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Environmental Regulation and Innovation: A Panel Data Study

Adam B. Jaffe and Karen Palmer*

I. Introduction

Environmentalists and other proponents of new and more stringent environmental regulations have argued that increasing the stringency of environmental regulations provides an incentive for firms to develop new and less costly ways of reducing pollution, or, potentially, entirely new methods of production that eliminate particular types of emissions *and* reduce costs of production.[1] Proponents of this view, including Professor Michael Porter of Harvard Business School, have gone on to suggest that if one country adopts stricter environmental regulations than its competitors, the resulting increase in innovation will enable that country to become a net exporter of the newly developed environmental technologies.[2] This view of the relationship between environmental regulation and economic performance has come to be known as "the Porter hypothesis."

The evidence offered in support of this hypothesis is largely anecdotal. For example, Michael Porter (1991) claims that the phase-out of ozone-depleting CFCs led DuPont to develop a less harmful substitute. Other examples that are discussed in a recent report to the U.S. EPA (Bonifant, forthcoming b and forthcoming a) include (1) the development of new paints and coatings with lower volatile organic compound (VOC) content in response to Clean Air Act regulations limiting VOC emissions from users of industrial coatings and (2) innovations in the paper production process in Sweden in

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[1] See, for example, Gardiner (1994).

[2] For a review of the evidence on the relationship between environmental regulation and international competitiveness see Jaffe, Peterson, Portney and Stavins (1994).

response to biological oxygen demand (BOD) regulations on water emissions. While these case studies indicate that environmental regulation may create incentives for innovation in certain situations, they do not provide a general assessment of the impact of environmental regulation on innovative activity.[3]

More systematic economic analysis of the Porter hypothesis is hindered by ambiguity as to exactly what the hypothesis is. One can distinguish at least three different hypotheses. First, Porter himself emphasized that to stimulate innovation, environmental regulation should focus on outcomes and not processes. Thus the "narrow" version of the hypothesis is that *certain types* of environmental regulation stimulate innovation. Unfortunately, almost all existing U.S. environmental regulations are not of this type, as they prescribe both the goals of regulation and the processes for achieving those goals.[4] Thus it is not clear that the "narrow" Porter hypothesis has any empirical implications regarding existing regulations.

A second version of the hypothesis is that environmental regulation places constraints on the profit opportunities of firms that were not there before, and that firms maximizing profits subject to those constraints will do a variety of things differently than they would have without the constraints, with a likely area of new activity being investment in ways to meet the constraint at lower cost. This "weak" version of the hypothesis says only that regulation will stimulate certain kinds of innovation. Further, since addition of constraints to a maximization problem cannot improve the outcome, the weak version implies that the additional innovation must come at an opportunity cost that exceeds its benefits (ignoring the social value of reduced pollution).[5]

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[3] In a related analysis, Meyer (1993) examined the relationship between environmental regulation and rates of economic growth across U.S. states.

[4] Strictly speaking environmental regulations rarely require polluters to employ a particular pollution control technology. However, since emissions standards are often based on the performance of a particular technology, regulated firms have an easier time obtaining environmental permits and may be less heavily scrutinized when they employ the technology that provides the basis for the standard.

[5] Of course, firms that have previously invested in pollution-reducing technology or those that have a comparative advantage in environmental compliance would prosper even under this "weak" version of the hypothesis.

Finally, the "strong" version of the hypothesis rejects the narrow profit-maximizing paradigm and posits that firms under normal operating circumstances do not necessarily find or pursue all profitable opportunities for new products or processes. The shock of a new regulation may therefore induce them to broaden their thinking and to find new products or processes that both comply with the regulation and increase profits.[6] In this strong form, the Porter hypothesis has been construed to imply that environmental regulation is a free lunch (or even a "paid lunch"), i.e., that regulation induces innovation whose benefits exceed its costs, making the regulation socially desirable even ignoring the environmental problems it was designed to solve.[7]

Even if the model were more precisely specified, its systematic testing would be severely limited by data problems. Regulatory compliance expenditures, the only comprehensive measure of environmental regulatory burden on industry, fall short of providing a truly exogenous measure of regulatory burden since the level of these costs also depend on the nature of an industry's response to regulation. Moreover, if industries do *fundamentally* reengineer products or processes in response to stricter regulations to make them "more green" as Porter suggests, these changes are unlikely to be reflected to any significant extent in published industry output measures.

For all these reasons, our aim in this paper is extremely modest. We do not attempt to "test" the Porter hypothesis. Rather, we attempt to summarize the broad statistical relationships that exist among pollution control expenditures and measures of innovative activity and performance across industries and time. Using panel data at the two and three digit SIC code industry-level and a fixed effects model, we seek to determine whether changes in regulatory stringency, measured by regulatory compliance

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[6] Another version (narrowly strong?) allows that individual firms do not miss individually profitable innovation opportunities, but that in a setting of dynamic international competition the government can garner dynamic comparative advantage for its domestic environmental technology industry by inducing early innovation in environmental technology.

[7] See for example, Bezdek (1993) or Ayres (1994). For further discussion of different interpretations of the hypothesis, see Oates, Palmer and Portney (1993) and Schmalensee (1994).

costs in prior years, are associated with more or less innovative activity by regulated industries. We consider two measures of innovative activity: total private expenditures on research and development and the number of successful patent applications by domestic firms in an industry. Our hope is that documentation of the extent of broad statistical patterns in these data will provide input to further theoretical and empirical analyses of the issues surrounding regulation and innovation.

Our findings differ across the two measures of innovative activity. We find that lagged environmental compliance expenditures have a significant positive association with R&D expenditures when we control for unobserved industry-specific effects. These results indicate that increases in compliance expenditures within an industry are associated with increases in R&D shortly thereafter. We find little evidence, however, that industries' inventive output (as measured by successful patent applications) is related to compliance costs.

The remainder of the paper is organized as follows. In the next section we put this paper in the context of the existing literature on environmental regulation and innovation. In the subsequent section we specify the econometric model and describe the data. The fourth section presents the results of our analysis. In the fifth and final section we present our conclusions and recommendations for future research.

II. Previous Literature

Almost all of the existing literature on environmental regulation and R&D is theoretical in nature. A large subset of this literature focuses on the incentives a firm faces to undertake R&D to reduce environmental compliance costs (or to reduce emissions) under different approaches to environmental regulation.[8] In general, this

[8] See Zerbe (1970), Downing and White (1986) and Milliman and Prince (1989, 1991).

group of papers finds that R&D incentives tend to be stronger under incentive-based environmental policies than under command and control.[9]

There also has been some research exploring the relationship between stringency of environmental regulation and incentives for R&D and technology diffusion. Oates, Palmer and Portney (1993) use a simple model of a profit-maximizing firm in a perfectly-competitive industry to show that increasing the level of the pollution tax rate increases the firm's incentive to adopt a more efficient abatement technology. Schmalensee (1994) suggests that while research and development devoted to environmental compliance may increase with stricter environmental regulation, this increase will likely come at the expense of other research efforts that could have been more profitable. McCain (1978) notes that regulated firms may be reluctant to innovate or to adopt more efficient pollution control technologies if they anticipate that any resulting gains in the efficiency of pollution control will lead to subsequent tightening of regulatory standards.

