

PRODUCT MARKET COMPETITION AND UPSTREAM INNOVATION: EVIDENCE FROM THE U.S. ELECTRICITY MARKET DEREGULATION

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Abstract—This paper studies the innovation response of upstream technology suppliers when their downstream buyers transition from regulation to competition. By modeling the impact of the 1990s U.S. electricity deregulation on patenting, we find that after deregulation, the net competition effect (comprising the pure competition and the escape competition effect) decreased innovation by 18.3% and the appropriation effect increased innovation by 19.6%. Other deregulation factors have led to a 20.6% decline. In aggregate, after deregulation, innovation by the upstream technology suppliers has declined by 19.3%, and upstream innovation quality and generality have declined as well.

I. 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. The “Darwinian” tradition, however, argues that the most efficient and most innovative firms survive under competition, an argument that has been central to the “creative destruction” literature, formalized by several seminal papers, such as Aghion and Howitt (1992, 1996). In the standard setup of these studies, innovations take place within the firm. Using this as the starting point, researchers study the implications of competition on innovation incentives. 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 from papers that have considered the effect of competition on innovation incentives in a horizontal setup.¹

To study this question, we use the deregulation of the U.S. 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, 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 particular geographical region and was subject to cost-of-service regulation that ensured that electricity prices and returns to investment for utilities were stable and not subject to market volatility. In addition, such regulation implied that most costs incurred by utilities (such as investment in new technology) could be passed on to final consumers.

During the early to mid-1990s, this regulation paradigm underwent significant changes that were geared toward competitive electricity markets.² In 1992, the passing of the Energy Policy Act (EPAct) gave rise to open-access transmission grids for wholesale transactions and formally introduced wholesale competition, thus subjecting incumbent utilities to price uncertainties and entry pressures.³ After the introduction of the EPAct, consumers such as municipalities and large industrial customers 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 (see Sanyal & Cohen, 2009, and Cohen & Sanyal, 2007). In particular, the EEMs, which 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 setup make it ideal for studying innovation behavior in an upstream-downstream setup.

Our investigation is motivated by the observed changes in innovation behavior of EEMs that are coincident with

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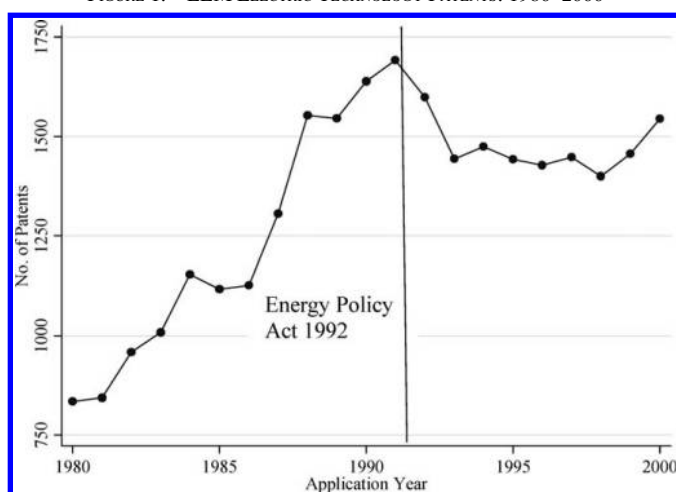
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¹ See Scherer and Ross (1990) and Gilbert (2006) for surveys on this topic.

² For studies on electricity deregulation in the United States, see Blumstein (1997), Borenstein and Bushnell (1999), Borenstein, Bushnell, and Stoft (2000), Joskow (1997, 1999), Wolak (2004), Puller (2007), Sanyal and Cohen (2009), and Cohen and Sanyal (2007).

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. 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.

FIGURE 1.—EEM ELECTRIC TECHNOLOGY PATENTS: 1980–2000



deregulation and restructuring activity in the electricity market. As figure 1 illustrates, with the introduction of the competition that was ushered in by the EPAct which was passed in the January 1992, there was a significant drop in the absolute number of electric technology patents granted to EEMs.⁴

This decline is even more puzzling when one observes that this is a period when other technologies boomed. In figures A1 in the appendix, we show that the number of drug and medical patents obtained by corporations (U.S. and non-U.S.) during our sample period increased. This increase is also reflected in other technology classes, such as chemicals and biotech. As a consequence, the share of electric technology patents granted to EEMs declined during this period (see figure A2). This paper explores why EEM innovation declined when other technologies boomed.

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 U.S. 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% after deregulation. In addition, EEM patent quality has been adversely affected, and these patents have become less general since the establishment of the EPAct.

Before proceeding, we briefly review the work that is most closely related to our study. 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.⁵ Conversely, the litera-

ture 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.⁶ 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. Another recent paper, on a related theme, is that of Reisinger and Schnitzer (2010). In an upstream-downstream framework with endogenous entry, they show that the downstream conditions dominate overall profitability, while the upstream conditions mainly affect the distribution of profits. Finally, a related literature studies the effect of product market competition on managerial incentives.⁷ 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. A few years later, Raith (2003) showed that changes in competition affected incentives if these changes lead to higher firm-level output, and Karuna (2007) showed that particular industry characteristics play a major role in influencing incentives.

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 organized as follows. Section II briefly discusses the theoretical findings that serve as a backdrop to our empirical results that help in understanding the mechanisms at work. Section III describes the data and empirical methodology, and section IV discusses the results. The last section concludes.

II. Theoretical Underpinnings

Common models of innovation and market structure cannot adequately explain innovation behavior by EEMs since these models focus on a horizontal organization structure where innovation takes place within the firm. In our setup 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-on price that 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

⁴ In figure 1 we draw the EPAct line closer to 1991 since the act was passed in January 1992 and the patent total correspond to December of each year. There appears to be an increase in the innovation magnitude of EEMs in 1999 and 2000, although the shares are nowhere near the prederegulation levels.

⁵ See, for example, Arrow (1962), Loury (1979), and, more recently, Aghion et al. (2005) and Vives (2008) on this.

⁶ Chen and Sappington (2010), Choi, Lee, and Stefanadis (2003), Brocas (2003), Buehler, Schmutzler, and Benz (2004), and Buehler, Gartner, and Halbherr (2006) are some papers that delve into such issues.

⁷ Schmidt (1997), Hart (1983), Hermalin (1992, 1994), and Scharfstein (1988) are some papers in this vein.

share the monopoly rents thus generated. After the introduction of the EPAct, wholesale competition was made possible in the downstream market. This had two effects. On the one hand, the profitability of the incumbent utilities declined due to increased competition with nonutility generators (often called the independent power producers, IPPs). This affected the innovation incentive and competition in the upstream EEM sector. On the other hand, the entry of these IPPs in the downstream generation market created new customers for the innovation product being sold by upstream EEMs. We explain in detail how these changes influenced upstream innovation.

First, in the presence of competitors (IPPs) in the downstream sector, the pricing of the final goods (electricity price per megawatthour) to consumers would potentially change by becoming more competitive compared to the high regulated rates. This would reduce the profits of the incumbent downstream utilities. This decline in downstream profitability due to competition decreased the buying power of utilities and translated to a lower demand (from incumbent utilities) for upstream innovation. For upstream EEMs, this had a negative impact on the profit generated by selling their innovation to downstream utilities. As predicted by the standard Schumpeterian model, increased competition (in this case, among downstream utilities after restructuring) reduces the monopoly rents that reward successful innovators (in this case, the upstream EEMs), and thus we expect declining downstream profits to dampen upstream innovation.⁸ We call this the *pure competition effect*.

