implies that

$$\overline{\pi}_{12} < \pi^1{}' \text{ but } I^{**} < I^*.$$

From the convexity of the g function then we could infer that

$$g'(I^{**}) < g'(I^*).$$

But then from the above equations (3) and (5) this would in turn imply that

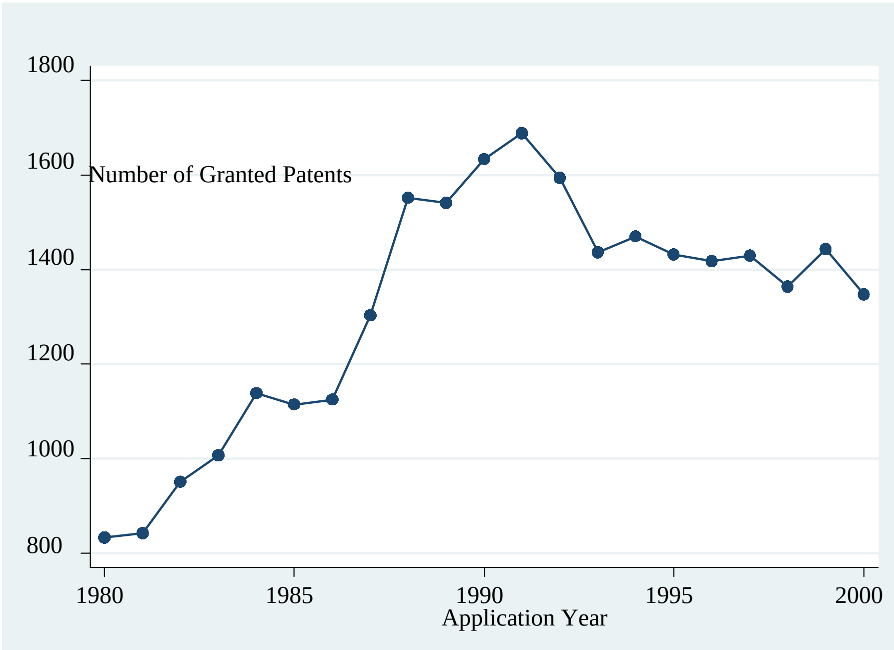
$$\overline{\pi^C}'((c(I^{**}),\phi_C) + \pi^1{}'(I^{**}) < \overline{\pi}'((c(I^*),\phi_M).$$

Given our assumptions that $\pi_{12}, \pi_{21} < 0$

and $\pi^1{}' > 0$ this would be true only if $\overline{\pi}_{12} > \pi^1{}'$, which is a contradiction.

APPENDIX FIGURE I

Patents Obtained by Electric Equipment Manufacturers in Electric Equipment Patent Classes