Placing the firm within the context of an imperfectly competitive market and imposing other regulatory requirements can also change the nature of the firm's incentives. Biglaiser and Horowitz (1995) explicitly model strategic interactions among regulated firms in the research market. They show that given a requirement that the more inefficient firms adopt one of the newly developed efficient technologies after it becomes available (akin to adoption standards found in existing environmental regulations), an increase in the emission tax rate will decrease aggregate research.[10]

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[9] In contrast, Malueg (1989) finds that under certain conditions, a permit trading program may produce a smaller incentive for innovation than would exist with an equivalent command-and-control program, that is one that leads to the same level of aggregate pollution. All of these earlier papers ignore potential market failures in the innovation market; however, some more recent contributions to this literature (Parry (1994a, 1994b), Biglaiser and Horowitz (1994), and Hackett (1995)) explicitly consider the interactions among participants in the R&D market and the associated market failures in their analyses of the dynamic efficiency implications of different approaches to environmental regulation.

[10] Even without a technology adoption standard, regulators may not want to rely on more stringent environmental regulation to obtain optimal levels of research and development. Parry (1994a) shows that in the presence of endogenous technologies and perfect patent protection, the optimal emission tax rate is likely to be lower than marginal damages as a result of the common pool effect of research, monopoly pricing of licenses by patent holders and convex environmental damages. Parry goes on to suggest that

The only prior empirical study of the relationship between stringency of environmental regulation and development of new technologies is a study by Lanjouw and Mody (1993). In this study, Lanjouw and Mody analyze the impacts of increases in environmental compliance costs on patenting of environmental technologies using international data on expenditures for compliance with environmental regulation and environmental patents. They find that increases in environmental compliance costs lead to increases in patenting of new environmental technologies with a one to two year lag.[11] Thus Lanjouw and Mody provide support for what we dubbed the "weak" version of the hypothesis. In this paper we take a broader view, looking at R&D in addition to patents and looking at aggregate innovative activity rather than just new environmental technology.

III. Modeling and Data

III.A. Modeling

We analyze the relationship between stringency of environmental regulation and innovative activity by manufacturing firms using industry-level data over time. We use information on environmental regulatory compliance expenditures to measure regulatory stringency. We consider two different measures of innovative effort: industry-wide expenditures on research and development, and total number of successful patent applications.

It is very difficult to specify a theoretically satisfying structural or reduced-form R&D equation at the industry level because the exogenous shifters of both demand and supply are difficult to measure or do not vary across industries. In particular, there are no data showing how the real cost of scientists or research equipment vary, and most of the

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even if patent protection is imperfect, it is still unlikely that the dynamically efficient emission tax should exceed marginal damages.

[11] They also show that developing countries tend to adopt technologies that were developed elsewhere for regulatory compliance and that the patents obtained in these developing countries tend to be for adopting generic technologies to local conditions.

determinants of the returns to R&D are themselves endogenous. Thus we estimate a very crude reduced-form equation:

$$\log(R\&D)_{it} = \beta_1 \log(\textit{value added})_{it} + \beta_2 \log(\textit{Government } R\&D)_{it} + \beta_3 \log(PACE)_{i,t-l} + \alpha_i^R + \mu_t^R + \varepsilon_{it}^R \tag{1}$$

where i denotes industries, t denotes years, R&D is industry-funded R&D expenditures, value-added is industry value added, Government R&D is a proxy for government-funded R&D within the industry, and PACE pollution control expenditures from the Census Bureau's Pollution Abatement Costs and Expenditure survey. Equation (1) posits that current R&D is affected by lagged regulatory stringency; we experiment below with different lag structures. We have written the error term as composed of fixed industry and time components and a residual error that we will assume is independently, but not necessarily identically, distributed across i and t.

We include industry value-added to preclude a spurious correlation between R&D and pollution control expenditures due to the variation of both with industry size.[12] Value added is the appropriate size-scaling variable, because R&D/sales ratios across industries are distorted by industries' position in the value-added chain. We include a measure of government-funded R&D at the industry level, as public research is one of the few measurable external drivers of R&D at the industry level (Jaffe, 1988; Levin and Reiss (1984))

Equation (1) allows for fixed, unobservable effects associated with industries and years. Industry effects are extremely important for R&D, as industries vary with respect both to technological opportunity and the importance of technological characteristics to market demand (Jaffe 1988; Scherer, 1965). While it is unclear whether or not such unobservable determinants of industry R&D would also be correlated with pollution

[12] An alternative would be to regress R&D/value added on PACE/value added. In log form, such a scaling amounts to constraining β_1 to unity. Further, measurement error in value-added will cause the ratio form to exhibit spurious correlation. In any event all of the results on the PACE variable reported below are qualitatively similar in a model in ratio form.

control, estimation with industry fixed effects (industry dummies) ensures that biases from that source will be eliminated. Similarly, there are likely to be time-dependent determinants of R&D, particularly inflation and tax law changes.[13] Inclusion of time effects (year dummies) removes any such effects.[14]

There is an extensive literature on the advantages and disadvantages of patents as proxies for inventive or innovative output.[15] Typically, it is assumed that patents are proportional to (unobserved) innovative output, with a constant of proportionality that may vary across industries and across time. This implies that the log of patents measures innovative output, with an additive error. We control for this error by using combinations of the foreign patent variable, time dummies and industry fixed effects:

$$\begin{aligned}\log(\mathit{patents})_{it} &= \gamma_1 \log(\mathit{value\ added})_{it} + \gamma_2 \log(\mathit{Foreign\ patents}) \\ &\quad + \gamma_3 \log(\mathit{PACE})_{i,t-l} + \alpha_i^P + \mu_t^P + \varepsilon_{it}^P\end{aligned} \tag{2}$$

where patents is successful U.S. patent applications in year t by U.S. corporations, and Foreign patents is successful U.S. applications in year t by foreign corporations. Value added is included for the same reason as in the R&D equation, and we allow for an analogous pattern of industry and time fixed effects.

There are several reasons for including foreign patents as a control variable on the right-hand side. First, the number of patents by an industry will vary across industries and time because of variations in the factors affecting the decision to patent. Assuming these factors affect foreign patents proportionally, then including the log of foreign patents in the regression controls for these variations in patenting incentives. Further, at least one version of the Porter hypothesis suggests that U.S. regulation causes U.S. firms to become more innovative *relative to their foreign competitors*. Equation (2)

[13] A Research and Experimentation Tax Credit was first introduced in 1981, and was revised or extended several times during the 1980s.