The second effect, which may boost innovation incentives as competition increases, is called the *escape competition* by Aghion et al. (2001, 2005).⁹ They argue that if incumbent firms are allowed to innovate, then competition may actually increase innovation in certain cases. When there is more competition, innovation incentives depend not so much on postinnovation rents but on the difference between postinnovation and preinnovation rents of incumbent firms.¹⁰ We argue that increased competition may reduce a firm's preinnovation rents by more than it reduces its postinnovation rents: that is, doing nothing may be more costly than investing in more innovation when faced with more competition. Thus, greater competition "may increase the incremental profits from innovating and thereby encourage R&D investments aimed at 'escaping competition'" (Aghion et al., 2001).

We extend their logic in the context of our upstream-downstream setup. In our setup, the downstream incumbent utilities buy innovation from the upstream EEMs. The effect of increased downstream competition would lead to a

decline in profits for incumbent utilities and hence reduce their demand for upstream innovation. The upstream EEMs would now have to fight harder to maintain (and or increase) their market share.¹¹ One potential path is to innovate their way out of competition, or escape competition by increasing innovation and becoming the market leader in certain innovation products. Following Aghion et al.'s (2005) logic, the drive to become the technological leader and maintain or increase market share may drive EEMs to innovate more when faced with shrinking downstream demand (from incumbent utilities).

According to Aghion et al. (2005), which of these two effects dominates depends on the industry structure—whether the industry is leveled (firms are neck-and-neck competitors) or whether it is unleveled (the industry has technological leaders and laggards) and the level of competition in the industry. Their model predicts that the reduction of rents due to competition induces the neck-and-neck competitors to innovate to escape competition, whereas the Schumpeterian effect decreases the innovation incentives for the laggards. If the industry composition is such that it is characterized by a larger share of laggards, increased competition would decrease innovation as the negative Schumpeterian effect (the pure competition effect) would dominate the positive escape competition effect. In the case of the electricity industry, we expect the negative pure competition effect to dominate the positive escape competition effect, leading to a negative net competition effect. A majority of the equipment manufacturers are small, privately owned firms, leading to an unleveled industry structure. In this case, the net effect of competition on innovation should be negative; as downstream profits fall due to competition, upstream innovation should decline as well.

The third effect is an appropriation effect, which is due to the entry of the nonutility generation firms (the IPPs) in the wholesale market.¹² This effect arises because of the downstream-upstream industrial organizational structure particular to our setup. Thus, previous theoretical work on competition and innovations, where innovations occur within the firm, has not considered this effect in their analysis. Two related explanations comprise the aggregate appropriation effect: a bargaining power effect related to the reaction of downstream stream incumbent utilities and a demand-push story based on the reaction of new downstream entrants (the IPPs). We briefly explain these two effects.

¹¹ The number of upstream EEMs remained fairly unchanged during the sample period. Thus, the incentive to escape competition is not coming from new competitors; rather, existing firms are fighting harder to maintain or gain market share in the context of a shrinking profit scenario.

¹² The Public Utility Regulatory Policy Act (PURPA) (1978) required utilities to purchase power from local nonutility 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.

⁸ See Dasgupta and Stiglitz (1980) and the first generation of Schumpeterian growth models (Aghion and Howitt, 1992, and Caballero and Jaffe, 1993).

⁹ We thank the anonymous referee for pointing us in this direction.

¹⁰ According to the authors, this depends on whether the innovation is done by technology laggards or leaders.

In the regulated regime, when there was a stable core of downstream utilities, the upstream EEMs had little bargaining power in the division of rents since they could not sell their innovations to other competing nonutility downstream firms. 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 explanation shows how the EEMs may obtain a bigger share of profits from incumbent firms due to increased bargaining power. In addition to this explanation is a demand-side story that focuses on the new entrants, the IPPs. With an exogenous shift in downstream demand (exogenous from the point of view of the upstream EEMs) due to IPP entry downstream, the size of the pie increases. These IPPs will demand newer kinds of technology, and this demand push will incentivize EEMs to increase their innovation effort, since the upstream EEMs will now be able to capture a larger share of this growing market. Thus, both the bargaining power effect and the demand-push effect originate from downstream IPP entry and will lead to increased innovation by upstream EEMs. Both effects are captured by the aggregate appropriation effect.

From this discussion, we find that there are three possible forces driving the innovation incentives of upstream EEMs: the negative pure competition effect, the positive escape competition effect arising out of competition among the upstream EEMs, and the positive appropriation effect arising out of IPP entry downstream. The structure of the electricity industry is such that the negative pure competition effect will likely dominate the positive escape competition effect, leading to a negative net competition effect: as competition among EEMs increases, innovation would decline. Whether the absolute value of innovations increases or decreases as a result depends on the magnitude of the positive appropriation effect and the negative net competition effect. We now take up this question section.

III. Data

A. 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 change 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 (electricity patent classes or the EEMs), firm, or patent class

characteristics $Char_{it}$; the appropriation effect, A_t , the net competition effect, C_t , and macrocontrols M_t :

$$Y_{it} = (D_{treatment}, D_{treated}, Char_{it}, A_t, C_t, M_t). \quad (1)$$

Thus, the primary categories of data that this paper relies on are (a) information on patents, (b) variables measuring the appropriation and net competition effects, and (c) firm-level data on financial and other firm characteristics. The patent data are from the National Bureau of Economic Research (NBER) Patent Citations Database. We augment this with the new patent and citation numbers from the recent NBER patent database that contains patents applied for from 1976 to 2006.¹³ The data comprise application and grant years, geographical distribution of these patents, technology classifications, number of claims per patent, backward and forward citations (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 database with assignee numbers.¹⁵

We then identify the treated group as either electric technology patent classes or firms that can be categorized as EEMs. First, to identify core electricity technology classes, we cross-reference the U.S. Patent Office electricity technology classes with those in which the EEMs patent¹⁶. This yields 42 electric technology-related patent classes.¹⁷ 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 type of technology they supply. These manufacturers fall into three main categories: boiler manufacturers, flue gas desulfurization unit manufacturers, and manufacturers of low nitrogen oxide control burners. It is important to note that there is considerable overlap in these groups. In all three categories, 89 EEMs are identified by the EIA. General Electric, Babcock, and Wilcox are some of the larger manufacturers in this group.¹⁸ In order to obtain the patents granted to each EEM, we matched the list mentioned above with the standardized patent assignee names from the 2006 updated 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

¹³ This latter data, however, do not contain information on the generality or number of claims.

¹⁴ U.S. citation only. Since the current NBER database has 2006 application-year patents and we use data only to 2000, we are fairly certain that truncation is not a severe problem for the citation numbers. Additionally, the new database has truncation corrected citations that we use in the estimation.

¹⁵ The COMPUSTAT database contains financial data on all publicly traded companies in the United States.

¹⁶ <http://www.uspto.gov/web/offices/ac/ido/oeip/taf/stelec.pdf>.

¹⁷ Refer to the online appendix, table I, for details.

¹⁸ A detailed list of the equipment manufacturers is provided in the online appendix, table II.

firm is relatively easy to determine. The CUSIP and assignee match from the NBER database 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 Web sites, to observe whether the subsidiary is engaged in the electric technology sector. We keep only those subsidiaries that are directly involved in the electricity sector, and the patents granted to these remaining subsidiaries are classified under the firm. 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 straightforward. 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.¹⁹

From the data we find that of the 89 equipment manufacturers identified by the EIA, approximately 55% patented in the United States during our sample period. In addition, these firms most frequently patented in U.S. patent class 110 (Furnaces).²⁰ Matching the EEM list to COMPUSTAT leaves us with 15 firms, and we use this information to classify large firms in the sample. For all our samples, if a patent assignee or firm does not patent in a given year, we set the number of patents to 0 in that year.²¹ In the estimation, we use two samples: all EEMs and those with at least one U.S. patent during the period 1980 to 2000. Although the updated NBER patent database comprises grant data to 2006, we restrict our sample to 2000 to avoid truncation issues. When the data were collected in 2007, patent applied for from 2001 to 2006 may not have been granted due to significant grant lags in certain technology areas. Additionally, most patents require a significant number of years to reach their full citation potential (Hall, Adam, & Trajtenberg, 2001). By allowing at least six years from the date of application, we attempt to minimize this problem.