APPENDIX FIGURE II

Patents Obtained by Corporations in "Drug" Classes

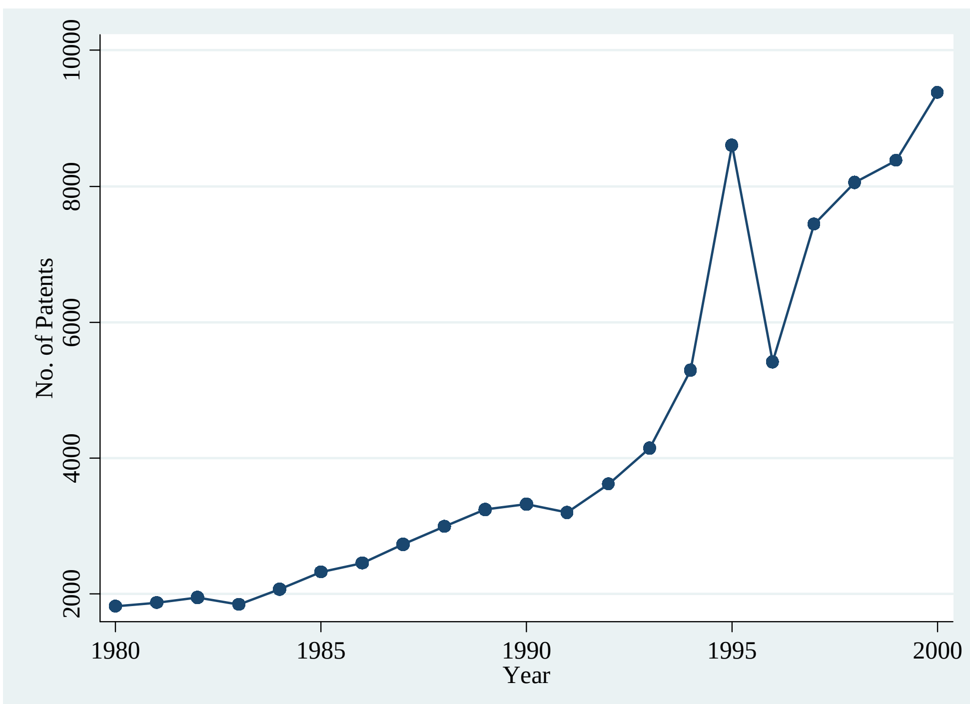


Table 1A
Summary Statistics for Table 2 and 4

Sample: All Patent Classes (Table 2)					
Dummy Variables	**Obs.**	**Zeros**	**Ones**		
EPAct Dummy (Lag 2 Yrs.)	11298	8070	3228		
Dummy for Electric Equipment Patent Classes	11298	10416	882		
Continuous Variables	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Percentage of Patents Per Patent Class (Dep. Var.)	11298	0.169	0.281	0	3.314
Patent Stock (Lag 2 Yrs.)	11298	774.132	1274.76	0	19010.27
Quality Stock (Lag 2 Yrs.)	11298	5958.205	10359.92	0	101075
Mean Adjusted Generality (Lag 2 Yrs.)	11298	0.971	0.757	0	17.221
Mean Adjusted Claims (Lag 2 Yrs.)	11298	0.703	0.507	0	10.533
Sample: Electric Equipment Patent Classes (Table 2 and Table 4)					
Dummy Variables	**Obs.**	**Zeros**	**Ones**		
EPAct Dummy (Lag 2 Yrs.)	44625	31875	12750		
Dummy for EEMs	44625	42000	2625		
Continuous Variables					
Percent. of Patents Per Assignee (Dep. Var. Table 2)	44625	0.001	0.013	0	0.418
Average (Adjusted) Quality (Dep. Var. Table 4)	44625	0.082	0.452	0	16.946
Aggregate (Adjusted) Quality (Dep. Var. Table 4)	44625	0.996	16.088	0	570.918
Average (Adjusted) Generality (Dep. Var. Table 4)	44625	0.095	0.428	0	4.994
Patent Stock (Lag 2 Yrs.)	44625	5.028	72.626	0	2221.944
Quality Stock (Lag 2 Yrs.)	44625	39.410	582.729	0	18199.97
Mean Adjusted Generality (Lag 2 Yrs.)	44625	0.102	0.442	0	4.994
Mean Adjusted Claims (Lag 2 Yrs.)	44625	0.079	0.358	0	11.524
Number of Boilers (CAAA)	44625	579.762	813.219	0	2000
US Total R&D Stk (Bill. 2000$) (Lag 2 Yrs)	44625	611.880	165.024	397.629	970.85
GDP (Billions of 2000$) (Lag 2 Yrs.)	44625	6696.848	1228.972	5015	9066.9
Sample: EEM Electric Equipment Patents (Table 4)					
Average (Adjusted) Quality (Table 4)	2625	0.179	0.564	0	7.437
Aggregate (Adjusted) Quality (Table 4)	2625	11.310	60.917	0	570.918
Average (Adjusted) Generality (Table 4)	2625	0.214	0.574	0	3.805