[14] In particular, the use of time dummies in the log-log regression obviates the need for any kind of deflation of nominal dollar data. This is important because there are no good deflators for R&D.

[15] For a survey, see Griliches (1990).

incorporates this idea by asking whether PACE expenditures are associated with higher patenting rates, controlling for the rate of foreign patenting in the same industry.

III.B. Data[16]

The environmental compliance cost data come from the PACE survey, which has been conducted annually in each year since 1973, except for 1987. The survey covers manufacturing firms (SIC codes 20 - 39) and collects information on both the capital and operating costs of complying with environmental regulations, typically at the 4-digit SIC level.[17] Previous studies of the impacts of regulation have used the operating cost data to measure regulatory stringency, because the capital cost data have more missing values (e.g., Gray and Shadbegian, 1993). The operating cost data, however, contain the cost of capital expenditures in the "smoothed" form of yearly depreciation. Since we are looking for the effects of "shocks" to compliance costs, the capital cost series is arguably the better measure, so the results that we report are based on capital costs. We obtained very similar results using operating costs instead.[18]

The PACE data and the value-added data from the Census of Manufacturing are available at the 4-digit SIC level. The R&D data, however, come from a survey done by the Census for the NSF, and are tabulated at the level of 2 or 3 digit SICs, depending on the industry (NSF 1973-1991)[19] In order to estimate Equation (1), we aggregated the PACE and value-added data from the 4-digit SIC level to the level of the NSF industries. Government R&D is measured as the employee-weighted fraction of firms in the industry

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[16] A detailed data appendix, describing the mappings between SIC codes and industry definitions in the R&D and patent data, and providing means and standard deviations of all variables used in the regressions, is available from either of the authors on request.

[17] These data include the costs of complying with regulations that apply to potential releases from the manufacturing facility only. This means that the costs of complying with product regulations such as regulations limiting emissions from new cars are not included.

[18] We use the published data from 1973 to 1991 to interpolate PACE values for 1987 for each sector based on the data provided for other years. We also interpolated missing values for particular industries, but this is a smaller issue because the PACE 4-digit totals must be aggregated to higher levels to match with the R&D and patent data. Thus, at the 2 to 3 digit SIC level used in the regressions, a particular year's data contain interpolated values for only 1 or 2 4-digit SICs.

[19] The mapping between SIC codes and NSF industries is available from the authors on request.

that report receiving government research funding, calculated from NSF data reported for 1974-1991 (except 1985).

The second measure of innovative activity that we analyze is industry-wide patenting activity. The data for the patent analysis is an industry panel of U.S. patents by year of application.[20] Because of the lag between patent application and grant, reasonably complete patent totals by year of application cannot be determined until two or three years after the year in question. We utilize data based on all patents granted through the end of 1992 and confine our analysis to patent application totals through 1989. The Patent Office uses its own set of about 40 2 and 3-digit SIC industries, which are listed in Appendix Table 2 with their corresponding SIC definitions. Hence to undertake the patent regressions, the 4-digit SIC PACE and value-added data were re-aggregated to correspond to these industry definitions.

The classification of patents by industry is inherently problematic. For our purposes, we would like to know the number of patents produced by the firms in particular SIC groupings, so we can relate these totals to the PACE expenditures by those same firms. We call this the "industry of origin" for the patent. The industry of origin for a patent is not known by the patent office, because neither the inventor nor the firm for which she works (if any) is asked to identify themselves by industry. All that the patent office knows is the technological nature of the invention, which is captured in the U.S. Patent Classification System. This system currently contains about 400 main classes with about 100,000 subclasses. The patent office has a "concordance" that maps patent classes into its industry groups (Office of Technology Assessment and Forecast, 1985).

[20] When using patents as a proxy for inventive output, it is preferable to count them by date of application rather than date of grant, because that is the time at which the inventor perceives that she has made a potentially valuable invention, and the lag between application and grant is somewhat variable and affected by the vagaries of the patent office operations. There is no publicly available data on pending or unsuccessful patent applications. Once a patent has been granted, the application date is part of the information that is contained in the public patent record.

The industry patent totals published by the patent office are based on this concordance. This creates two distinct forms of misassignment relative to industry of origin. First, firms get patents completely unrelated to their core technologies. For example, if GM develops a new digital controller for fuel injectors, this would most likely be classified as an electronics patent, and hence the concordance would attribute the patent to the electronics industry rather than to the auto industry. Second, many inventions, and particularly those most relevant to pollution control, involve new processes that may be embedded in capital goods. Looking only at the technology, it is ambiguous whether to attribute this to the capital-good-using industry or the capital-good-supplying industry. Whichever choice the concordance makes, it will be "wrong" some of the time, if what is desired is a measurement of patent output by industry of origin.

To summarize, the data on patents by industry are only a crude measure of inventive output by that industry. For industries that do much of the research that leads to improvements in their basic products and processes, it is probably pretty good. For industries that rely heavily on equipment suppliers for research, it is not as good a measure.

The patent office also breaks down the annual patent totals by the nature of the organization (if any) to which the inventor assigns the patent right.[21] In this paper we use the totals for U.S. corporations as a dependent variable, and patents assigned to foreign corporations as a regressor. The means and standard deviations by industry for each of the variables used in the patent applications model are presented in Table 2.

[21] The categories are unassigned, assigned to a U.S. individual, assigned to a foreign individual, assigned to a U.S. corporation, assigned to a foreign corporation, assigned to the U.S. government and assigned to a foreign government.

IV. Results

Our analysis shows that the relationship between regulatory stringency and innovative activity by the regulated industry depends on which measure of innovative activity is employed. We present the results for the R&D expenditures model first, followed by the results for the patent count model.

IV.A R&D Expenditure Model Results

In the R&D expenditure model, company-funded expenditures on R&D are modeled as a function of government R&D intensity, industry value added, a lagged PACE variable and year dummies as well as, for the fixed effects model, industry dummies. We consider two different forms of the lagged PACE variable: a single year lagged value (LPACEL1) and a moving average of the prior 5 years (LPACE5). In the case of the former PACE variable, we estimate the model using data from 1975 to 1991, excluding 1985 when there are no data for the government R&D variable. In the case of the latter PACE variable, we use data from 1978 to 1991 excluding 1985.

The coefficient estimates and associated t-statistics are presented in Table 3. This table includes both the pooled model and the fixed effects results. The government R&D intensity variable has a significant and positive coefficient in both the pooled model and in the fixed effects model. This finding is consistent with the hypothesis that government R&D dollars are being directed towards fruitful areas that also attract higher levels of private R&D expenditure, that government-funded research produces findings that increase the productivity of private research, or both. The positive significant coefficient on the value-added variable is also consistent with our expectations.

All versions of the model exhibit time dummies that rise more less steadily over the sample period. This pattern reflects the significant increase in economy-wide real corporate R&D that occurred over the decade of the 1980s (National Science Board, 1993; Jaffe, forthcoming). There is no pattern in the time dummy coefficients that corresponds to identifiable episodes with respect to the nature or stringency of environmental policy. Hence we have no choice but to look for the effects of environmental regulations within industry fluctuations in R&D intensity rather than in any common movements across all industries.

