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

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Abstract

This paper studies the innovation response of upstream technology suppliers when their downstream technology buyers transition from regulation to product market competition. Using the unique opportunity afforded by the US electricity deregulation in the 1990's and using patents as a metric for innovation, we identify two primary channels through which the effects of deregulation are transmitted to innovation: (a) the net competition effect (comprised of the pure competition and the escape competition effect) which has decreased innovation by 18.3 percent after deregulation, and (b) the appropriation effect which has increased innovation by 19.6 percent after deregulation. Other unobserved effects of deregulation have led to a 20.6 percent decline in innovation. In aggregate we find that electric technology innovation by electric equipment manufacturers (who were the upstream innovators) has experienced a 19.3 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: Innovation, Patents, Competition, Electricity Deregulation

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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 use the deregulation of the US electric utility industry and the effect this had on the innovation behavior of electric equipment manufacturers. 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 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

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

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.

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

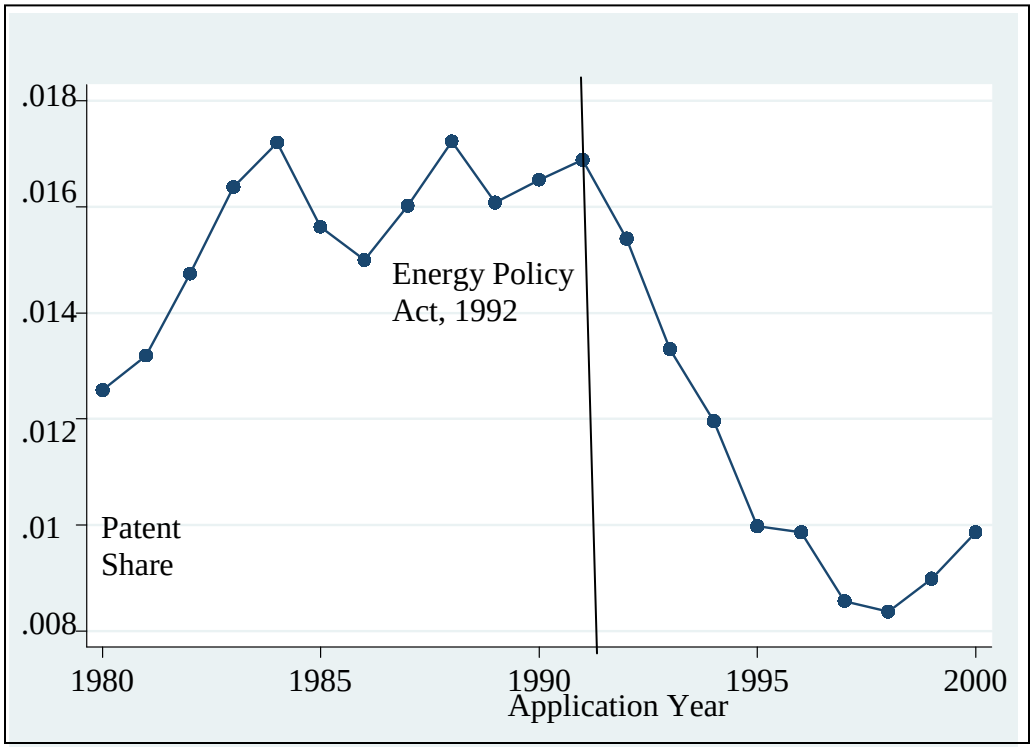
[2] For studies on the electricity deregulation in the US, see Blumstein (1997); Borenstein & Bushnell (1999); Borenstein, Bushnell, and Stoft (2000); Joskow (1997, 1999); Wolak (2004); Puller (2007); and Sanyal and Cohen (2007a,b).

[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.

EPAct (1992), there was a significant drop in the share of electric technology patents granted to EEMs after 1992. [5]

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 from 1992 - 1998. 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.

[5] There appears to be an increase in the innovation magnitude of EEMs in 1999 and 2000 although the shares are no where near the pre deregulation levels.

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 and in aggregate, electric technology innovation by EEMs declined by 19.3 percent after deregulation. In addition, EEM patent 'quality' has been adversely affected and they have become less 'general' 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, 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.

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

Our paper adds to the innovation-competition literature in important ways. It empirically models the effect of downstream competition on upstream innovation behavior in situations where the technology buyer and seller are not vertically integrated. This 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 briefly discusses the theoretical findings that serve as a backdrop to our empirical results and help 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

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. In our set-up there is a vertical organization structure where innovation is done by upstream equipment manufacturers and bought by downstream utilities. The innovations were bought at an agreed upon price which was determined by the profits generated from the final product. Since the downstream utilities were allowed to maintain a geographic monopoly, the upstream manufacturers and the downstream utilities could share the monopoly rents thus generated. After the introduction of the EPAct, wholesale competition was made possible in the downstream market. This affected the upstream firms' innovations in the following 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), since now they could not charge the higher regulated price. This led to a reduction in the profits of the downstream

utilities, which, in turn, affected the innovation incentives of the upstream sector negatively, since they were getting a share of these profits. We call this the "*pure competition effect*". As predicted by standard IO theory, increased competition reduces the monopoly rents that reward successful innovators[9] and thus we expect declining downstream profits to dampen upstream innovation.

The second effect[10] which boosts innovation incentives as competition increases is termed as "*escape competition*" by Aghion-Harris-Howitt-Vickers (2001). The idea is that when there is more competition within the upstream EEMs, innovation incentives depend not so much upon post-innovation rents but upon the difference between post innovation and pre-innovation rents of incumbent firms.[11] In this case, more competition may foster innovation because it may reduce a firm's pre-innovation rents by more than it reduces its post-innovation rents. Thus, greater competition may increase the incremental profits from innovating and thereby encourage R&D investments aimed at "escaping competition".