Table 1B
Summary Statistics for Table 3

Sample: All Electric Equipment Manufacturers					
Dummy Variables	**Obs.**	**Zeros**	**Ones**		
EPAct Dummy (Lag 2 Yrs.)	1764	1260	504		
Dummy for Low Nox Burner and Desulfurization Unit Producers	1764	378	1386		
Large EEM Dummy	1764	1260	504		
Dummy for Large US Firms	1764	546	1218		
Continuous Variables	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
No. of Patents (Dependent Variable)	1764	15.701	63.664	0	483
Mean Adjusted Quality Stock (Lag 2 Yrs.)	1764	654.390	2683.054	0	18524.43
Mean Adjusted Generality (Lag 2 Yrs.)	1764	0.257	0.609	0	3.805
Mean Adjusted Claims (Lag 2 Yrs.)	1764	0.193	0.473	0	4.403
Sample: Electric Equipment Manufacturers that Have At Least 1 US Patent					
Dummy Variables	**Obs.**	**Zeros**	**Ones**		
EPAct Dummy (Lag 2 Yrs.)	924	660	264		
Dummy for Low Nox Burner and Desulfurization Unit Producers	924	189	735		
Large EEM Dummy	924	546	378		
Dummy for Large US Firms	924	210	714		
Continuous Variables		**Mean**	**Std. Dev.**	**Min**	**Max**
No. of Patents (Dependent Variable)	924	29.975	85.519	0	483
Mean Adjusted Quality Stock (2 Yrs.)	924	1284.998	3606.513	0	18524.43
Mean Adjusted Generality (Lag 2 Yrs.)	924	0.488	0.770	0	3.805
Mean Adjusted Claims (Lag 2 Yrs.)	924	0.366	0.601	0	4.403
Both Samples					
Appropriation and Competition Effect					
Utility ROA (Lag 2 Yrs.) (Appropriation Effect)	1764	0.117	0.007	0.104	0.130
Share of Non-Utility Generation (Lag 2 Yrs.)(Competition Effect)	1764	0.042	0.044	0.001	0.111
	Pre-Deregulation			**Post-Deregulation**	
Utility ROA (Percentage)	1092	13.9		672	10.9
Percentage of Non-Utility Generation	1092	2.76		672	9.44
Macro Variables					
Number of Boilers (CAAA)	924	579.762	813.651	0	2000
Energy R&D Stk (Bill. of 2000$) (Lag 2 Yrs)	924	4.257	1.185	1.769	6.176
GDP (Billions of 2000$) (Lag 2 Yrs.)	924	6696.848	1229.623	5015	9066.9

Table 2
Patenting in Electric Technology after Restructuring

Sample (All Firms)	All Patent Classes	Electric Technology Classes
Dependent Variable	Percentage of Patents Per Patent Class	Percentage of Patents Per Assignee
	(1)	(2)
EPAct Dummy (Lag 2 Yrs.)	-0.007 (0.008)	-0.0002 (0.001)
Electric Equipment Patent Class Dummy	0.083*** (0.006)	
EPAct Dummy(Lag 2 Yrs.) * Electric Equip. Patent Class Dummy	-0.074*** (0.025)	
EEM Dummy		0.013*** (0.001)
EPAct Dummy(Lag 2 Yrs.) * EEM Dummy		-0.009*** (0.003)
Innovation Inputs		
Patent Quality Stock (Adjusted) (Lag 2 Yrs.)	0.00002*** (0.0000001)	0.00002*** (0.000002)
Mean (Adjusted) Generality (Lag 2 Yrs.)	0.034*** (0.003)	0.008*** (0.0004)
Mean (Adjusted) Number of Claims (Lag 2 Yrs)	0.111*** (0.005)	0.004*** (0.0005)
Macro Environment		
Number of Clean Air Act Affected Boilers	0.00001* (0.000005)	0.000001 (0.000001)
EEM Dummy * Number of Clean Air Act Affected Boilers	-0.00003** (0.00001)	-0.00001*** (0.000002)
Total R&D Stock (Billions of 2000$) (Lag 2 Yrs)	0.001*** (0.0001)	0.000003 (0.000002)
GDP (Billions of 2000$) (Lag 2 Yrs)	0.000002 (0.00001)	-0.000001 (0.000002)
Relevant Statistics		
Observations	11298	44625
No. of Patent Classes/ Assignee	538	2125
Log Likelihood	3972.401	2966.4257
Chi-Square	18145.42	9714.46