The most striking finding in Table 3 is that the coefficient on each of the lagged PACE variables is significant and negative in the pooled models, but *significant and positive* in the fixed effects regressions. A Hausman-type test strongly rejects the hypothesis that the fixed-effects estimator is indistinguishable from the pooled estimator, indicating that the α_i's in Equation (1) are significant and are correlated with the other regressors. The fact that lagged PACE is negatively associated with R&D in the pooled model but positively associated in the fixed-effects model implies that the α_i's are positively correlated with R&D but negatively correlated with PACE expenditures, i.e., that "high-tech" industries are less pollution-expenditure intensive than low-tech industries on average. Controlling for these industry-specific effects and for the impacts of the other variables included in the model, the within-industry elasticity of R&D with respect to lagged PACE expenditures appears to be about .15. This result is robust to several changes in the model specification, including: deleting the government R&D intensity variable; substituting lagged value added for contemporaneous value added; substituting shipments, either lagged or contemporaneous, for value added; and removing value added from the equation and instead scaling the R&D and PACE variables by value added prior to estimation.

The fixed effects model captures all permanent inter-industry variation in R&D expenditures in the coefficients on the industry dummies. The coefficients on other variables are therefore determined entirely by intra-industry variation in the dependent variable over time. Thus, the positive coefficient on the PACE variable in the fixed effects model indicates a positive relationship between changes in PACE and R&D expenditures over time. This relationship is weakly confirmed in some regressions we performed using growth rates. In order to remove the noise associated with year to year growth rates, we divided the sample period into three periods of roughly five to six years in length and calculated average annual growth in each of the variables during these periods for each industry. We also calculated growth rates for R&D and PACE scaled by value added within the same periods. We then regressed growth in the R&D variable on growth in the other variables. The results of this analysis (not reported) indicate that growth in value added and growth in the government R&D intensity variable both have a positive and statistically significant association with growth in R&D expenditures. The growth rate of the PACE variable also is positively associated with growth in R&D, although the statistical significance of the PACE variable was marginal.

Figure 1 also illustrates the positive relationship between growth in R&D and growth in pollution control expenditures. This graph is a scatter plot of the mean annual growth in R&D expenditures and corresponding mean annual growth in lagged PACE by industrial sector. Those sectors with the highest annual rates of growth in both lagged PACE and R&D expenditures are Other Instruments, Other Transportation, and Radio & TV Receiving Equipment.[22] The lowest-R&D-growth-lowest-PACE-growth sectors are Ferrous Metals, Non-ferrous Metals, Textiles and Apparel, and Lumber and Wood. It is unclear whether or not these extremes are consistent with the anecdotal evidence surrounding the Porter hypothesis. It seems clear, however, that there is a strong positive association in these data between R&D and lagged pollution expenditures in the within-industry-across-time dimension.

Although the fixed-effects model controls for unobservable industry effects, it does impose the constraint that the slope coefficients are the same for all industries. We also estimated Equation (1) allowing each industry both its own intercept term *and* its own PACE expenditure coefficient. An F-test rejects the constraint that the PACE

[22] "Other" instruments includes all instrument subsectors other than Scientific and Mechanical Measuring Instruments. "Other" transportation equipment excludes Motor Vehicles, Missiles, and Aircraft. Because of missing PACE capital expenditures data, the PACE growth rate in Figure One for these two sectors is based on O&M expenditures. Excluding these two sectors from the regression analysis does not change the results significantly.

coefficients are equal across industries. Figure 2 summarizes the results across industries for the PACE coefficients; it is a histogram showing the number of industries with coefficients in various ranges for both the 1-year lag and the 5-year lagged moving average (corresponding to columns 3 and 4 of Table 3). This graph shows that the industry-specific PACE coefficients are more dispersed for the model employing the 5-year lagged moving average than for the 1-year lagged PACE variable. The graph also indicates that more of the industry-specific PACE coefficients are statistically significant for the model using the 5-year lagged measure than for the other model.

Table 4 presents the estimated coefficient values underlying the graph. Only one industry, fabricated metal products, has a significant negative coefficient in both specifications. One third of the industries have significant and positive coefficients in both specifications. Three diverse sectors, electronic components, ferrous metals and products and lumber and wood products, exhibit positive coefficients generally in excess of 0.5. The other sectors that exhibit a weaker positive response of R&D expenditures to lagged compliance costs are largely "high tech" or R&D-intensive sectors, including drugs and medicine, office, computing, and accounting machines, and communication equipment.

The table also reveals some non-trivial differences in the estimated coefficients for the PACE variables between the two models. In a few cases the coefficients are even of different signs. The differences in coefficient estimates across these two specifications suggest that there are severe limits to the inferences that can be drawn from the kind of reduced-form regressions that we are running. Clearly, the overall positive effect found in Table 3 has to be thought of as an average of effects that vary significantly across industries, and we simply cannot say whether the industry-specific results are spurious or reflect something real about the regulation/innovation nexus, without more detailed research that directly examines the regulatory and technological events in specific industries.

IV.B Patent Model Results

In this model domestic industry patent applications are related to foreign patent applications, domestic value added, a lagged PACE variable, year dummies and, in the case of the fixed effects model, industry dummies. The patent model coefficient estimates and associated t-statistics are presented in table 5. In all of the regressions we find, as expected, that both foreign patenting and domestic value added have a positive and generally significant coefficient. The foreign patent variable is highly significant (even after controlling for time and industry effects), indicating that it is an effective proxy for many of the factors affecting the attractiveness of obtaining patent protection in the industry. The time dummies in the patent regression are generally decreasing over time, reflecting a combination of the long-term decline in the aggregate ratio of domestic to foreign patents (Griliches, 1990), and inflation, which causes the ratio of patents to value added to fall over time.[23]

In none of these regressions is the coefficient on the lagged PACE variable statistically significant. These findings suggest that regulatory compliance costs have no detectable impact on patenting activity.

One could argue that our test is not a good test of the Porter contention that more stringent environmental regulation will lead to the development of new processes since most of the patents that are obtained (and therefore most of the patents included in our data) are for wholly new products, not new processes. In order to explore this effect, we used data on the percent of patents obtained by each industry that are process patents (Scherer 1984)[24] to divide the industries in our sample into the process innovation industries (those with more than 40 % process patents) and the product innovation

[23] The large drop in the time dummy coefficient in 1989 reflects truncation bias resulting from the fact that a significant number of 1989 application year patents were still pending when these data were collected in 1992.