The third effect is an "*appropriation effect*," which is due to the entry of the non-utility generation firms (called independent power producers, or IPPs) in the wholesale market.[12] This effect arises because of the downstream-upstream industrial organizational structure as is particular to our set-up. Thus previous theoretical work on competition and innovations where innovations occur within the firm, has not considered this effect in their analysis. In the regulated regime, when there was a monopoly in the downstream utility market then the upstream EEMs had no bargaining power in the division of the monopoly rents that arose since they could not

[9] See, Dasgupta-Stiglitz(1980) and also the first generation of Schumpeterian growth models (Aghion-Howitt (1992) and Caballero-Jaffe (1993)).
[10] We would like to thank the anonymous referee for pointing us in this direction.
[11] According to the authors this depends on whether the innovation is done by technology laggards or leaders.
[12]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.

sell their innovations to other competing downstream utilities. With the expansion of IPPs, EEMs could increasingly sell their innovation to these competing firms, and this raised their status quo payoff with the current incumbent firm. The existence of this outside option implied that the price that they received for their innovations from the downstream incumbent firms would probably increase as a result of the increase in bargaining power of the EEMs. In other words, the share from the gains from innovations was higher compared to the regulated regime. This in turn would increase the innovation incentives of the upstream EEMs.

Thus, whether innovation will actually increase or decrease depends on the relative magnitude of the opposing forces. The 'appropriation effect' and the 'escape competition effect' have a positive influence on innovation incentives while the 'pure competition effect' has a negative influence. Now, whether the absolute value of innovations increases or decreases as a result depends upon the magnitude of each effect. When the pure competition effect is strong enough to counter the positive influences on innovation incentives then we would find that innovations as a whole decreases for upstream EEMs. 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] 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, to identify core electricity technology classes, we cross reference the US Patent Office electricity technology classes[16] with those in which the EEMs patent. This yields 42 electric technology-related patent classes. Second, to classify firms as EEMs, we use the Energy Information Administration's (EIA) Form EIA 767 which 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

[13] The updated data till 2002 is provided by Prof. Browyn Hall. We augment this data by the new patent and citation numbers from the recent NBER patent database that contains patents applied for from 1976-2006. This latter data however does not contain information on the 'generality' or number of claims.
[14] US citation only. Since the current NBER database has 2006 application year patents and we only use data till 2000, we are fairly certain that truncation is not a severe problem for the citation numbers. Additionally, the new database has truncation corrected citations which we use in the estimatiom.
[15] The COMPUSTAT database contains financial data on all publicly traded companies in the US.
[16] Source table: http://www.uspto.gov/web/offices/ac/ido/oeip/taf/stelec.pdf

any of these companies that patent in the US. 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[17] 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 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

[17] Updated COMPUSTAT-assignee match is provided by James Bessen.

match, we retain all the similar assignee names and classify them under one EEM[18]. 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).[19] 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. Supplementary Appendix Table II provides the matched list of EEMs, assignee numbers and CUSIPs. In the estimation we use two samples: all EEMs and those with atleast 1 US patent during the period under investigation.

3.2. Variable Construction

Dependent Variables

Our primary dependent variables fall into two categories: measures of patenting activity and citation-based patent characteristics. To measure patenting activity, we construct the percentage of patents and patent counts by patent class and by patent assignee. When the unit of observation is the patent class, the percentage of patents per class in a given year is constructed by dividing the number of patents granted in each patent class by all patents granted in the US in that year. [20] When the patent assignee is the unit observation, our sample is all electric technology classes. Thus the percentage of patents for each assignee is calculated as the number

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

[19] 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.

[20] For robustness, we have constructed alternative patent share measures, where the numerator is number of patents granted in each patent class and the denominator is USPTO patents granted to all corporations, or granted to US corporations.

of electric technology patents granted to that assignee by application year, divided by the total number of granted patents for that application year. From Table 1A we find that on average each class has 0.15 percent of overall patents with the highest patenting class having 3.3 percent of all patents. On average, each assignee has 0.001 percent of patents, with the maximum share being 0.41 percent within the electric technology category for our sample. Additionally, on average each assignee has only 1 patent in our sample, with the highest being 483 patents granted to one assignee for a given application year. When we focus on EEMs in particular, from Table 1B we find that on average each EEM has 15.3 patents with the highest innovating firm holding 483 patents.

Next, we use 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 every year can be misleading. First, there may be significant truncation issues for newer patents since it takes time for a patent to get cited. Second, 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. The problem of truncation is minimized in our context since we have citation data till 2006 and only use patents applied for till 2000. Thus the year 2000 patents have had atleast 6 years to get cited. Additionally, we use the truncation corrected citations from the NBER patent database. To solve the second problem, we purge the truncation corrected citations of the field effects as suggested by Hall, et al. (2001). We then create demeaned average and total citation measures, and citation

stocks[21] 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 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.[22]

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. The *deregulation dummy* is 1 after the passage of the EPAct in 1992. We use the two year lag of this dummy to allow the firms to adjust to the new regulatory scenario. It may not be possible for a firm to instantaneously change its innovation strategy in response to a policy change – thus the lag reflects this gradual response. We then construct dummies that identify the electricity patent classes and the EEMs. The *EEM dummy* is 1 if the company was identified as an EEM in Form EIA 767. The *electricity patent class dummy* is 1 if it is a electricity-related patent class and there is EEM patenting activity in that class.[23]

As discussed earlier, the main channels through which downstream competition may affect upstream innovation behavior are the competition effect, 'escape competition' effect and appropriation effect. In the empirical model both the (negative) pure competition and (positive) 'escape competition' effect are subsumed in the *net competition effect* variable which 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. Basically,

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[21]We use the declining balance formula outlined in Hall et all. (2005) to create the citation stocks, and use a 15 percent depreciation rate.