Note: Estimation done by a random effects panel data model with standard errors clustered by patent class or patent assignee. For column 1 the sample consists of all patents given to corporations, the unit of observation is the patent class and the treated groups are the electric equipment patent classes. For column 2 the sample consists of electric equipment patents given to EEMs and a random sample of 2000 firms, the unit of observation is the patent assignee and the treated groups are the EEMs (electric equipment manufacturers). All specifications contain a time trens and a constant. The sample is from 1980 – 2000. Standard errors are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3
Channels of Influence
Dependent Variable: Number of Patents for Each EEM

	1a	1b	2a	2b
	Semi- Elasticity	Elasticity#	Semi- Elasticity	Elasticity#
EPAct Dummy (Lag 2 Yrs.)	-9.683**	-14.531**	-8.720*	-13.191***
	(4.851)	(5.144)	(4.771)	(5.057)
Appropriation Effect (Lag 2 Yrs.)	-15.934		-12.802	
	(11.062)		(10.375)	
Competition Effect (Lag 2 Yrs.)	0.907		0.720	
	(3.853)		(3.757)	
EPAct Dummy (Lag 2 Yrs.)*	55.116*	6.450**	50.212*	5.876***
Appropriation Effect (Lag 2 Yrs.)	(30.913)	(0.272)	(25.918)	(0.265)
EPAct Dummy (Lag 2 Yrs.) *	38.253***	1.602***	33.558***	1.406***
Competition Dummy (Lag 2 Yrs.)	(12.934)	(0.564)	(12.638)	(0.551)
Innovation Inputs				
Patent Quality Stock (Adjusted)	0.0003***	0.168*	0.0002***	0.305*
(Lag 2 Yrs.)	(0.0001)	(0.102)	(0.0001)	(0.175)
Mean (Adjusted) Generality (Lag 2	1.497***	0.384*	1.459***	0.712***
Yrs.)	(0.336)	(0.204)	(0.333)	(0.257)
Mean (Adjusted) Number of Claims	-0.376		-0.430*	
(Lag 2 Yrs)	(0.318)		(0.261)	
Firm Characteristics				
Dummy for Low Nox Burner and	-0.251		-0.231	
Desulfurization Unit Producers	(0.569)		(0.541)	
No. of CAAA Affected Boilers	0.0002		0.0002	
	(0.0002)		(0.0002)	
Dummy for Low Nox & Desulf. *	0.0003*	0.163*	0.0003**	0.187*
No. of CAAA Affected Boilers	(0.0002)	(0.099)	(0.0001)	(0.105)
Large EEM Dummy	0.661		0.805	
	(0.757)		(0.721)	
Large EEM Dummy * EPAct	-0.284		-0.286	
Dummy (Lag 2 Yrs.)	(0.830)		(0.796)	
Dummy for US Firms	-1.659**		-1.728**	
	(0.752)		(0.755)	
Macro Environment				
Energy R&D Stock (Billions of	0.080		0.097	
2000$) (Lag 2 Yrs.)	(0.073)		(0.081)	
GDP (Billions of 2000$) (Lag 2	0.0001		0.0001	
Yrs.)	(0.0004)		(0.0004)	
Relevant Statistics				
Observations	1764		924	
Wald Statistic	822.26		1085.54	

Note: Estimation done by a zero inflated negative binomial model where the inflation model is a logit. All specifications contain a constant and a time trend. Range: 1980-2000. In col. 1a and b the sample consists of all EEMs. In col. 2a and b the sample is restricted to EEMs that have at least 1 patent during the sample period. Standard errors are in parentheses and are robust and clustered by firm. * significant at 10%; ** significant at 5%; *** significant at 1%. # In col. 1b and 2b, elasticities are presented for significant variables only. For the EPAct dummy, these columns present aggregate semi-elasticities that are calculated taking into account the direction and magnitude of the interaction terms.