[24] Scherer and his colleagues manually inspected all patents granted during an 18-month period in the late 1970s and classified each according to whether it was a product or process patent.

industries (those with less than 40 % process patents).[25] We then re-estimated Equation (2) separately on each of these groups. The results (not reported) continue to show no significant effects of pollution control expenditures on patents after controlling for fixed effects, even in the *ad hoc* group of "high-process innovation" industries.[26]

V. Conclusions and Topics for Further Research

Overall, we find that data at the industry level are mixed with respect to the hypothesis that increased stringency of environmental regulation spurs increased innovative activity by firms. We find no statistically significant relationship between regulatory compliance expenditures and patenting activity. We do find a significant positive relationship between regulatory compliance expenditures and R&D expenditures by the regulated industry when we control for industry-specific effects, although the magnitude of the effect is small. This latter finding is robust to a number of changes in the specification of the model and in the set of industries included in the analysis.

Our findings offer limited insights regarding some of the different versions of the Porter Hypothesis described above. First, since we have no experience with strictly outcome-oriented environmental regulations, these data cannot be used to draw any conclusions as to the validity of the "narrow" version of the hypothesis that switching to regulations of this type will stimulate innovation. Second, our empirical findings are consistent with the "weak" version of the hypothesis that environmental regulation will stimulate certain types of innovation. In this regard, our results build on those of Lanjouw and Mody who find that regulatory compliance costs have a positive effect on patenting of environmental technologies. Taken together, these two studies suggest that, in the aggregate, the disincentives for R&D attributed to a command-and-control

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[25] When we rank ordered the industries according to percent of process patents, we find a natural break at the 40% point. The industry immediately below the 40% point has only 24% process patents.

[26] We also analyzed the relationship between growth rates in patenting activity and regulatory stringency, as we did with the R&D equation. This analysis confirmed the absence of any within-industry correlation between patents and PACE.

approach to environmental regulation may be overcome by the high returns that regulation creates for new pollution-control technology.

These results do not, however, distinguish between what we have called the "weak" and "strong" forms of the Porter hypothesis. That is, we cannot say whether this increased R&D is merely an expensive diversion from firms' other R&D efforts, designed to find a way to cope with the burden of regulation, or whether it is evidence of the shock of regulation causing the firms to wake up and think in new and creative ways about their products and processes.

It is also unclear how this finding, if real, would alter the social benefit/cost analysis of regulation. There is evidence that, in general, the social rate of return to R&D exceeds the private return (Jaffe 1986; Griliches 1991), implying an increase in R&D spending creates net social benefits. It is unclear whether this general result would apply to the specific R&D that is induced by regulation. Further, in the short run, research resources are inelastically supplied, so that increases in research effort in highly regulated industries may be offset by reductions elsewhere.

Given the inconsistency between our findings for R&D expenditures and for patents, the highly aggregate nature of the data used in this study, the difficulty of classifying patents by industry of origin and the shortcomings of using compliance expenditures as a measure of regulatory stringency, further research is necessary before these results can be considered conclusive. It is to these topics for future research that we now turn.

Since compliance costs in some sense measure an industry's response to regulation, high compliance costs could indicate an ineffective response instead of high levels of stringency. Alternatively, extremely severe regulations might cause many plants to close down, leading to measured compliance costs being low rather than high. The compliance cost data used in this study also fail to capture the effect of environmental regulations on performance of consumer products such as auto-emissions standards.

Therefore, it would be interesting to attempt to replicate this study using another measure of aggregate environmental regulatory stringency. Aggregate measures of this type are difficult to find, but one possibility might be the prior estimates of regulatory cost to industry which are estimated in regulatory impact analyses (RIAs) of proposed environmental regulations which are conducted by the EPA. RIAs are required for all major proposed environmental regulations and would provide a better measure of anticipated cost of future regulations. Another possibility might be the number of pages in the federal registry in a particular year devoted to environmental regulations that affect each industry. Both the length of the regulation itself and the length of the comments from affected industries generated by the proposed regulation provide some indication of the anticipated burden of that regulation.

Another potentially interesting study would be to see if there is a relationship between environmental regulatory stringency faced by an industry and the patenting levels of its suppliers. Case study research on the paint and coatings industry reveals that much of the recent innovative activity in that industry has been in response to environmental regulations applied to manufacturers who use paints and coatings in their manufacturing processes (Bonifant, forthcoming b). The suppliers of materials and capital for use by regulated industries could be identified using information from the Input-Output tables for the U.S.

Perhaps the best way to overcome the aggregate nature of the data used in this study and to develop a better understanding of the nature of the relationship between regulation and innovation would be to conduct some focused industry studies. These studies could focus on firms in heavily regulated industries (such as petroleum refining, chemicals, metal products, and paper) and could include a more detailed analysis of the impacts of particular classes of regulation, say, by media, on innovative effort.[27] Ideally

[27] The selection of industries for this case study analysis would be based on some objective criteria such as the ratio of regulatory costs to value added. For example, the industries listed here are those with the highest average ratios of maintenance pollution abatement and control expenditures to average value added

an in-depth study of one or two companies in a particular industry, such as chemicals, could be used to develop an understanding about how regulated firms respond to new regulations and some related hypotheses which could then be tested using data from other firms in the industry.

Whether or not regulation-inspired R&D leads to lower costs of production or new and improved products in the future remains an unanswered question. While there is anecdotal and case study evidence that new technologies developed in response to environmental regulations do lower costs, there are several econometric studies that suggest that environmental regulation has a negative impact on productivity growth.[28] One possible explanation for the inconsistency between our finding of no impact of PACE on patenting and a positive impact of PACE on R&D expenditures is that incremental R&D induced by regulation is unproductive, or produces results that help with regulatory compliance but do not appear as patentable inventions. If the additional R&D does not accomplish anything beyond facilitating regulatory compliance, then its appearance does not foster productivity growth and does not have major policy implications. If, however, environmental regulation-inspired R&D does increase productivity, then regulators may want to find a way to anticipate this benefit in their cost-benefit analyses of proposed environmental regulations.

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ranging from 8% for petroleum refining to 2.5% for paper. The candidate industries for previous case study analyses were selected because these industries were known to have innovated in response to particular environmental regulations.

[28]See, for example, Gray and Shadbegian (1993), Barbera and McConnell (1986, 1990), Gollop and Roberts (1983) and Haveman and Christainsen (1981).