[22] 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).

[23] Supplementary appendix tables I, II and III provide the details.

the innovations that are brought about by the upstream EEMs are reaped in by the downstream utilities and are passed on to the final consumers. This is reflected in their profits, which in turn is divided between the upstream and downstream firms. Thus the downstream utility profits give us a net effect of both these forces mentioned above. The *appropriation effect* measures the impact of new downstream entry, and hence increased upstream bargaining power, 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.

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 patent stock of other firms, lagged quality stock, lagged average generality, and the average number of claims as input measures. First, we use the *lagged patent stock of other firms*[24] to capture any spillover effects that may exist. When the unit of observation is the patent class, this variable captures the patenting activity in all other classes. When the unit of observation is the assignee or firm in the electric equipment classes, this stock is calculated based on the number of patents obtained by other assignees/firms (j,…n) in the patent classes that assignee/firm i patents in. This variable captures the innovation activity of the firm's competitors and shows whether there is a positive or negative spillover when competitors increase their patenting activity.

[24] 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 to create the stock of innovation inputs.

Second, we use the firm's own patent characteristics from the past to capture the idea that past patents serve as knowledge inputs for current patents. We construct a *lagged quality stock* using past citation stocks to indicate the quality of innovation inputs that the firm can build on. 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. Therefore, the former will have more inventions than the latter. Additionally, we also use a l*agged average generality measure* to indicate the range of past innovation. A firm with more general patents can draw from a broader base of knowledge and may stave off diminishing returns to innovation longer than a firm who patents within a very narrow range of technologies. Thus we argue that a firm with a higher generality score should produce more patents than another with a very narrow and specific patent portfolio.

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 dependent variables, we include the *lagged own firm patent stock*[25] as an additional control. To create this stock we only consider the past electric equipment technology patents for each firm. We hypothesize that a firm that has a high electric technology patent stock also has a greater number of inputs at its disposal and is, therefore, more likely to come up with higher quality and more general inventions.

[25] Own firm patent stocks only include patents in the electricity classes that are assigned to the firm. Since we argue that past patent stocks serve as inputs to current innovation, including only the electricity patents are included.

Firm Characteristics

When we restrict our estimation sample to all EEMs, we are able to construct several firm-level variables to account for the nature of the firm. The summary statistics for these variables are presented in Table 1B. 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 1990 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 depending on the sample. We use the total *R&D expenditure stock* in the US to capture the overall research spending in the economy, and the *total energy R&D expenditure* (federal and company) to capture any spillovers that may occur between an EEM's innovation and overall energy R&D. All dollar figures are in real terms (2000 dollars), and all time-varying explanatory variables are lagged by 2 years.[26]

2. 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[27] 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 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.

[26] We lag the variables by 2 years to allay concerns about endogeneity issues. Later in the paper (Table 3B) we present a sensitivity analysis for different lags of the deregulation dummy.

[27] 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.

If deregulation was responsible for a significant negative impact on the innovation behavior, we expect θ to have a negative sign. We use a random effect GLS model with robust and clustered standard errors.[28] We present the results in Table 2. However, we have conducted using several robustness checks using a first order autocorrelated model and a random effects tobit 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.[29] The treated groups are the electric equipment patent classes. First, we find that the passage of the EPAct (or other event captured in this post-1992 dummy) has had a negative impact influence on patenting in general. Second, electric equipment classes have a higher number of patents when compared to non-electric equipment classes, holding all else constant. But the difference-in-difference coefficient (-0.080) 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.[30] To create the control group we draw a random sample of 2000 firms from non-EEM assignees who patent in the electric equipment classes.[31] We find that, all else equal, the passage of the EPAct

[28] See "How Much Should We Trust Differences-in-Differences Estimates?" Marianne Bertrand, Esther Duflo and Sendhil Mullainathan; *Quarterly Journal of Economics*, 2004, *119*(1), pp. 249-75 for an extensive discussion.
[29] All counts are by application year, i.e., out of all the patents applied for in year t, the number that were granted.
[30] The unit of observation is the patent assignee and the sample comprises the electric equipment patent classes.
[31] 2000 firms are selected for reasons of tractability.

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 (-0.004), implying that patenting by EEMs declined following the EPAct.

The dependent variable in both column 1 and 2 are in percentages. Thus it could be the case that EPAct has not negatively impacted the magnitude of innovation by EEMs, but rather that the electric technology patents (column 1) or the EEM electric technology patents (column 2) are growing more slowly compared to other patents, and hence the percentage is declining. To investigate whether deregulation has actually decreased the absolute number of patented innovations by EEMs we turn to column 3, where the dependent variable id the number of patent count per assignee. Here we too find that the EEMs patent more than the non-EEM counterparts in the electric technology classes, and that deregulation has had a negative impact on the magnitude of EEM innovation. 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 stock of patent "quality" in past years[32] 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 technology class or firm 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

[32] 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.

that a 1 percent increase in past patent quality stock increases the percentage of patents in each class (on average) by 0.001 percent (column 1) and the number of firm patents (in the electric equipment class) increase by 0.04 percent. Additionally, a firm's innovation may also be influenced by that of its competitors. As discussed earlier, we used the past patent stock of other patent classes to measure this, and find a negative spillover effect. Own firm innovation is adversely affected as innovation by competitors' increase.