B. 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 technology class and patent assignee. When the unit of observation is the patent class, the percentage of patents per class in a given application year is constructed by dividing the number of patents granted in each patent class by all patents granted in the United States for that particular application year.²² When the patent assignee is the unit of observation, our sample is all electric technology classes. Thus, the percentage of patents for each assignee is calculated as the number of electric technology patents granted to that assignee by application year, divided by the total number of granted patents (in all electric technology classes) for that application year. From panel A in table 1, we find that on average, each class has 0.17% of overall patents, with the highest patenting class having 3.3% of all patents. On average, each assignee has 0.001% of patents, with the maximum share being 0.42% within the electric technology category for our sample. Additionally, on average, each assignee has only one patent in our sample, with the highest being 484 patents granted to one assignee for a given application year. When we focus on EEMs in particular, from panel B of table 1, we find that on average, each EEM has 15.7 patents, with the highest-innovating firm holding 590 patents.²³

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: a greater number of other patents will cite these patents than those that embody minor innovations (Jaffe, Trajtenberg, & Henderson, 1993; Jaffe, Trajtenberg, & Fogarty, 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 to 2006 and use patents applied for only to 2000. Thus the year 2000 patents have had at least six years to get cited.²⁴ Additionally, we use the truncation-corrected citations from the updated 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

¹⁹ As a robustness check we have excluded these companies from the sample, and there is no significant difference to the estimation results.

²⁰ Placement of an original patent into class 110 requires the following minimum structure or steps for operating such structure: (a) means or a step to either convey or support solid combustible material during combustion, (b) means or a step to supply either directly or indirectly a noncombustible fluid to the solid combustible material, and (c) means or a step to enclose or control the combustion reaction.

²¹ Web appendix table III provides the matched list of EEMs, assignee numbers, and CUSIPs.

²² 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 U.S. corporations.

²³ The reason the maximum number varies when we the count by assignee and by firm is that there are multiple assignee numbers under one firm.

²⁴ See Hall et al. (2001) for a discussion of the distribution of citations over time.

TABLE 1.—SUMMARY STATISTICS FOR TABLES 2 TO 4

A. Statistics for Tables 2 and 4					
Sample: All Patent Classes (Table 2)					
	Observations	Mean	S.D.	Minimum	Maximum
Dependent variable					
Percentage of patents per patent class	12,012	0.148	0.258	0	3.347
Number of patents per patent class	12,012	156.137	319.697	0	5,062
Regressors: Dummy variables	Observations	Zeros	Ones		
EPAct dummy (lag two years)	12,012	8580	3432		
Dummy for electric equipment patent classes	12,012	11130	882		
	Observations	Mean	S.D.	Minimum	Maximum
Regressors: continuous variables (lag two years)					
Other patent stock ^a	12,012	14354.22	4780.03	7648	24,411
Own patent stock	12,012	639.98	1195.90	0	19,220.93
Quality stock	12,012	9947.61	23697.23	0	426,819.8
Mean adjusted generality	12,012	1.013	0.927	0	30.262
Mean adjusted claims	12,012	0.661	0.519	0	10.533
Sample: Electric Equipment Patent Classes (Tables 2 and 4)					
	Observations	Mean	S.D.	Minimum	Maximum
Dependent Variables					
Percent age of patents per assignee (Dependent variable table 2)	41,929	0.001	0.014	0	0.418
Number of patents per assignee (Dependent variable table 2)	41,929	1.101	15.129	0	484
Average (adjusted) quality (Dependent variable table 4)	41,929	1.074	5.636	0	297.70
Aggregate (adjusted) quality (Dependent variable table 4)	41,929	1.276	18.480	0	629.76
Average (adjusted) generality (Dependent variable table 4)	41,929	0.110	0.482	0	6.676
Dummy variables	Observations	Zeros	Ones		
EPAct dummy (lag two years)	41,929	30,991	10,938		
Dummy for EEMs	41,929	38,594	3,335		
	Observations	Mean	S.D.	Minimum	Maximum
Continuous variables (lag two years)					
Other patent stock ^a	41,929	59,431.1	30,832.8	38	415,685.8
Own patent stock	41,929	4.717	68.656	0	2,191.206
Quality stock	41,929	69.694	1,068.30	0	35,517.77
Mean adjusted generality	41,929	0.119	0.501	0	7.788
Mean adjusted claims	41,929	0.081	0.343	0	7.342
Variables Common to Both Sample					
	Observations	Mean	S.D.	Minimum	Maximum
Number of boilers (CAAA)	41,929	529.348	794.045	0	2000
U.S. total R&D stock (billions of \$2000) (lag two years)	41,929	592.147	170.159	381.565	970.85
GDP (billions of \$2000) (lag two years)	41,929	6,518.487	1,309.21	4,540.9	9,066.9
Statistics for Table 3					
Sample: All Electric Equipment Manufacturers					
	Observations	Mean	S.D.	Minimum	Maximum
Dependent Variables					
Number of patents	1,743	16.321	66.297	0	590
Dummy variables	Observations	Zeros	Ones		
EPAct dummy (lag two years)	1,743	1,245	498		
Dummy Low NOx Burner/ Desulfurization unit Product	1,743	357	1,386		
Large EEM dummy	1,743	1,260	483		
Dummy for large U.S. firms	1,743	548	1,195		
	Observations	Mean	S.D.	Minimum	Maximum
Continuous variables					
Other firms's electric technology patent stock ^a	1,743	67,760.89	45,542.91	1,611.26	415,685.8
Mean adjusted quality stock (lag two years)	1,743	968.366	4,308.10	0	34,530.9
Mean adjusted generality (lag two years)	1,743	0.287	0.679	0	4.141
Mean adjusted claims (lag two years)	1,743	0.196	0.476	0	4.403
Sample: Electric Equipment Manufacturers that Have At Least One U.S. Patent					
	Observations	Mean	S.D.	Minimum	Maximum
Dependent variable					
Number of patents	945	30.103	87.724	0	590
Dummy variables	Observations	Zeros	Ones		
EPAct dummy (lag two years)	945	675	270		
Dum. Low NOx Burner/ Desulfurization unit product	945	189	756		
Large EEM dummy	945	567	378		
Dummy for large U.S. firms	945	212	733		
	Observations	Mean	S.D.	Minimum	Maximum
Continuous variables					
Other firms's electric technology patent stock ^a	945	67,439.06	56,189	1,611.26	415,685.8
Mean adjusted quality stock (two years)	945	1,785.92	5,726.04	0	34,530.9
Mean adjusted generality (lag two years)	945	0.527	0.848	0	4.141
Mean adjusted claims (lag two years)	945	0.358	0.596	0	4.403

TABLE 1.—(CONTINUED)

Both Samples					
Total competition and appropriation effect (lag two years)					
Utility ROA (competition effect)	1,743	0.117	0.007	0.104	0.130
Share of nonutility generation (lag two years)(appropriation effect)	1,743	0.042	0.044	0.001	0.111
	Observations	Mean	Post-EPAct	Observations	Mean
Pre-EPAct					
Utility ROA (Percentage)	1,079	12.04		664	10.30
Percentage of nonutility generation	1,079	2.31		664	11.24
	Observations	Mean	S.D.	Minimum	Maximum
Macrovariables					
Number of boilers (CAAA)	1,743	579.762	813.651	0	2,000
Energy R&D Stock (lag two year)	1,743	4.257	1.185	1.769	6.176
GDP (Billions of 2000\$) (Lag two years)	1,743	6,696.848	1,229.623	5,015	9,066.9

^aCalculation of this patent stock is based on patents in all other classes or patents granted to all other assignees (j, \dots, n) in the patent technology classes assignee i patents in (all within the sample of electric equipment technology patent classes).

demeaned average and total citation measures, and citation stocks by patent class and year and by firm and year.²⁵

We use the generality measure developed by Trajtenberg, Jaffe, and Henderson (1997) to investigate whether firms are investing in specific innovations. This measure is also based on citations received by individual patents. Generality implies that patents from a variety of other classes cite this particular patent, that is, it has a significant impact on a wide variety of fields.²⁶ With deregulation and the associated uncertainties facing the firms, we expect EEMs to produce more targeted and less general patents.