Table 4
Patent Characteristics

Sample (By Patent Assignee)	Electricity Patent Classes		
Dependent Variable	Average (Adjusted) Quality	Aggregate (Adjusted) Quality	Average (Adjusted) Generality
	(1)	(3)	(4)
EPAct Dummy (Lag 2 Yrs.)	-0.025***	-0.049	-0.021*
	(0.009)	(0.084)	(0.011)
EEM Dummy	0.085***	5.986***	0.105***
	(0.028)	(0.579)	(0.026)
EPAct Dummy (Lag 2 Yrs.)* EEM Dummy	-0.069**	-2.687***	-0.109**
	(0.028)	(0.333)	(0.049)
Innovation Inputs			
Patent Stock (Lag 2 Yrs.)	0.001***	0.085***	-0.001***
	(0.0001)	(0.002)	(0.0002)
Patent Quality Stock (Adjusted) (Lag 2 Yrs.)			0.0002***
			(0.00004)
Mean (Adjusted) Generality (Lag 2 Yrs.)	0.101***	0.003	
	(0.015)	(0.040)	
Mean (Adjusted) Number of Claims (Lag 2 Yrs)	0.094***	0.072	0.204***
	(0.020)	(0.049)	(0.019)
Macro Environment			
Number of Clean Air Act Affected Boilers	-0.00002**	-0.001	-0.00002***
	(0.00001)	(0.0001)	(0.00001)
EEM Dummy * Number of Clean Air Act Affected Boilers	-0.00003*	-0.002***	-0.0000002
	(0.00002)	(0.0002)	(0.00003)
R&D Stock (Billions of 2000$) (Lag 2 Yrs.)	-0.001***	-0.003***	-0.001***
	(0.0001)	(0.001)	(0.0001)
GDP (Billions of 2000$) (Lag 2 Yrs.)	0.00004*	0.0003	0.00002
	(0.00002)	(0.0002)	(0.00002)
Relevant Statistics			
Observations	44625	44625	44625
No. of Assignees	2125	2125	2125
R-Square	0.4588	0.636	0.4372
Wald Statistic (Chi-Square)	802.35	3239.17	913.29

Note: In col. (1) and (3), estimation is done using a random effects GLS model with robust and clustered standard errors. In col. (2) we use a random effects AR(1) panel data model. Average quality is measured by the average number of citations (adjusted for year and field effects) received by an assignee in each year. The aggregate quality is measured by the total amount of citations (adjusted for year and field effects) received by the assignee in a given year. Aggregate quality stock is calculated by a declining balance formula using unadjusted citations. All specifications contain a year trend and a constant. The sample consists of electric equipment patents given to EEMs and a random sample of 2000 firms, the unit of observation is the patent assignee and the treated groups are the EEMs (electric equipment manufacturers). The sample is from 1980 – 2000. Coefficients are marginal effects. * significant at 10%; ** significant at 5%; *** significant at 1%.

SUPPLEMENTARY APPENDIX

Table I
List of Electric Equipment Manufacturers from EIA From 767

Boiler Manufacturers
Aalborg Industries, Alstom, American Shack, Applied Thermal Systems, BROS, Babcock and Wilcox, Combustion Engineering, De Jong Coen, Deltak, Doosan, Econotherm, Erie City Iron Works, Foster Wheeler, General Electric, Gotaverken, Hitachi, Indeck, Innovative Steam Technology, Keeler Dorr Oliver, Kvaerner Pulping, Kawaskit Heavy Industries, Nooter/Erickson, Peabody, Pyro Power, Riley Stoker, Sterling, Tampella, Toshiba, Vogt Machine Company, Westinghouse, Wiegl Engineering, Wickes, Zurn
Flue Gas Desulfurization Unit Manufacturer
American Air Filter, Babcock and Wilcox, Chemico, Combustion Engineering, Combustion Equipment, Davey McKee, Environmental Engineering, Flakt Inc, FMC, General Electric, Joy Manufacturing, M W Kellogg, Krebs Engineers, Mitsubishi Industry, Peabody, Research Cottrell, Riley Stoker, Thyssen/CEA, Universal Oil Products
Manufacturer of Low Nitrogen Oxide Control Burners
Advanced Burner Technologies, Advanced Combustion Technology, Alstom, Applied Thermal Systems, Applied Utility Systems (AUS), Alzeta, Babcock Borsig Power, Bloom, Babcock and Wilcox, Combustion Engineering, Combustion Components Associates Inc, Coen, Deutsche-Babcock, Damper Design Inc, Duquense Light Company & Energy Systems Associates, Davis, Eagle Air, Energy and Environmental Research Corp (EER), Electric Power Technologies, EPRI, Entropy Technology and Environmental Construction Corp (ETEC), Faber, Forney, Fuel Tech Inc., Foster Wheeler, GE Energy and Environmental Research Corp (GEEER), Holman, International Combustion Limited, Indeck, In house, John Zink Todd Combustion, Keeler Dorr Oliver, Mitsui-Babcock, Mitsubishi Industries, Mobotec, Nebraska Boiler Company, Natcom, Inc, NEI, Noell, Inc., Procedair, Peabody, Pillard, Peerless Manufacturing Company, Phoenix Combustion, Rodenhuis and Verloop, RJM, Rolls Royce, Riley Stoker, RV Industries, Siemens-Westinghouse, Tampella, Toshiba, Weigel Engineering, Zeeco