We also control for the average generality of a patent 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. There could be several alternative explanations for this finding. First, 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. Another possible explanation is that firms had already done the research in earlier years in anticipation of the passage of the CAAA, an argument that is supported by Taylor et al (2003). 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,[33] 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.[34] In addition, these counts have a disproportionate number of zeros[35] 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.[36] 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

[33] Supplementary Appendix Table 1b provides a list of these companies along with their assignee codes (from the NBER Database) and patenting rank.
[34] 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.
[35] About 55 percent of the dependent variable has zero value.
[36] See "Econometric Analysis" (Fifth Edition, Prentice Hall) by W. H. Greene for a discussion of the model.

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.[37]

The patent counts are then modeled using a negative binomial function[38] with robust standard errors that are clustered by firm. This specification is given by equation 9 below.

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

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 net 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 3A, 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

[37] 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.

[38] 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.

one patent during our sample period, 1980-2000. Columns 1a and 2a report the semi-elasticities for each term 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 20.6 percent decline in patenting by EEMs. We also find that both the appropriation effect and the net competition effects 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 *net competition 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 discussion we know that if the profitability from adopting a new technology declines, then on one hand, innovations will decline (pure competition effect). On the other hand, the 'escape competition' effect may increase innovation. Our results show that for our sample period, the pure competition effect swamps the escape competition effect leading to a decrease in innovation. We find that a 1 percent decline in downstream profits decreases upstream innovation by approximately 9.18 percent post-EPAct (competition effect). From Table 1B we observe that for our sample period, profits have declined on average, by 2 percent after deregulation. Thus the competition effect is responsible for a18.3 percent decrease in innovation.

The *appropriation 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 predictions from the theoretical literature, 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 the appropriation effect, as captured by the non-utility generation share, increases innovation by approximately 2.2 percent following the introduction of the EPAct. From Table 1B we observe that for our sample period, non-utility generation share has increased on average, by 8.9 percent after deregulation. Thus the appropriation effect is responsible for a 19.6 percent increase in innovation.

In addition, we find that external spillovers and the quality of innovation inputs matter (Popp, 2002, 2006). An increase in innovation by other EEMs had a positive spillover effect and a 1 percent increase in electric equipment patenting by other firms increased a firm's innovation by 0.68 percent. Additionally, companies whose past patent portfolios were more general also showed an increase in current patenting. The breadth or quality 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.[39] The R&D and GDP variables are not significant in any specification.

In the results discussed above (Table 3A) we lagged the deregulation dummy by 2 years. We assumed that this is the time it takes to adjust a firm's innovation strategy to reflect the new market conditions, especially since EPAct was the first deregulation policy instituted in the US

[39] While interpreting this result it is important to remember that this may be the result of a selection effect. Non-US firms that patent in the US would probably be the top innovators in their countries, while for domestic firms even the least innovative may still apply for a US patent due to low entry barriers.

electricity market and firm's would have little prior experience in negotiating the new market structure. However, since theory does not provide us with a concrete answer about the length of time it takes such market deregulation to affect upstream innovation, in Table 3B we provide a sensitivity analysis to different lags. From columns 1 and 2 we find that using the deregulation status for the current year (column 1) or using a 1 year lag (column 2) provides results that are very similar to those presented in Table 3A. However, the results in column 3 are substantially different. The EPAct dummy does not influence upstream innovation when it is lagged by three years suggesting that its influence decays over time. The coefficients for the appropriation and net competition effects are still significant and of the same sign, although the magnitude is smaller.

4.3. Patent Characteristics

Guided by the discussion from the theoretical literature, so far 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[40], 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). However, when we purge these of technology and year effects, and use the means and stocks of these variables (by firm), it makes 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

[40] 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.

allow one to correct errors for clustering and heteroscedasticity. Therefore we use a random effects GLS model[41] 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[42] 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. We find that the difference-in-difference coefficient is strongly negative and significant for all three columns implying that both quality and patent generality declined sharply after 1992. Thus after deregulation, patents generated by EEMs became less general and of lower quality alluding to the fact that equipment manufacturers may be concentrating on a narrow set of innovations.[43] However we cannot definitively rule out alternative explanations for this finding. It could be that the case that for EEMs, there were diminishing returns to innovation for the electric equipment classes that manifest themselves around the same time as EPAct took effect, although the comparison with the random sample of firms who also patent in

[41] 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 ($\varepsilon_{it} \sim N(0, \sigma^2_\varepsilon)$).
[42] We selected a random sample of 2000 firms for tractability.
[43] However, on average EEM patent quality and generality is higher than other patents in the electric technology category.

the electric equipment class but suffer no such decline may tease out some of the deregulation effect.

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 (columns 1 – 3), while there is a negative externality as other competitor's increase their innovation activity (column 1 and 3). 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 literature proposes three opposing effects of deregulation: the pure competition, escape competition and the appropriation effect. The pure competition 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 escape competition effect is positive and is driven by the effect of competition on pre and post innovation profits, which spurs firms to innovate more in order to gain advantage over their competitors. In the empirical model these two effects are subsumed in the net competition effect that is measured by the average profit of the downstream utilities. Additionally, the appropriation effect has a positive effect on innovation. Increased participation of non-utilities in the wholesale market increases the EEM customer base, thus increasing its status-quo bargaining power, and thus positively affecting innovation. The relative strength of these effects determines the overall effect of downstream product market competition on upstream innovation.

The empirical results show that for the electricity industry, deregulating the downstream sector has adversely affected the innovation behavior of EEMs during our sample period. First,

using difference-in-difference models, we show that restructuring 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 model the channels through which such a decline may have occurred. We find that deregulation alone has led to a 20.6 percent decline in patenting by EEMs. We also find that both the appropriation effect and the net competition effect are significant after the introduction of the EPAct, but not before. Following the passage of the EPAct, the total competition effect has led to a 18.3 percent decline in innovation which has been offset by an increase of 19.6 percent due to the appropriation 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. We take the empirical model further by investigating the impact of deregulation on innovation characteristics. 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 an empirical framework that models upstream innovation behavior as a function of downstream competitive forces. 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.