Variables capturing the effects of deregulation. To implement the empirical model, we first need to identify deregulation dummies, electricity technology classes, and the EEMs that supplied technology to downstream utilities. The deregulation dummy is 1 after the passage of the EPAct in 1992.²⁷ We use a two-year lag of this dummy in our empirical specification, that is, we assume that the deregulation affects the innovation behavior of EEMs with a two-year lag.²⁸ In the literature there is no clear theoretical or empirical finding that allows us to pick a particular lag structure. We use a two-year lag to allow the firms to adjust to the new regulatory scenario. R&D is usually a long-term strategy developed by a firm, and it may not be possible to instantaneously change this in response to a policy change; thus, the lag reflects this gradual response.²⁹ Next we construct dummies that identify the electricity patent classes and the EEMs. The EEM dummy is 1 if the company was

identified as an EEM on form EIA 767.³⁰ The electricity patent class dummy is 1 if it is an electricity-related patent class and there is EEM patenting activity in that class.³¹

The theoretically identifiable channels through which downstream competition may affect upstream innovation behavior are the pure competition effect, the escape competition effect, and the appropriation effect. In the empirical model, both the (negative) pure competition and the (positive) escape competition effect are subsumed in the net competition effect variable, which captures the profits of 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. Falling downstream profits will reduce the demand for new technology, and since profits were shared between the upstream and downstream, declining downstream profits imply declining upstream profits from innovation and thus reduced innovation incentives (pure competition effect). However, such a reduction in profits may spur upstream firms to innovate more (escape competition effect) if this allows them to capture a larger share of the declining profits. Thus the downstream utility profits give us a net effect of both of these forces.

The appropriation effect measures the impact of new downstream entry, and hence increased upstream bargaining power and increased demand, on EEM innovation. Ideally, we want to obtain the number of entrants to the generation sector in each year and their generation capacity. However, these data are difficult to obtain, so we use the share of generation by nonutilities as a proxy for new IPP entry.

Innovation inputs. We use several past patent characteristics to capture the innovation landscape of a firm or patent class. First, to capture aggregate knowledge stock, we construct the lagged patent stock of other patent classes or firms (other patent stock) to capture any spillover effects that may exist.³² When the unit of observation is the patent

²⁵ We use the declining balance formula outlined in Hall, Jaffe, & Trajtenberg (2005) to create the citation stocks and use a 15% depreciation rate.

²⁶ $\text{Generality} = 1 - \sum_{j=1}^J \left(\frac{n_{ij}}{n_i} \right)^2$, 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 et al. (2001).

²⁷ Deregulation dummy = 1 if year > 1992 (1993 and after).

²⁸ Later in the paper, we provide robustness checks for various lags.

²⁹ A paper that investigates the efficiency effects on deregulation (Fabrizio, Rose, & Wolfram, 2007) does not use any lags for the deregulation dummy since they study labor and capital efficiency of utilities, metrics that can be changed on a shorter term compared to innovation of the upstream firms, which are one step removed from the deregulation process.

³⁰ The EEM dummy is 1 for all the firms listed in the Web appendix, table II.

³¹ The electricity patent class dummy is 1 for all the classes listed in the Web appendix, table I.

³² We use the declining balance formula outlined in Hall et al. (2005) to create the citation stocks and use a 15% depreciation rate to create the stock of innovation inputs.

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 or firms (j, \dots, n) in the patent classes that assignee or firm i patents within the electric technology classes. 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.

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 own 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. We also use a lagged 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 that 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, van Pottelsberghe de la Potterie, & van Zeebroeck, 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 is unclear. If past patents have greater breadth, then numerous potential applications may have already been covered, and 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 as an additional control.³³ To create this stock, we consider only 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.

Firm characteristics. When we restrict our estimation sample to 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 panel B of table 1. 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 units. 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 nitrogen oxide (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 United States. This variable serves as a proxy for firm size and R&D because we lack data for these variables. Finally, we include a U.S. firm dummy that captures whether the EEM is headquartered in the United States, since our sample includes both domestic and foreign EEMs.

Macroenvironment. In all specifications, we include three main macrocontrols: the number of boilers affected by the CAAs, 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 are from the EIA Clean Air Act Database. The GDP variable captures the overall health of the economy and controls for macrofluctuations; 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: the total R&D expenditure stock in the United States 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 two years.³⁴

IV. Empirical Methodology and Results

A. Deregulation and Electricity Innovation

We begin by estimating a simple difference-in-difference model in table 2 to test 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

³³ Own firm patent stocks include only patents in the electricity classes that are assigned to the firm. Since we argue that past patent stocks serve as inputs to current innovation, only electricity patents are included.

³⁴ We lag the variables by two 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.

TABLE 2.—PATENTING IN ELECTRIC TECHNOLOGY AFTER RESTRUCTURING

Sample (All Firms) Dependent Variable	All Patent Classes		Electric Technology Classes	
	Percentage of Patents per Patent Class (1)	Number of Patents per Patent Class (2)	Percentage of Patents per Assignee (3)	Number of Patents per Assignee (4)
EPAct dummy (lag two years)	−0.055*** (0.013)	0.065*** (0.021)	0.0001 (0.0001)	0.139* (0.083)
Electric equipment patent class Dummy	0.137*** (0.034)	0.904*** (0.058)		
EPAct dummy(Lag two years) × Electric Equipment Patent Class Dummy	−0.080*** (0.015)	−0.082** (0.040)		
EEM Dummy			0.005** (0.002)	0.506*** (0.086)
EPAct Dummy(Lag two years) × EEM Dummy			−0.004** (0.0017)	−0.407** (0.164)
Innovation inputs (lag two years)				
Other Class/Firm Patent Stock ^a	−0.0001*** (0.00002)	0.00002** (0.00001)	0.0000001 (0.0000002)	−0.00001*** (0.000001)
Own Patent Quality Stock (Adjusted)	0.00001*** (0.000001)	0.00001*** (0.000002)	0.00001*** (0.000001)	0.0001*** (0.00001)
Mean (Adjusted) Generality	0.003 (0.004)	0.185*** (0.009)	0.001*** (0.0004)	0.319*** (0.022)
Mean (Adjusted) Number of Claims	0.055*** (0.007)	0.436*** (0.018)	0.001*** (0.0002)	0.323*** (0.029)
Macroenvironment				
Number of Clean Air Act Affected Boilers	0.0001*** (0.00002)	−0.00002 (0.00002)	0.0000001* (0.00000007)	−0.00003 (0.0001)
EEM Dummy × Number of Clean Air Act Affected Boilers	−0.0001*** (0.00002)	−0.00004* (0.00002)	−0.000002** (0.000001)	−0.0002** (0.0001)
Total R&D Stock (Billions of \$2000) (Lag two years)	0.001*** (0.0004)	0.004*** (0.0003)	−0.000006* (0.000002)	0.002*** (0.0008)
GDP (Billions of 2000\$) (Lag two years)	0.0001*** (0.00004)	0.0001 (0.0001)	0.0000003* (0.000002)	0.0003 (0.0002)
Relevant statistics				
Observations	12,012	12,012	41,929	41,929
Number of patent classes/assignee	572	572	1,823	1,823
R ²	0.703		0.645	
Chi square	2,340.52	11,301.15	1,965.90	1,784.18

Columns 1 and 3: Random effects panel data model with standard errors clustered by patent class or patent assignee. Columns 2 and 4: Random effects panel negative binomial model. For columns 1 and 2, 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 columns 3 and 4, the sample consists of electric equipment patents given to EEMs and a random sample of 2,000 firms, the unit of observation is the patent assignee, and the treated groups are the EEMs (electric equipment manufacturers). All specifications contain a time trend and a constant. The sample is from 1980 to 2000. Standard errors are in parentheses. Significant at *10%, **5%, and ***1%.