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Table 1
Means And Standard Deviations ( ) For Variables Used In The R&D Expenditure Model

Industry	R&D Expenditures ($ millions)	Government R&D Intensity	PACE Capital ($ millions)	Value Added ($ millions)
1. Food & Kindred Products/	1196.17	0.02397	196.93	130420.22
Tobacco Manufactures	(79.63)	(0.01993)	(31.31)	(16703.91)
2. Textile Mill Products/ Apparel	187.63	0.01756	34.61	44248.88
	(49.48)	(0.01305)	(14.35)	(10429.42)
3. Lumber & Wood Products, except	140.07	0.04373	75.38	33015.68
Furniture/ Furniture & Fixtures	(21.91)	(0.05714)	(22.76)	(10679.05)
4. Paper & Allied Products	584.10	0.10137	397.20	34787.88
	(56.84)	(0.05749)	(147.98)	(13419.63)
5. Industrial Chemicals	2430.19	0.59707	588.10	36704.28
	(1010.16)	(0.08564)	(175.81)	(12765.27)
6. Drugs & Medicines	3363.90	0.35086	40.51	17698.81
	(1108.90)	(0.17804)	(23.99)	(8507.59)
7. Other Chemicals	1407.70	0.09810	139.35	29486.56
	(554.35)	(0.08236)	(50.29)	(10025.39)
8. Petroleum Refining & Extraction	1582.13	0.63452	467.60	19401.85
	(584.17)	(0.14458)	(104.86)	(5815.05)
9. Rubber Products	638.56	0.35387	34.46	28743.69
	(30.06)	(0.19227)	(13.09)	(11203.47)
10. Stone, Clay, & Glass Products	652.73	0.23659	118.36	24929.92
	(261.13)	(0.04441)	(44.87)	(6455.65)
11. Ferrous Metals & Products	310.07	0.27790	370.06	27337.28
	(66.81)	(0.06417)	(209.17)	(4854.24)
12. Non-ferrous Metals & Products	317.13	0.45359	182.36	15023.56
	(92.29)	(0.07468)	(71.83)	(3571.91)
13. Fabricated Metal Products	537.75	0.23470	98.01	58862.64
	(181.23)	(0.10181)	(32.08)	(14734.13)
14. Office, Computing, & Accounting	5425.00	0.31035	14.35	20659.73
Machines	(3041.65)	(0.14234)	(10.97)	(9720.90)
15. Other Machinery, except	2103.31	0.14441	63.29	74372.71
Electrical	(478.65)	(0.03809)	(33.89)	(17406.52)
16. Radio & TV Receiving Equipment	216.43	0.10776	2.22	3327.53
	(125.18)	(0.15038)	(1.49)	(704.23)
17. Communication Equipment	3449.31	0.71793	11.96	22983.89
	(1778.12)	(0.11780)	(6.30)	(10165.93)
18. Electronic Components	2411.64	0.53029	38.46	20056.74
	(1357.10)	(0.17380)	(19.91)	(10322.26)

Table 1 (Continued)

Industry	R&D Expenditures ($ millions)	Government R&D Intensity	PACE Capital ($ millions)	Value Added ($ millions)
19. Other Electrical Equipment	1330.00	0.24525	42.83	32164.57
	(266.20)	(0.10064)	(21.36)	(9364.71)
20. Motor Vehicles & Motor Vehicles	4783.75	0.43963	176.51	45461.91
Equipment	(2096.99)	(0.13830)	(130.75)	(17192.43)
21. Other Transportation Equipment	211.50	0.48898	9.03	10137.72
	(130.34)	(0.10652)	(8.66)	(2161.23)
22. Aircraft & Missiles	3637.75	0.92096	30.76	38384.89
	(1917.94)	(0.01938)	(22.38)	(16731.60)
23. Scientific & Mechanical	1102.56	0.37319	7.24	15743.43
Measuring Instruments	(596.22)	(0.20869)	(8.68)	(13645.34)
24. Optical, Surgical, Photographic, &	2037.06	0.33726	19.70	20726.63
Other Instruments	(1088.56)	(0.09452)	(8.49)	(8373.60)

Table 2
Means And Standard Deviations ( ) For Variables Used In The Patent Count Model

Industry	Domestic Patents	Foreign Patents	PACE Capital ($ millions)	PACE O&M ($ millions)	Value Added ($ millions)
Food & Kindred Products	248.58	145.58	179.26	685.69	90882.49
	(16.63)	(33.47)	(19.73)	(255.99)	(23153.05)
Textile Mill Products	306.17	311.42	33.00	120.69	20558.17
	(23.21)	(57.94)	(15.39)	(35.57)	(3157.87)
Industrial Inorganic Chemistry	667.08	468.17	156.69	372.92	9473.93
	(65.65)	(26.76)	(63.28)	(79.53)	(1906.29)
Industrial Organic Chemistry	1776.25	1358.25	286.78	907.33	16331.46
	(310.52)	(94.56)	(99.75)	(202.39)	(4052.26)
Plastics Materials & Synthetic Resins	698.33	526.17	125.99	332.45	12239.67
	(58.52)	(97.60)	(36.74)	(108.78)	(3858.43)
Agricultural Chemicals	894.08	946.42	73.17	245.69	5348.48
	(98.68)	(119.25)	(33.48)	(53.87)	(1077.31)
Soaps, Detergents, Cleaners,	246.42	129.92	18.77	62.14	15511.97
Perfumes, Cosmetics & Toiletries	(24.68)	(27.17)	(4.24)	(25.40)	(4361.53)
Paints, Varnishes, Lacquers,	419.00	274.58	8.84	32.46	4453.58
Enamels & Allied Products	(64.85)	(27.58)	(4.42)	(14.32)	(1223.77)
Miscellaneous Chemical Products	334.92	215.58	30.65	89.75	5911.77
	(23.05)	(40.08)	(12.44)	(39.36)	(1590.45)
Drugs & Medicines	328.17	192.50	41.04	129.08	18682.59
	(99.17)	(41.70)	(17.25)	(55.40)	(6903.96)
Rubber & Miscellaneous Plastics	1694.17	1217.75	30.50	155.86	30646.47
Products	(113.73)	(266.44)	(6.34)	(69.07)	(8998.83)
Stone, Clay, Glass & Concrete	441.67	370.75	109.11	334.70	26519.00
Products	(21.18)	(72.07)	(39.69)	(76.16)	(4556.39)
Primary Ferrous Products	136.00	186.42	351.51	1160.72	28381.67
	(20.88)	(15.68)	(232.37)	(159.18)	(4936.65)
Primary & Secondary Non-Ferrous	110.25	121.75	163.09	533.62	16852.55
Metals	(10.81)	(18.51)	(72.17)	(128.56)	(2835.90)
Fabricated Metal Products	2023.50	1457.08	89.46	306.41	57246.15
	(169.92)	(239.34)	(30.12)	(163.73)	(8597.15)
Engines & Turbines	479.00	864.08	5.35	33.45	6613.42
	(55.36)	(116.00)	(3.10)	(7.13)	(909.09)

Table 2 (Continued)