Table II
List of Electric Equipment Manufacturers who Patent & are Publicly Traded

Equipment Manufacturer	Assignee Code	Publicly Traded	Equipment Manufacturer	Assignee Code	Publicly Traded
Aalborg Industries	125		GE Energy & Env. Research Corp (GEEER)	218555	X
Advanced Combustion Technology	682503		General Electric	218505, 218510, 218520, 218525, 693310, 218550, 745764, 719174, 218550, 218535 683761, 218555, 218560, 721123, 218565, 691594, 548410, 119285, 217425	X
Alstom	762704		Gotaverken	1570, 229045, 229055	
Alzeta	22720	X	Hitachi	252865	X
American Air Filter	23765	X	Holman	696227	
Applied Utility Systems	719922		International Combustion Limited	280165	
Babcock and Wilcox	361325, 50200, 50205, 50945, 146265, 260010, 260075, 561950	X	Joy Manufacturing	297925, 297930	X
Bloom	68565		Krebs Engineers	321355	
BROS	11905		Kvaerner Pulping	711236	
Coen	109905		Mitsubishi Industry	379230, 379245, 379260, 379270, 703154 700287, 708293, 716780, 717788, 754465 755737, 756583	X
Combustion Engineering	112595	X	Mitsui-Babcock		X
Combustion Equipment	112600, 112605		NEI	396150	
Damper Design Inc	134430		Noell, Inc	694692	X
Davis	684311		Nooter/Erickson	178685, 406180	
Deltak	140895	X	Peabody	432355, 432380, 432395	X
Deutsche-Babcock	720127		Peerless Manufacturing Company	433070	X

Doosan	758831		Pillard	441115	
Eagle Air	160075		Research Cottrell	471745	X
Econotherm	162630, 49885	X	Riley Stoker	476345	X
Electric Power Technologies	167050		RJM	735343	
Energy and Environmental Research	173865		RV Industries	486830	
Entropy Technology and Environmental Construction Corp (ETEC)	822183		Siemens-Westinghouse	750633	
Environmental Engineering	747406		Sterling	544580, 687472	X
Faber	187125		Tampella	560031	
Flakt Inc	199865		Toshiba	581230, 581285, 581270	
FMC	202675	X	Westinghouse	785, 572490, 625115, 627555, 759659	X
Forney	204805, 204815, 744705	X	Zeeco	715247	
Foster Wheeler	205690, 205695, 205700, 205720 205730, 734405, 745677, 205710 772546, 738709, 205715, 205725 225950, 684994, 96350	X	Zurn	641390	X
Fuel Tech Inc	210555	X			

Note: The following EEMs have no USPTO patents. Advanced Burner Technologies, American Shack, Applied Thermal Systems, Babcock Borsig Power, Chemico,Combustion Components Associates Inc, Davey McKee, De Jong Coen b v, Duquense Light Company & Energy, Erie City Iron Works, In house, Indeck, Innovative Steam Technology, John Zink Todd Combustion, Kawaskit Heavy Industries, Rodenhuis and Verloop, Keeler Dorr Oliver, Rolls Royce, Mobotec, Pyro Power, Natcom, Inc, Procedair, Nebraska Boiler Company, Systems Associates, Phoenix Combustion, Thyssen/CEA, Universal Oil Products, Vogt Machine Company, Wiegl Engineering, Wickes