^aCalculation of this patent stock is based on patents in all other classes (columns 1 and 2) and patents granted to all other assignees (j, \dots, n) in the patent technology classes assignee i patents (columns 3 and 4).

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:

$$Y_{it} = \alpha + \beta D_{treatment} + \phi D_{treated} + \theta(D_{treatment} * D_{treated}) + \phi t + \sum_{j=1}^j \theta_j Z_{it}^j + v_i + \varepsilon_{it}. \quad (2)$$

In equation (2), Y_{it} is the number of patents or the percentage of patents for a given patent class or firm in a given application year, t is a time trend, and Z^j are other control variables.³⁵ $D_{treatment}$ is the deregulation dummy (lagged by two 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 the control group, which is a random sample of 2000 firms, selected for tractability, that patent in the electric equipment classes but are not EEMs).³⁶ The difference-in-difference coefficient is θ .

If deregulation was responsible for a significant negative impact on the innovation behavior of electric equipment producers, we expect θ to have a negative sign. For table 2, columns 1 and 3, when the dependent variable is in percentages, we use a random effect GLS model with robust and clustered standard errors.³⁷ However, even if we observe a decline in the percentage of electricity patents, we cannot fully conclude that deregulation has a negative impact on the electric technology innovation. An alternate explanation

³⁵ 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. Percentage of patents per assignee = (Number of electric equipment patents granted to an assignee in year t /Total number of electric equipment patents granted by the USPTO) ×100. The year refers to application year.

³⁶ When the unit of observation is the patent class, the sample is all patent classes. When the unit of observation is the assignee, the sample is electric equipment patent classes.

³⁷ See “How Much Should We Trust Differences-in-Differences Estimates?” Marianne Bertrand, Esther Duflo and Sendhil Mullainathan; *Quarterly Journal of Economics*, 119 (2004), 249–275 for an extensive discussion.

could be the case that EPAct has not had an absolute negative effect, but rather that electricity innovation is growing more slowly compared to other technologies. Thus, the percentages of electric technology innovation are declining. To investigate whether deregulation has actually decreased the absolute number of patented innovations by EEMs, we use number of patents in a patent class or by assignee in columns 2 and 4. Since the dependent variable is in counts, we use a random effects negative binomial model to estimate these two 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 columns 1 and 2, the sample consists of patents granted to corporations in all patent classes between 1980 and 2000, and the dependent variables are the percentage and number of patents granted in each patent class in a given year.³⁸ The treated groups are the electric equipment patent classes. First, we find that the difference-in-difference coefficients (-0.08) are negative and significant in both columns, implying that the introduction of competition in the power sector has had an adverse impact on both, the percentage and level of patenting in the electric equipment technologies compared to other technologies.³⁹ Second, electric equipment classes have a higher number of patents when compared to nonelectric equipment classes, holding all else constant. Third, the post-1992 period has seen a decline in the percentage of patents assigned to all classes (column 1) while the absolute number of patents has increased (column 2).⁴⁰ The 1990s was a decade of prolific growth in new technologies (giving rise to increasing number of new patent classes) and vigorous innovation in existing areas. This is reflected in the fact that the absolute number of patents went up in each patent class, while the share of each patent class in total patents declined. Based on these results, one can be fairly certain that the decrease in patenting for electricity patent classes that occurs after 1992 is because of deregulation rather than increases in patenting in nonelectricity classes.⁴¹

We find the same patterns from columns 3 and 4 where we test whether the EEMs were adversely affected compared to other groups within the electric equipment patent classes.⁴² To create the control group, we draw a random sample of 2,000 firms from non-EEM assignees that patent

in the electric equipment classes.⁴³ As before there are three coefficients of interest: (a) the effect of EPAct on electric equipment patents in general, (b) average EEM versus non-EEM patenting activity in the electric technology classes, and (c) the interaction between the two, that is, how EEM electric technology patenting activity changed after EPAct. We expect a significant interaction term since the EEMs should be more affected after deregulation compared to other entities that innovate in the electric equipment area. This is because the utilities, the primary clientele of the EEMs, were directly influenced by deregulation and experienced significant changes in their competitive landscape and profitability.

As before, the difference-in-difference coefficient (the interaction term) shows the effect of the treatment (the passage of EPAct in 1992) on the treated (the EEMs in this case). This interaction coefficient is negative and significant in both columns, implying that electric technology patenting by EEMs declined in both percentage and absolute terms following the 1992 EPAct. When we calculate the aggregate effect, we find that EEMs experience a 24.4% decline (based on column 4) in patenting compared to non-EEMs. We also find that all else equal, the passage of the EPAct has had no impact on the percentage of patents in electric equipment classes (column 3) while the number of electric equipment patents granted to EEMs increased after 1992 (column 4). Also, the percentage and numbers of EEM patents are higher when compared to other assignees in the electric equipment technology classes. Before investigating the channels through which such declines occurred, we briefly discuss how the other variables affected patenting.

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 in a given class.⁴⁴ A priori, 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 that an increase in past patent quality stock increases both the percentage and number of patents for each class or assignee.

Additionally, a firm's innovation may be influenced by that of its competitors. As discussed earlier, we use the past patent stock of other patent classes to measure this and find mixed results. From columns 1 and 2, we find that as the

³⁸ All counts are by application year—out of all the patents applied for in year t , the number granted.

³⁹ We find that deregulation was responsible for a 0.5% decline (based on column 2) in patenting for the 42 electric technology classes.

⁴⁰ This is the effect when the total impact is not taken into account, that is, we do not take into account the negative interaction terms between the EPAct dummy and the electric equipment class dummy.

⁴¹ If the decline was a result of increased patenting in other classes, then the difference-in-difference coefficient for the level equation (column 2) would not be negative and significant.

⁴² The unit of observation is the patent assignee, and the sample comprises the electric equipment patent classes.

⁴³ Two thousand firms were selected for reasons of tractability.

⁴⁴ We lag the patent class characteristics by two 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. However, our main results are not sensitive to the choice of lags. Results provided on request.

patent stock of other technology classes increases, the percentage of patents for an individual class falls, while the absolute number increases. The positive effect may imply positive spillovers and some form of unobservable innovative capacity increase effect. The negative effect on the percentage (column 1) may imply that although there are positive spillovers, there are diminishing returns to these spillovers. At the assignee level, we find that in electric technology classes, own firm innovation is adversely affected (column 4) as innovation by competitors increases.

We also control for the generality and breadth of the past patent portfolio and find that these positively influence current innovation activities. 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 breadth in the past encourages current innovation.

We also find that as the number of boilers affected by the Clean Air Act Amendments (CAAA) 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 groups. There could be several alternative explanations for this finding. First, instead of picking up the effect of the CAAA, this result could reflect 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 supported by Taylor, Rubin, and Hounshell (2003). Finally, on average, lagged R&D stock and income levels have a positive impact on innovation.