Industry	Domestic Patents	Foreign Patents	PACE Capital ($ millions)	PACE O&M ($ millions)	Value Added ($ millions)
Farm & Garden Machinery &	563.25	448.33	6.94	20.62	6078.50
Equipment	(77.22)	(58.46)	(4.35)	(5.06)	(738.49)
Construction, Mining & Material	684.08	559.00	10.89	43.32	14338.11
Handling Machinery & Equipment	(81.20)	(83.53)	(7.47)	(11.10)	(2862.51)
Metal Working Machinery &	676.50	757.00	3.41	19.87	12254.00
Equipment	(65.55)	(85.55)	(2.35)	(13.86)	(1943.18)
Office Computing & Accounting	1045.25	1091.42	15.08	41.18	22974.41
Machines	(83.14)	(376.38)	(10.31)	(21.88)	(7709.54)
Special Industry Machinery, Except	1043.67	1322.83	3.03	14.979	7685.40
Metal Working Machinery	(121.84)	(115.93)	(1.91)	(5.29)	(1477.49)
General Industrial Machinery &	1387.83	1501.58	8.58	39.62	13237.54
Equipment	(106.86)	(257.94)	(3.74)	(23.56)	(1642.48)
Refrigeration & Service Industry	184.67	126.75	9.10	39.53	8842.18
Machinery	(14.54)	(24.56)	(3.88)	(19.18)	(1883.79)
Miscellaneous Machinery, Except	42.83	63.50	6.43	19.66	10083.81
Electrical	(10.41)	(11.05)	(1.43)	(9.91)	(2609.90)
Electrical Transmission &	1031.50	781.75	5.89	31.77	8548.99
Distribution Equipment	(82.34)	(198.15)	(2.04)	(16.55)	(1721.41)
Electrical Industrial Apparatus	578.25	601.25	14.91	33.60	8050.74
	(28.35)	(97.03)	(15.26)	(11.28)	(1165.49)
Household Appliances	57.33	98.75	8.73	31.75	6546.13
	(23.17)	(17.41)	(1.47)	(9.74)	(899.16)
Electrical Lighting & Wiring	245.33	146.42	6.50	26.47	7588.59
Equipment	(24.91)	(40.66)	(1.33)	(12.08)	(1952.49)
Miscellaneous Electrical Machinery,	307.25	231.33	13.65	40.27	7872.40
Equipment & Supplies	(40.29)	(36.21)	(4.11)	(17.94)	(2263.65)
Radio & TV Receiving Equipment	464.17	583.50	2.60	9.84	3599.11
Except Communication Types	(41.13)	(141.16)	(1.68)	(2.82)	(491.23)
Electronic Components & Accessories	2951.08	2308.25	55.33	183.05	48214.14
& Communication Equipment	(317.99)	(799.77)	(22.42)	(118.83)	(15244.16)
Motor Vehicles & Motor Vehicle	213.67	351.33	202.99	380.04	47982.93
Equipment	(41.29)	(124.34)	(136.73)	(148.49)	(13647.18)
Guided Missiles & Space Vehicles &	13.42	6.17	9.97	27.35	11632.59
Parts	(5.89)	(3.07)	(6.81)	(17.71)	(5482.11)

Table 2 (Continued)

Industry	Domestic Patents	Foreign Patents	PACE Capital ($ millions)	PACE O&M ($ millions)	Value Added ($ millions)
Ship & Boat Building & Repairing	34.25	38.92	7.57	40.76	6725.53
	(6.77)	(8.07)	(2.33)	(19.10)	(1062.74)
Railroad Equipment	60.67	34.25	1.43	9.84	1885.08
	(16.21)	(6.57)	(0.45)	(3.67)	(807.02)
Motorcycles, Bicycles & Parts	12.67	21.42	0.60	3.24	427.25
	(4.56)	(6.82)	(N/A)	(2.02)	(49.52)
Miscellaneous Transportation	12.92	15.25	1.30	3.87	905.19
Equipment	(4.06)	(5.36)	(0.99)	(1.83)	(272.92)
Ordnance Except Missiles	89.92	100.92	11.90	44.51	4539.49
	(12.87)	(22.22)	(4.24)	(28.50)	(1484.19)
Aircraft & Parts	55.00	22.58	22.29	97.15	29869.49
	(10.24)	(6.50)	(14.33)	(72.70)	(8488.04)
Professional & Scientific Instruments	3014.42	3037.67	22.65	109.24	34359.98
	(309.18)	(618.30)	(5.52)	(48.77)	(17032.48)

Table 3
R&D Expenditure Regression Results*

Variable	Coefficient Values and [t-statistics]			
	Pooled Model		Industry Fixed Effects	
GOVR&D	2.748	2.850	0.536	0.323
	[13.652]	[15.964]	[2.729]	[2.462]
LVAL-ADD	0.700	0.510	0.438	0.325
	[8.918]	[5.497]	[4.323]	[5.180]
LPACE5	-0.162		0.131	
	[-4.607]		[2.474]	
LPACEL1		-0.124		0.152
		[-3.238]		[6.006]
Time Dummies				
1976		0.278		0.035
		[0.824]		[0.437]
1977		0.384		0.168
		[1.074]		[2.049]
1978		0.461		0.210
		[1.308]		[2.794]
1979	-0.017	0.332	0.085	0.252
	[-0.061]	[0.895]	[1.179]	[3.237]
1980	0.257	0.789	0.220	0.360
	[0.938]	[2.294]	[2.734]	[4.307]
1981	0.155	0.754	0.311	0.522
	[0.567]	[2.186]	[4.182]	[5.831]
1982	0.242	0.836	0.401	0.538
	[0.877]	[2.393]	[5.813]	[6.218]
1983	0.384	0.904	0.418	0.630
	[1.399]	[2.586]	[7.086]	[7.578]
1984	0.409	0.963	0.471	0.754
	[1.448]	[2.677]	[8.018]	[9.267]
1986	0.676	1.281	0.588	0.820
	[2.439]	[3.627]	[9.265]	[9.907]
1987	0.722	1.238	0.561	0.776
	[2.468]	[3.479]	[7.557]	[8.431]
1988	0.740	1.306	0.562	0.767
	[2.496]	[3.550]	[7.232]	[8.070]

Table 3 (Continued)

Variable	Coefficient Values and [t-statistics]			
	Pooled Model		Industry Fixed Effects	
1989	0.890	1.601	0.580	0.839
	[3.011]	[4.323]	[5.968]	[8.291]
1990	0.886	1.622	0.612	0.844
	[2.972]	[4.303]	[6.577]	[8.099]
1991	0.887	1.602	0.640	0.851
	[2.913]	[4.174]	[6.331]	[7.789]
R-squared	0.419	0.459	0.966	0.978
Adjusted R-squared	0.384	0.420	0.960	0.974

*T-statistics are calculated using heteroskedasticity-consistent standard errors.