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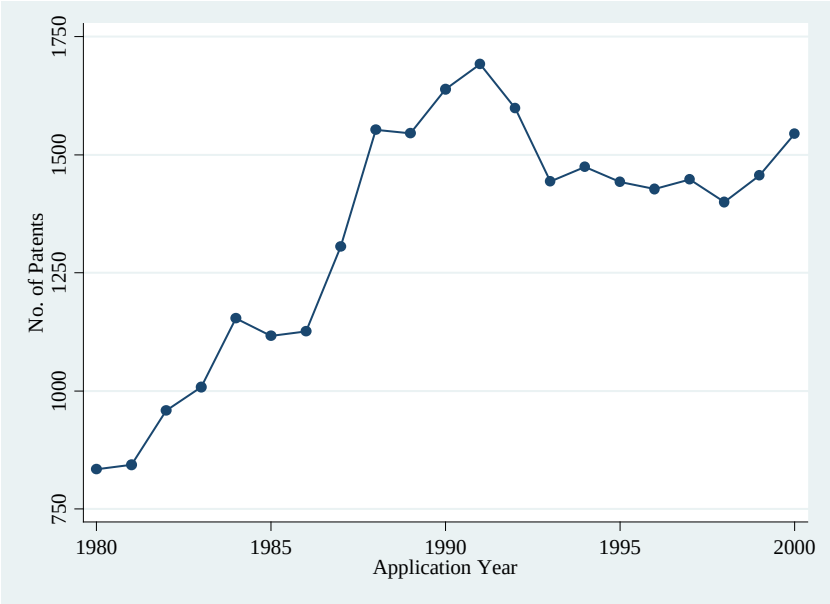
APPENDIX FIGURE I

Patents Obtained by Electric Equipment Manufacturers in Electric Equipment Patent Classes



APPENDIX FIGURE II

Patents Obtained by Firms in Drugs and Medical Classes

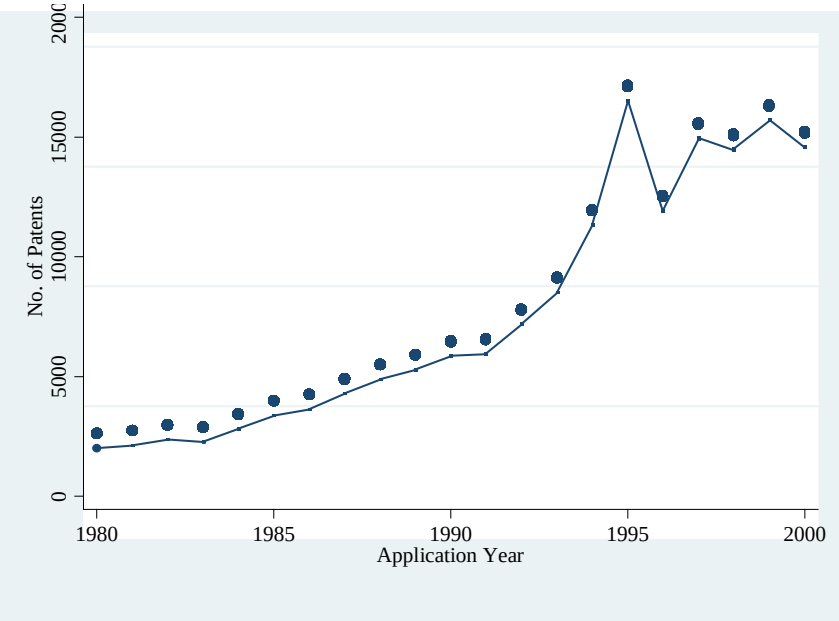


Table 1A
Summary Statistics for Table 2 and 4

Sample: All Patent Classes (Table 2)					
Dependent Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Percentage of Patents Per Patent Class (Dep. Var.)	12012	0.148	0.258	0	3.347
Regressors: Dummy Variables	**Obs.**	**Zeros**	**Ones**		
EPAct Dummy (Lag 2 Yrs.)	12012	8580	3432		
Dummy for Electric Equipment Patent Classes	12012	11130	882		
Regressors: Continuous Variables (Lag 2 Yrs.)	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Other Patent Stock #	12012	14354.22	4780.03	7648	24411
Own Patent Stock	12012	639.98	1195.90	0	19220.93
Quality Stock	12012	9947.61	23697.23	0	426819.8
Mean Adjusted Generality	12012	1.013	0.927	0	30.262
Mean Adjusted Claims	12012	0.661	0.519	0	10.533
Sample: Electric Equipment Patent Classes (Table 2 and Table 4)					
Dependent Variables	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Percent. of Patents Per Assignee (Dep. Var. Table 2)	41929	0.001	0.014	0	0.418
No. of Patents Per Assignee (Dep. Var. Table 2)	41929	1.101	15.129	0	484
Average (Adjusted) Quality (Dep. Var. Table 4)	41929	1.074	5.636	0	297.70
Aggregate (Adjusted) Quality (Dep. Var. Table 4)	41929	1.276	18.480	0	629.76
Average (Adjusted) Generality (Dep. Var. Table 4)	41929	0.110	0.482	0	6.676
Dummy Variables	**Obs.**	**Zeros**	**Ones**		
EPAct Dummy (Lag 2 Yrs.)	41929	30991	10938		
Dummy for EEMs	41929	38594	3335		
Continuous Variables (Lag 2 Yrs.)	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Other Patent Stock #	41929	59431.1	30832.8	38	415685.8
Own Patent Stock	41929	4.717	68.656	0	2191.206
Quality Stock	41929	69.694	1068.30	0	35517.77
Mean Adjusted Generality	41929	0.119	0.501	0	7.788
Mean Adjusted Claims	41929	0.081	0.343	0	7.342
Variables Common to Both Sample					
	Obs.	**Mean**	**Std. Dev.**	**Min**	**Max**
Number of Boilers (CAAA)	41929	529.348	794.045	0	2000
US Total R&D Stk (Bill. 2000$) (Lag 2 Yrs)	41929	592.147	170.159	381.565	970.85
GDP (Billions of 2000$) (Lag 2 Yrs.)	41929	6518.487	1309.21	4540.9	9066.9

Note: # Calculation of this patent stock is based on: Col. 1: patents in all other classes, Col. 2: patents granted to all other assignees (j,….,n) in the patent technology classes assignee i patents in (all within the sample of electric equipment technology patent classes).