B. Channels of Influence

Next, we focus solely on the EEMs and estimate a richer model that incorporates the appropriation and net competition effects, and illustrates the channels through which downstream deregulation affected upstream innovation. Our sample consists of all EEMs, 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.⁴⁵ Since these patent counts are nonnegative integer numbers, we cannot use the usual least squares approach.⁴⁶ In addition, these counts

have a disproportionate number of zeros since many of the smaller EEMs do not patent every year and some EEMs never patent during our sample period.⁴⁷ The data-generating process for the zero outcomes may be qualitatively different from the process that generates the positive outcomes. Therefore, we model such data using a zero-modified negative binomial specification.⁴⁸ 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 (3):

$$\Pr ob(Z = 1|X) = \frac{e^{X\beta}}{1 + e^{X\beta}}, \quad (3)$$

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 U.S. or foreign firm, lagged-energy R&D expenditure and GDP in the United States (in real \$2000), and year fixed effects.⁴⁹

The patent counts are then modeled using a negative binomial function with robust standard errors that are clustered by firm while factoring in the probabilities from the first stage.⁵⁰ This specification is given by

$$\begin{aligned} Y_{it} = & \alpha + \beta D_{treatment} + \chi A_t + \delta C_t + \phi_i(D_{treatment} \times A_t) \\ & + \phi_i(D_{treatment} \times C_t) + \sum_{p=1}^p \gamma_p Char_{it} \\ & + \sum_{M=1}^2 \delta_M Macro_t + \varepsilon_{it}, \end{aligned} \quad (4)$$

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.⁵¹ The appropriation effect, as explained earlier, arises due to the greater bargaining power of EEMs and a demand push effect, both of which originate from downstream IPP entry,

⁴⁵ Table 1b in the online appendix provides a list of these companies along with their assignee codes (from the NBER database) and patenting rank.

⁴⁶ Using OLS will yield some negative predicted values. But since the dependent variable is nonnegative, the predicted values should also be nonnegative 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 0, we prefer using a count data model.

⁴⁷ About 55% of the dependent variable has zero value.

⁴⁸ See Greene (2002) for a discussion of the model.

⁴⁹ From the estimation results, we find that EEMs that have more past patents and better-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. U.S. firms are less likely to patent. R&D and GDP have negligible impact.

⁵⁰ 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.

⁵¹ The net competition effect subsumes the pure competition and the escape competition effects that are discussed in section 2.

which is measured by the share of generation by nonutilities. The net competition effect variable captures the effect of downstream competition on upstream innovation (through changing the competitive conditions upstream due to downstream restructuring) and is measured by the average profit (return on assets) of all downstream utilities. The interaction terms between the treatment dummy and the appropriation and net 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 (boiler manufacturers, flue gas desulfurization manufacturers, low nitrogen oxide control burners, or a combination). $Macro_t$ denotes the macro controls.

In table 3, panel A, columns 1a and 1b, the sample consists of all EEMs, regardless of whether they have a patent. 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 semielasticities for each term, and columns 1b and 2b report the aggregate elasticities (or semielasticities for dummy variables) after taking into account the interaction terms. The results are similar in sign and significance across the two samples, and we discuss the results in columns 1a and b.

First, we find that after factoring in the direction and magnitude of the appropriation and net competition interactions, deregulation alone has led to a 20.6% decline in patenting by EEMs. A possible reason could be that the downstream utilities could not use a cost pass-through after deregulation. During the regulated era, utilities could pass on most costs to the final customers through the regulated rates. However, after deregulation, with fluctuating market-based wholesale electricity rates and mostly fixed retail rates, the utilities could not pass all costs to the customers. This dramatically reduced their own R&D budget and changed their technology buying behavior, quite apart from the direct effect of competition and declining profits. Additionally, rate-of-return regulation distorted investment incentives and resulted in Averch-Johnson types of distortion, where the regulated firm went off its path of equilibrium and chose a technology that led to overcapitalization (Granderson, 1999; Smith, 1975; Okuguchi, 1975). The lifting of the regulation may have corrected this distortion and reduced capital equipment investments by utilities. These effects in turn had an adverse influence on upstream innovation behavior.

We also find that both the appropriation effect and the net competition effects are significant after the passage of the EPAct but not before it. 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 deregulation, this effect determines in part the innovation response of EEMs. This is a combination of two opposing effects: the pure competition effect

that predicts a decline in innovation incentives and an opposing escape competition effect that points to an increase in innovation incentives with increasing competition. 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% decline in downstream profits decreases upstream innovation by approximately 9.18% post-EPAct (net competition effect). From table 1, panel B, we observe that for our sample period, profits declined on average by 2% after deregulation. Thus, the net competition effect is responsible for an 18.3% 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% increase in the appropriation effect, as captured by the nonutility generation share, increases innovation by approximately 2.2% following the introduction of the EPAct. From panel B of table 1, we observe that for our sample period, nonutility generation share increased on average by 8.9% after deregulation. Thus, the appropriation effect is responsible for a 19.6% 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% increase in electric equipment patenting by other firms increased a firm's innovation by 0.68%.⁵² 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 1990, 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

⁵² While this is a fairly large spillover effect, we believe there are two possible reasons for this: a true push toward more innovation and a strategic response. Both can be traced to the industrial structure of the EEM industry. First, since this is an industry with a limited number of players that mostly concentrate on a handful of major technologies, innovation by competitors necessitates a strong response from every firm wishing to maintain its market position. A second reason for observing this strong response could be strategic patenting by firms. Following the line of reasoning laid out in the literature on strategic patenting (Bessen, 2004) and patent thickets (Shapiro, 2000), one may argue that if a competitor is increasing patenting in an oligopoly setting, other firms may take out a greater number of patents around their own core innovations to protect them from infringement by others and to use them as bargaining tools in cross-licensing purposes.

TABLE 3.—CHANNELS OF INFLUENCE

Dependent Variable Number of Patents for Each EEM	A. Base Case			
	1a Semielasticity ^b	1b Elasticity ^c	2a Semielasticity ^b	2b Elasticity ^c
EPAct Dummy (Lag two years)	−13.613** (6.323)	−20.595** (6.591)	−12.205** (6.090)	−18.514*** (6.380)
Net Competition Effect (Lag two years)	−11.211 (11.620)		−8.979 (11.126)	
Appropriation Effect (Lag two years)	2.526 (4.049)		2.020 (3.901)	
EPAct Dummy (Lag two years) × Net Competition Effect (Lag two years)	78.456* (46.499)	9.182*** (0.343)	70.716* (44.331)	8.276*** (0.327)
EPAct Dummy (Lag two years) × Appropriation Dummy (Lag two years)	52.520*** (13.980)	2.200*** (0.610)	46.950*** (14.153)	1.967*** (0.618)
Innovation Inputs (Lag two years)				
Other Firms' Electric Technology Patent Stock ^a	0.00001* (0.000006)	0.680* (0.403)	0.00001* (0.000006)	0.627* (0.313)
Own Firm's Electric Technology Patent Quality Stock	0.00006 (0.00004)		0.00007 (0.00005)	
Mean (Adjusted) Generality for Own Firm's Electric Technology Patents	1.679*** (0.342)	0.482*** (0.098)	1.634*** (0.349)	0.861*** (0.184)
Mean (Adjusted) Number of Claims for Own Firm's Electric Technology Patents	−0.201 (0.429)		−0.265 (0.364)	
Firm Characteristics				
Dummy for Low NO _x Burner and Desulfurization Unit Producers	0.017 (0.489)		0.023 (0.490)	
Number of CAAA Affected Boilers	0.00001 (0.0002)		0.00003 (0.0002)	
Dummy for Low NO _x & Desulf. × Number of CAAA Affected Boilers	0.0004** (0.0002)	0.014** (0.008)	0.0004*** (0.0002)	0.008** (0.004)
Large EEM Dummy	0.662 (0.850)		0.809 (0.844)	
Large EEM Dummy × EPAct Dummy (Lag two years)	−0.309 (0.878)		−0.371 (0.876)	
Dummy for U.S. Firms	−1.303* (0.746)	−1.303* (0.746)	−1.381* (0.780)	−1.381* (0.780)
Macroenvironment				
Energy R&D Stock (billions of \$2000) (Lag two years)	0.066 (0.084)		0.086 (0.089)	
GDP (Billions of \$2000) (Lag two years)	0.0002 (0.0004)		0.0003 (0.0004)	
Observations (Number of firms)	1743 (83)		945 (45)	
Chi square	822.26		1,085.54	
B. Robustness to Lags: Dependent Variable: Number of Patents for Each EEM				
Lags of EPAct Dummy	1 No Lag	2 One Year	3 Three Years	
EPAct Dummy	−13.032** (6.204)	−14.201** (6.082)	−17.146 (11.970)	
Net Competition Effect	−8.102 (13.083)	−11.813 (13.653)	−7.867 (12.132)	
Appropriation Effect	4.689 (3.915)	2.794 (3.662)	−14.139 (24.617)	
EPAct Dummy × Net Competition Effect	74.645* (45.176)	82.097* (44.530)	67.257* (42.248)	
EPAct Dummy × Appropriation Dummy	43.524*** (14.137)	53.917*** (12.306)	56.404** (31.183)	
Innovation Inputs (Lag two years)				
Other Firms' Electric Technology Patent Stock ^a	0.00001* (0.000006)	0.00001* (0.000006)	0.00001* (0.000006)	
Own Firm's Electric Technology Patent Quality Stock	0.00006 (0.00004)	0.00006 (0.00004)	0.0001* (0.00004)	
Mean (Adjusted) Generality for Own Firm's Electric Technology Patents	1.686*** (0.333)	1.687*** (0.339)	1.631*** (0.356)	
Mean (Adjusted) Number of Claims for Own Firm's Electric Technology Patents	−0.224 (0.416)	−0.196 (0.446)	−0.164 (0.410)	

TABLE 3.—(CONTINUED)

Firm Characteristics			
Dummy for Low NOx Burner and Desulfurization Unit Producers	−0.030 (0.499)	0.021 (0.496)	0.003 (0.493)
Number of CAAA Affected Boilers	−0.000001 (0.0002)	−0.00001 (0.0002)	0.003 (0.004)
Dummy for Low NOx and Desulfurization × Number of CAAA Affected Boilers	0.001*** (0.0002)	0.001*** (0.0002)	0.0004*** (0.0002)
Large EEM Dummy	0.503 (0.845)	0.642 (0.859)	0.787 (0.893)
Large EEM Dummy × EAct Dummy (Lag two years)	0.039 (0.695)	−0.229 (0.750)	−0.691 (1.016)
Dummy for U.S. firms	−1.189* (0.693)	−1.274* (0.693)	−1.439* (0.814)
Macroeconomy			
Energy R&D stock (billions of \$2000) (Lag two years)	−0.082 (0.088)	−0.070 (0.086)	0.026 (0.088)
GDP (billions of \$2000) (lag two years)	−0.001 (0.001)	0.0002 (0.001)	0.00002 (0.001)
Observations (number of firms)	1,743 (83)	1,743 (83)	1,743 (83)
Chi square	822.26	777.99	823.12

Note to part A: Zero-inflated negative binomial model (inflation model: logit). Contains a constant and a time trend. Sample: 1980–2000. Columns 1a and 1b: all EEMs; columns 2a and 2b: EEMs that have at least one patent during the sample period. Robust and clustered (by firm) standard errors are in parentheses. Significant at *10%, **5%, and ***1% respectively.

^aStock based on the number of patents obtained by other firms (j, \dots, n) in the patent classes that firm i patents in.

^bColumns 1a and 2a (semielasticities): $d(\ln y)/dx$.

^cColumns 1b and 2b: elasticities for significant variables, EAct dummy (Columns 1b and 2b): aggregate semielasticities calculated taking into account the direction and magnitude of the interaction terms.

Note to part B: Zero-inflated negative binomial model (inflation model: logit). Specification is the same as table 3A and contains a constant and a time trend. Range: 1980–2000. Robust and clustered (by firm) standard errors are in parentheses. Significant at *10%, **5%, and ***1%.

^dThis stock is calculated based on the number of patents obtained by other firms (j, \dots, n) in the patent classes that firm i patents in. Columns 1–3 show results for the specification when the EAct dummy, and the net competition and appropriation variables are used as contemporaneous variables, with one- and two-year lags.

on innovation for these particular EEMs. Finally, we find that the size of the EEM has no impact on patenting, while U.S.-based EEMs appear to be less innovative than their foreign counterparts.⁵³ The R&D and GDP variables are not significant in any specification.

In the results discussed above (table 3, panel A), we lagged the deregulation dummy by two years. We assume that this is the time it takes to adjust a firm's innovation strategy to reflect the new market conditions, especially since the EAct was the first deregulation policy instituted in the U.S. electricity market and firms 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, we provide in panel B of table 3, sensitivity analysis to different lags of the deregulation dummy. From columns 1 and 2, we find that using the deregulation status for the current year (column 1) or using a one-year lag (column 2) provides results that are very similar to those presented in table 3, panel A. However, the results in column 3 are somewhat different. The EAct 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.

⁵³ While interpreting this result, it is important to remember that this may be the result of a selection effect. Non-U.S. firms that patent in the United States would probably be the top innovators in their countries, while for domestic firms, even the least innovative may still apply for a U.S. patent due to low entry barriers.

C. Patent Characteristics

Guided by the discussion from the theoretical literature, so far we have focused solely on the magnitude of innovations. 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. 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. In addition, the effect of deregulation may be the same for two firms in terms of patent numbers, but one may suffer a greater or lesser quality decline or may have a less general technology portfolio after deregulation.⁵⁴ To capture these changes in quality and generality, we use the difference-in-difference model outlined in equation (2).

⁵⁴ For example, firm A has 25 patents with an average of ten citations per patent before deregulation. The firm has 15 patents, each with an average of five citations, after deregulation. Firm B also has 25 patents before deregulation and 15 patents after. However, it has five citations per patent on average prederegulation and three 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. Before 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.

We use two metrics to measure patent quality, the average and the aggregate adjusted quality of a firm's patent portfolio, since neither one alone may be sufficient to capture true innovation quality.⁵⁵ 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 the patent quality of EEMs.

Quality, as explained earlier, is measured by the number of backward citations (a count variable) received by a patent. But to make these citation counts a true measure of patent quality and make them comparable across technologies and time, we purge these of technology and year effects, that is, demean these using patent field and year fixed effects. Additionally, we use the means and stocks of these variables (by firm). These two modifications turn the count variable into a continuous variable. The adjusted generality measure is a continuous variable for the same reason. When measured in levels, all of the above variables are bounded by 0 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 clustering and heteroskedasticity. Therefore, we use a random effects GLS model with clustered and robust standard errors when estimating the average quality and generality specifications.⁵⁶ We have conducted 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; 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 2,000 firms that patent in the electric equipment classes but are not EEMs.⁵⁷ 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.⁵⁸

There may be alternative explanations for these findings, however. One possible explanation is that of declining productivity. Focusing on energy patents from 1974 to 1980, Popp (2002) shows that the productivity of new innovations tends to decline over time, and thus newer innovations add less to the existing knowledge stock than old ones. This leads to a decline in the quality of knowledge stocks, and in turn such diminishing returns affect future patent quality. Following this line of reasoning, it can be argued 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, and hence the observed decline in quality and generality. However, such a decline would have been more gradual for the entire electric technology class than that observed in the data. Additionally, the comparison with the random sample of firms who also patent in the electric equipment class but suffer no such decline concurrent with the passage of the EPAct may imply that at least part of this decline was due to deregulation.