Table 1B
Summary Statistics for Table 3

Sample: All Electric Equipment Manufacturers					
Dependent Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
No. of Patents	1743	16.321	66.297	0	590
Dummy Variables	**Obs.**	**Zeros**	**Ones**		
EPAct Dummy (Lag 2 Yrs.)	1743	1245	498		
Dum. Low Nox Burner/ Desulf. Unit Prod.	1743	357	1386		
Large EEM Dummy	1743	1260	483		
Dummy for Large US Firms	1743	548	1195		
Continuous Variables	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Other Firms's Electric Tech. Patent Stock #	1743	67760.89	45542.91	1611.26	415685.8
Mean Adjusted Quality Stock (Lag 2 Yrs.)	1743	968.366	4308.10	0	34530.9
Mean Adjusted Generality (Lag 2 Yrs.)	1743	0.287	0.679	0	4.141
Mean Adjusted Claims (Lag 2 Yrs.)	1743	0.196	0.476	0	4.403
Sample: Electric Equipment Manufacturers that Have At Least 1 US Patent					
Dependent Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
No. of Patents	945	30.103	87.724	0	590
Dummy Variables	**Obs.**	**Zeros**	**Ones**		
EPAct Dummy (Lag 2 Yrs.)	945	675	270		
Dum. Low Nox Burner/ Desulf. Unit Prod.	945	189	756		
Large EEM Dummy	945	567	378		
Dummy for Large US Firms	945	212	733		
Continuous Variables	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Other Firms's Electric Tech. Patent Stock #	945	67439.06	56189	1611.26	415685.8
Mean Adjusted Quality Stock (2 Yrs.)	945	1785.92	5726.04	0	34530.9
Mean Adjusted Generality (Lag 2 Yrs.)	945	0.527	0.848	0	4.141
Mean Adjusted Claims (Lag 2 Yrs.)	945	0.358	0.596	0	4.403
Both Samples					
Total Competition and Appropriation Effect (Lag 2 Yrs.)					
Utility ROA (Competition Effect)	1743	0.117	0.007	0.104	0.130
Share of Non-Utility Generation (Lag 2 Yrs.)(Appropriation Effect)	1743	0.042	0.044	0.001	0.111
Pre-EPAct	**Obs.**	**Mean**	**Post-EPAct**	**Obs.**	**Mean**
Utility ROA (Percentage)	1079	12.04		664	10.30
Percentage of Non-Utility Generation	1079	2.31		664	11.24
Macro Variables	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Number of Boilers (CAAA)	1743	579.762	813.651	0	2000
Energy R&D Stk (Bill. of 2000$) (Lag 2 Yrs)	1743	4.257	1.185	1.769	6.176
GDP (Billions of 2000$) (Lag 2 Yrs.)	1743	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	Number of Patents Per Assignee
	(1)	(2)	(3)
EPAct Dummy (Lag 2 Yrs.)	-0.055***	0.0001	0.139*
	(0.013)	(0.0001)	(0.083)
Electric Equipment Patent Class Dummy	0.137***		
	(0.034)		
EPAct Dummy(Lag 2 Yrs.) * Electric Equip. Patent Class Dummy	-0.080***		
	(0.015)		
EEM Dummy		0.005**	0.506***
		(0.002)	(0.086)
EPAct Dummy(Lag 2 Yrs.) * EEM Dummy		-0.004**	-0.407**
		(0.0017)	(0.164)
Innovation Inputs (Lag 2 Yrs.)			
Other Firm's Patent Stock #	-0.0001***	0.0000001	-0.00001***
	(0.00002)	(0.00000002)	(0.000001)
Patent Quality Stock (Adjusted)	0.00001***	0.00001***	0.0001***
	(0.000001)	(0.000001)	(0.00001)
Mean (Adjusted) Generality	0.003	0.001***	0.319***
	(0.004)	(0.0004)	(0.022)
Mean (Adjusted) Number of Claims	0.055***	0.001***	0.323***
	(0.007)	(0.0002)	(0.029)
Macro Environment			
Number of Clean Air Act Affected Boilers	0.0001***	0.0000001*	-0.00003
	(0.00002)	(0.00000007)	(0.0001)
EEM Dummy * Number of Clean Air Act Affected Boilers	-0.0001***	-0.000002**	-0.0002**
	(0.00002)	(0.000001)	(0.0001)
Total R&D Stock (Billions of 2000$) (Lag 2 Yrs)	0.001***	-0.000006**	0.002***
	(0.0004)	(0.000002)	(0.0008)
GDP (Billions of 2000$) (Lag 2 Yrs)	0.0001***	0.0000003*	0.0003
	(0.00004)	(0.000002)	(0.0002)
Relevant Statistics			
Observations	12012	41929	41929
No. of Patent Classes/ Assignee	572	1823	1823
R-Square	0.703	0.645	
Chi-Square	2340.52	1965.90	1784.18

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). # Calculation of this patent stock is based on: Col. 1: patents in all other classes, Col. 2: patents granted to all other assignees (j,….,n) in the patent technology classes assignee i patents in. All specifications contain a time trend and a constant. The sample is from 1980 – 2000. Standard errors are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3A
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.)	-13.613**	-20.595**	-12.205**	-18.514***
	(6.323)	(6.591)	(6.090)	(6.380)
Net Competition Effect (Lag 2 Yrs.)	-11.211		-8.979	
	(11.620)		(11.126)	
Appropriation Effect (Lag 2 Yrs.)	2.526		2.020	
	(4.049)		(3.901)	
EPAct Dummy (Lag 2 Yrs.)* Net	78.456*	9.182***	70.716*	8.276***
Competition Effect (Lag 2 Yrs.)	(46.499)	(0.343)	(44.331)	(0.327)
EPAct Dummy (Lag 2 Yrs.) *	52.520***	2.200***	46.950***	1.967***
Appropriation Dummy (Lag 2 Yrs.)	(13.980)	(0.610)	(14.153)	(0.618)
Innovation Inputs (Lag 2 Yrs.)				
Other Firms's Electric Tech. Patent	0.00001*	0.680*	0.00001*	0.627*
Stock [#]	(0.000006)	(0.403)	(0.000006)	(0.313)
Own Firm's Electric Tech. Patent	0.00006		0.00007	
Quality Stock	(0.00004)		(0.00005)	
Mean (Adjusted) Generality for Own	1.679***	0.482***	1.634***	0.861***
Firm's Electric Tech. Patents	(0.342)	(0.098)	(0.349)	(0.184)
Mean (Adjusted) No. of Claims for	-0.201		-0.265	
Own Firm's Electric Tech. Patents	(0.429)		(0.364)	
Firm Characteristics				
Dummy for Low Nox Burner and	0.017		0.023	
Desulfurization Unit Producers	(0.489)		(0.490)	
No. of CAAA Affected Boilers	0.00001		0.00003	
	(0.0002)		(0.0002)	
Dummy for Low Nox & Desulf. * No.	0.0004**	0.014**	0.0004**	0.008**
of CAAA Affected Boilers	(0.0002)	(0.008)	(0.0002)	(0.004)
Large EEM Dummy	0.662		0.809	
	(0.850)		(0.844)	
Large EEM Dummy * EPAct Dummy	-0.309		-0.371	
(Lag 2 Yrs.)	(0.878)		(0.876)	
Dummy for US Firms	-1.303*	-	-1.381*	
	(0.746)		(0.780)	
Macro Environment				
Energy R&D Stock (Billions of	0.066		0.086	
2000$) (Lag 2 Yrs.)	(0.084)		(0.089)	
GDP (Billions of 2000$) (Lag 2 Yrs.)	0.0002		0.0003	
	(0.0004)		(0.0004)	
Observations (No. of Firms)	1743 (83)		945 (45)	
Chi-Square	822.26		1085.54	

Note: Estimation - zero inflated negative binomial model (inflation model: logit). Specifications contain a constant and a time trend. Range: 1980-2000. Sample: Col. 1a & b - all EEMs; Col. 2a & b - restricted to EEMs that have at least 1 patent during the sample period. Robust and clustered (by firm) standard errors are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. # This stock is calculated based on the number of patents obtained by other firms (j,…n) in the patent classes that firm i patents in. '§': In col. 1a and 2a the semi-elasticities are given by d(lny)/dx. '§§': 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 3B
Channels of Influence: Robustness to Lags
Dependent Variable: Number of Patents for Each EEM

	1	2	3
Lags of EPAct Dummy	No Lag	1 Year	3 Years
EPAct Dummy	-13.032**	-14.201**	-17.146
	(6.204)	(6.082)	(11.970)
Net Competition Effect (Lag 2 Yrs.)	-8.102	-11.813	-7.867
	(13.083)	(13.653)	(12.132)
Appropriation Effect (Lag 2 Yrs.)	4.689	2.794	-14.139
	(3.915)	(3.662)	(24.617)
EPAct Dummy (Lag 2 Yrs.)* Net Competition	74.645*	82.097*	67.257*
Effect (Lag 2 Yrs.)	(45.176)	(44.530)	(42.248)
EPAct Dummy (Lag 2 Yrs.) * Appropriation	43.524***	53.917***	56.404**
Dummy (Lag 2 Yrs.)	(14.137)	(12.306)	(31.183)
Innovation Inputs (Lag 2 Yrs.)			
Other Firms's Electric Tech. Patent Stock #	0.00001*	0.00001*	0.00001*
	(0.000006)	(0.000006)	(0.000006)
Own Firm's Electric Tech. Patent Quality Stock	0.00006	0.00006	0.0001*
	(0.00004)	(0.00004)	(0.00004)
Mean (Adjusted) Generality for Own Firm's	1.686***	1.687***	1.631***
Electric Tech. Patents	(0.333)	(0.339)	(0.356)
Mean (Adjusted) No. of Claims for Own Firm's	-0.224	-0.196	-0.164
Electric Tech. Patents	(0.416)	(0.446)	(0.410)
Firm Characteristics			
Dummy for Low Nox Burner and	-0.030	0.021	0.003
Desulfurization Unit Producers	(0.499)	(0.496)	(0.493)
No. of CAAA Affected Boilers	-0.000001	-0.00001	0.003
	(0.0002)	(0.0002)	(0.004)
Dummy for Low Nox & Desulf. * No. of CAAA	0.001***	0.001***	0.0004***
Affected Boilers	(0.0002)	(0.0002)	(0.0002)
Large EEM Dummy	0.503	0.642	0.787
	(0.845)	(0.859)	(0.893)
Large EEM Dummy * EPAct Dummy (Lag 2	0.039	-0.229	-0.691
Yrs.)	(0.695)	(0.750)	(1.016)
Dummy for US Firms	-1.189*	-1.274*	-1.439*
	(0.693)	(0.693)	(0.814)
Macro Environment			
Energy R&D Stock (Billions of 2000$) (Lag 2	-0.082	-0.070	0.026
Yrs.)	(0.088)	(0.086)	(0.088)
GDP (Billions of 2000$) (Lag 2 Yrs.)	-0.001	0.0002	0.00002
	(0.001)	(0.001)	(0.001)
Observations (No. of Firms)	1743 (83)	1743 (83)	1743 (83)
Chi-Square	822.26	777.99	823.12