We also find that past patent stock has a positive effect on the quality and generality of current patents: 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 (columns 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 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, aggregate patent quality and generality have suffered. In addition, in column 2, the interaction between the EEM dummy and the CAAA term is negative and significant, implying that aggregate EEM patent quality suffered after CAAA. However, we do not believe that this is the effect of the CAAA. Rather, 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. The effects of the aggregate R&D stock and GDP are mixed. The main finding of table 4 is the decline in patent quality and generality after 1992.

⁵⁵ Average adjusted quality is measured by the mean number of citations (purged of year and field effects) that each firm or assignee receives. Aggregate adjusted quality is the total number of citations (purged of year and field effects) that each firm or assignee receives. When we purge the citations of year and field effects, this in essence controls for technology and year fixed effects.

⁵⁶ The error can be disaggregated into two components: v_i , the random disturbance that varies by firm but not over time ($v_i \sim N(0, \sigma_v^2)$), and ε_{it} , is the idiosyncratic error component ($\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$).

⁵⁷ We selected a random sample of 2,000 firms for tractability.

⁵⁸ However, on average, EEM patent quality and generality are higher than other patents in the electric technology category.

TABLE 4.—PATENT CHARACTERISTICS

Sample (by Patent Assignee) Dependent Variable	Electricity Patent Classes		
	Average (Adjusted) Quality (1)	Aggregate (Adjusted) Quality (2)	Average (Adjusted) Generality (3)
EPAct Dummy (lag two years)	0.009 (0.014)	0.171* (0.095)	−0.004 (0.014)
EEM Dummy	0.044** (0.019)	2.165*** (0.413)	0.076*** (0.024)
EPAct Dummy (Lag two years) × EEM Dummy	−0.095*** (0.032)	−0.875*** (0.314)	−0.139** (0.050)
Innovation inputs (lag two years)			
Other Firm's Electric Technology Patent Stock ^a	−0.000003*** (0.000001)	0.00003*** (0.000004)	−0.00001*** (0.000001)
Own Firm's Electric Technology Patent Stock	0.001*** (0.0001)	0.213*** (0.001)	0.002*** (0.0005)
Own Firm's Electric Technology Patent Quality Stock (Adjusted)			−0.0001* (0.00004)
Mean (Adjusted) Generality for Own Firm's Electric Technology Patents	0.035*** (0.010)	0.0004 (0.040)	
Mean (Adjusted) number of Claims for Own Firm's Electric Technology Patents	0.112*** (0.019)	0.116** (0.060)	0.204*** (0.021)
Macroenvironment			
Number of Clean Air Act Affected Boilers	0.00001 (0.00001)	−0.0001* (0.00006)	−0.00002** (0.00001)
EEM Dummy × Number of Clean Air Act Affected Boilers	0.00001 (0.00002)	−0.0004** (0.0002)	0.00001 (0.00003)
R&D Stock (Billions of \$2000) (Lag two years)	−0.0002 (0.0001)	−0.0006 (0.0001)	−0.0003** (0.0001)
GDP (Billions of 2000\$) (Lag two years)	−0.00001 (0.00002)	−0.0005*** (0.0002)	−0.00001 (0.00002)
Relevant statistics			
Observations	41,929	41,929	41,929
Number of assignees	1,823	1,823	1,823
R ²	0.435	0.861	0.730
Wald statistic (chi square)	299.54	2,916.11	559.14

In columns 1 and 3, estimation is done using a random effects GLS model with robust and clustered standard errors. In column 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 number 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 2,000 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%, **5%, and ***1%.

^aThis stock is calculated based on the number of patents obtained by other assignees (j, \dots, n) in the patent classes that assignee i patents in.

V. Conclusion

Deregulation has dramatically changed the landscape of the U.S. electric utility industry by introducing competition in the generation sector. Product market competition from nonutilities (such as the independent power producers) has made utilities more conscious of their bottom line. This shift has had an effect on their technology buying behavior, which in turn has affected the innovation behavior of the electric equipment manufacturers. 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. Postderegulation, the value added (to utilities) due to new technology adoption decreases because of the competition that utilities face. This decline in value added decreases the demand for

new technology, which in turn has a negative effect on 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 postinnovation profits. This effect spurs firms to innovate more in order to gain advantage over their competitors, that is, to escape competition. In the empirical model, these two effects are subsumed in the net competition effect, which is measured by the average profit of the downstream utilities. In addition, the appropriation effect has a positive effect on innovation. Increased participation of nonutilities in the wholesale market increases the EEM customer base, thus increasing their status quo bargaining power and the price for their innovations and 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 sam-

ple 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% 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 an 18.3% decline in innovation that has been offset by an increase of 19.6% due to the appropriation effect.

In addition, the innovation environment of a firm matters, and the quality, breadth, and generality of past innovation inputs positively influence 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 it 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. In addition, by modeling both the magnitude and attributes of innovation, it provides a comprehensive account of the innovation response of upstream technology-producing firms when their downstream buyers are subject to product market competition.

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APPENDIX

FIGURE 1A.—PATENTS OBTAINED BY FIRMS IN DRUGS AND MEDICAL CLASSES

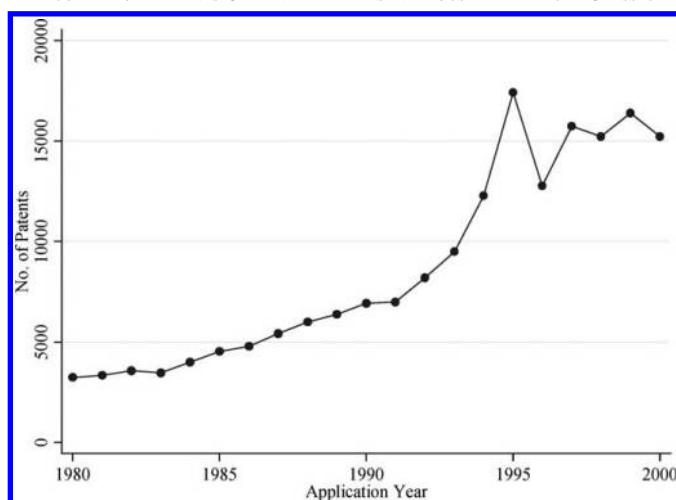
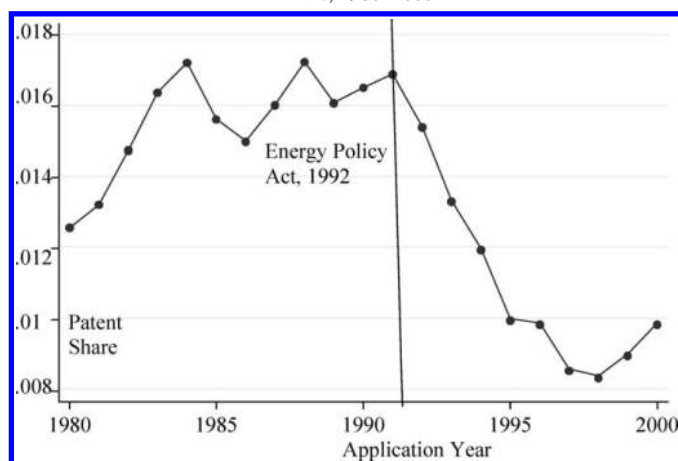


FIGURE 1B.—SHARE OF EEM ELECTRIC TECHNOLOGY PATENTS IN TOTAL USPTO PATENTS, 1980–2000



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