Note: Estimation - zero inflated negative binomial model (inflation model: logit). Specification is the same as Table 3 and contains a constant and a time trend. Range: 1980-2000. Robust and clustered (by firm) standard errors are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. # This stock is calculated based on the number of patents obtained by other firms (j,…n) in the patent classes that firm i patents in. Col. 1, 2 and 3 show results for the specification when the EPAct dummy is used as a contemporaneous variable, with a 1 and 2 year lag respectively.

Table 4
Patent Characteristics

Sample (By Patent Assignee)	Electricity Patent Classes		
Dependent Variable	Average (Adjusted) Quality	Aggregate (Adjusted) Quality	Average (Adjusted) Generality
	(1)	(2)	(3)
EPAct Dummy (Lag 2 Yrs.)	0.009	0.171*	-0.004
	(0.014)	(0.095)	(0.014)
EEM Dummy	0.044**	2.165***	0.076***
	(0.019)	(0.413)	(0.024)
EPAct Dummy (Lag 2 Yrs.)* EEM Dummy	-0.095***	-0.875***	-0.139**
	(0.032)	(0.314)	(0.050)
Innovation Inputs (Lag 2 Yrs.)			
Other Firm's Electric Tech. Patent Stock #	-0.000003***	0.00003***	-0.00001***
	(0.000001)	(0.000004)	(0.000001)
Own Firm's Electric Tech. Patent Stock	0.001***	0.213***	0.002***
	(0.0001)	(0.001)	(0.0005)
Own Firm's Electric Tech. Patent Quality Stock (Adjusted)			-0.0001*
			(0.00004)
Mean (Adjusted) Generality for Own Firm's Electric Tech. Patents	0.035***	0.0004	
	(0.010)	(0.040)	
Mean (Adjusted) No. of Claims for Own Firm's Electric Tech. Patents	0.112***	0.116**	0.204***
	(0.019)	(0.060)	(0.021)
Macro Environment			
Number of Clean Air Act Affected Boilers	0.00001	-0.0001*	-0.00002**
	(0.00001)	(0.00006)	(0.00001)
EEM Dummy * Number of Clean Air Act Affected Boilers	0.00001	-0.0004**	0.00001
	(0.00002)	(0.0002)	(0.00003)
R&D Stock (Billions of 2000$) (Lag 2 Yrs.)	-0.0002	-0.0006	-0.0003**
	(0.0001)	(0.001)	(0.0001)
GDP (Billions of 2000$) (Lag 2 Yrs.)	-0.00001	-0.0005***	-0.00001
	(0.00002)	(0.0002)	(0.00002)
Relevant Statistics			
Observations	41929	41929	41929
No. of Assignees	1823	1823	1823
R-Square	0.435	0.861	0.730
Wald Statistic (Chi-Square)	299.54	2916.11	559.14

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). # This stock is calculated based on the number of patents obtained by other assignees (j,…n) in the patent classes that assignee i patents in. 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

Table III
List of USPTO Classes Used in the Paper

Patent Tech. Class	Description
29	Metal Working
55	Gas Separation
60	Power Plants
95	Gas Separation: Process
96	Gas Separation: Apparatus
110	Furnaces
122	Liquid Heaters and Vaporizers
123	Internal-Combustion Engines
137	Fluid Handling
165	Heat Exchange
174	Electricity: Conductors and Insulators
200	Electricity: Circuit Makers and Breakers
210	Liquid Purification or Separation
228	Metal Fusion Bonding
250	Radiant Energy
257	Active Solid-State Devices
290	Prime-Mover Dynamo Plants
307	Electrical Transmission or Interconnection Systems
310	Electrical Generator or Motor Structure
318	Electricity: Motive Power Systems
320	Electricity: Battery of Capacitor Changing or Discharging
322	Electricity: Single Generator Systems
323	Electricity: Power Supply or Regulator Systems
324	Electricity: Measuring and Testing
326	Induced Nuclear Reactions: Processes, Systems and Elements
327	Misc. Active Electrical Nonlinear Devices, Circuits, and Systems
335	Electricity: Magnetically Operated Switches, magnets, and Electromagnets
337	Electricity: Electrothermally or Thermally Actuated Switches
338	Electrical Resistors
361	Electricity: Electrical Systems and Devices
363	Electric Power Conversion Systems
372	Coherent Light Generators
374	Thermal Measuring and Testing
376	Induced Nuclear reactions: Processes, Systems, and Elements
377	Electrical Pulse Counters, Pulse Dividers, or Shift Registers: Circuits and Systems
415	Rotary Kinetic Fluid Motors or Pumps
416	Fluid Reaction Surfaces (i.e., Impellers)
423	Chemistry of Inorganic Compounds
428	Stock Materials or Miscellaneous Articles
431	Combustion
439	Electrical Connectors
477	Interrelated Power Delivery Controls, Including Engine Control.

Note: U.S. Patent Classes as of 31st December 1999. To identify core electricity equipment technology classes, we cross reference the US Patent Office electricity technology classes with those in which the EEMs patent. This yields 42 electric equipment technology-related patent classes.