Table 4

Industry-Specific PACE Coefficients for R&D Model

Industry Name	Single-Year Lagged PACE	Five-Year Moving Average PACE
1. Food & Kindred Products/ Tobacco Manufactures	-0.149	-0.434 (*)
2. Textile Mill Products/ Apparel	-0.192	-0.303 (**)
3. Lumber & Wood Products, except Furniture & Fixtures	0.412 (*)	0.850 (**)
4. Paper & Allied Products	-0.004	0.174
5. Industrial Chemicals	0.093	-0.018
6. Drugs & Medicines	0.328 (**)	0.385 (**)
7. Other Chemicals	0.358 (**)	-0.520 (*)
8. Petroleum Refining & Extraction	0.205	0.716 (**)
9. Rubber Products	-0.127	-0.221 (**)
10. Stone, Clay, & Glass Products	-0.323 (**)	-0.255
11. Ferrous Metals & Products	0.507 (**)	0.635 (**)
12. Non-ferrous Metals & Products	0.188	-0.115
13. Fabricated Metal Products	-0.296 (**)	-0.375 (**)
14. Office, Computing, & Accounting Machines	0.200 (*)	0.433 (**)
15. Other Machinery, except Electrical	0.074	0.102
16. Radio & TV Receiving Equipment	-0.123	-1.557 (**)
17. Communication Equipment	0.221 (**)	0.375 (**)
18. Electronic Components	0.892 (**)	0.826 (**)
19. Other Electrical Equipment	-0.162	-0.384

Table 4 (Continued)

20. Motor Vehicles & Motor Vehicles Equipment	0.053	0.108
21. Other Transportation Equipment	0.157 (**)	1.015
22. Aircraft & Missiles	0.168 (**)	0.126 (*)
23. Scientific & Mechanical Measuring Instruments	0.142 (*)	0.109 (*)
24. Optical, Surgical, Photographic, & Other Instruments	0.100	-0.213

(*) indicates coefficient is significant at the 5% level.

(**) indicates coefficient is significant at the 1% level.

T-statistics are calculated using heteroskedasticity-consistent standard errors.

Table 5
Patent Regression Results*

	Coefficient Value and [t-statistic]			
Variable	Pooled Model		Industry Fixed Effects	
LPFOR	0.909	0.907	0.437	0.362
	[55.762]	[62.943]	[5.329]	[5.111]
LVAL-ADD	0.150	0.127	0.147	0.281
	[5.534]	[5.664]	[2.748]	[4.965]
LPACE5	-0.007		-0.011	
	[-0.441]		[-0.325]	
LPACEL1		-0.006		-0.014
		[-0.433]		[-0.785]
Time Dummies				
1977		-0.292		-1.156
		[-3.771]		[-9.659]
1978		-0.352		-1.234
		[-4.634]		[-10.358]
1979		-0.384		-1.262
		[-5.148]		[-10.319]
1980		-0.429		-1.304
		[-5.113]		[-10.922]
1981	-0.052	-0.468	-0.048	-1.362
	[-0.646]	[-6.051]	[-1.542]	[-11.092]
1982	-0.074	-0.447	-0.041	-1.347
	[-0.865]	[-4.836]	[-1.49]	[-11.254]
1983	-0.116	-0.556	-0.108	-1.437
	[-1.337]	[-6.301]	[-3.805]	[-11.586]
1984	-0.156	-0.592	-0.116	-1.454
	[-1.837]	[-6.838]	[-4.297]	[-12.149]
1985	-0.248	-0.678	-0.157	-1.474
	[-2.806]	[-7.605]	[-4.591]	[-13.115]
1986	-0.317	-0.751	-0.188	-1.493
	[-3.7]	[-8.662]	[-5.039]	[-13.701]
1987	-0.292	-0.715	-0.153	-1.478
	[-3.661]	[-8.531]	[-3.600]	[-13.823]
1988	-0.298	-0.738	-0.186	-1.547
	[-3.536]	[-8.170]	[-4.005]	[-13.539]

Table 5 (Continued)

Variable	Coefficient Value and [t-statistic]			
	Pooled Model		Industry Fixed Effects	
1989	-0.344	-0.790	-0.551	-1.973
	[-4.077]	[-8.704]	[-9.173]	[-12.128]
R-squared	0.922	0.930	0.989	0.987
Adjusted R-squared	0.920	0.927	0.987	0.985

*T-statistics are calculated using heteroskedasticity-consistent standard errors.

APPENDIX

Appendix Table 1
Industries included in the R&D Expenditure Data and Corresponding SIC Codes

Industry Name	SIC Code
1. Food & Kindred Products/ Tobacco Manufacturers	20 - 21
2. Textile Mill Products/ Apparel	22 - 23
3. Lumber & Wood Products, except Furniture and Fixtures	24 - 25
4. Paper & Allied Products	26
5. Industrial Chemicals	281 - 282, 286
6. Drugs & Medicines	283
7. Other Chemicals	284 - 285, 287 - 289
8. Petroleum Refining & Extraction	20
9. Rubber Products	30
10. Stone, Clay, & Glass Products	32
11. Ferrous Metals & Products	331 - 332, 339
12. Non-ferrous Metals & Products	333 - 336
13. Fabricated Metal Products	34
14. Office, Computing, & Accounting Machines	357
15. Other Machinery, except Electrical	351 - 356, 358 - 359
16. Radio & TV Receiving Equipment	365
17. Communication Equipment	366
18. Electronic Components	367
19. Other Electrical Equipment	361 - 364, 369
20. Motor Vehicles & Motor Vehicles Equipment	371
21. Other Transportation Equipment	373 - 375, 379
22. Aircraft & Missiles	372, 376
23. Scientific & Mechanical Measuring Instruments	381 - 382
24. Optical, Surgical, Photographic, & Other Instruments	383 - 387

Appendix Table 2
Industries included in the Patent Data and Corresponding SIC Codes

Industry Name	SIC Code
Food & Kindred Products	20
Textile Mill Products	22
Industrial Inorganic Chemistry	281
Industrial Organic Chemistry	286
Plastics Materials & Synthetic Resins	282
Agricultural Chemicals	287
Soaps, Detergents, Cleaners, Perfumes, Cosmetics & Toiletries	284
Paints, Varnishes, Lacquers, Enamels & Allied Products	285
Miscellaneous Chemical Products	289
Drugs & Medicines	283
Rubber & Miscellaneous Plastics Products	30
Stone, Clay, Glass & Concrete Products	32
Primary Ferrous Products	331, 332, 3399, 3462
Primary & Secondary Non-Ferrous Metals	333 - 336, 339 (except 3399), 3463
Fabricated Metal Products	34 (except 3462, 3463, 348)
Engines & Turbines	351
Farm & Garden Machinery & Equipment	352
Construction, Mining & Material Handling Machinery and Equip.	353
Metal Working Machinery & Equipment	354
Office Computing & Accounting Machines	357
Special Industry Machinery, Except Metal Working Machinery	355
General Industrial Machinery & Equipment	356
Refrigeration & Service Industry Machinery	358
Miscellaneous Machinery, Except Electrical	359
Electrical Transmission & Distribution Equipment	361, 3825
Electrical Industrial Apparatus	362
Household Appliances	363
Electrical Lighting & Wiring Equipment	364
Miscellaneous Electrical Machinery, Equipment and Supplies	369
Radio & TV Receiving Equipment Except Communication Types	365
Electronic Components & Accessories & Communication Equip.	366 - 367
Motor Vehicles & Motor Vehicle Equipment	371
Guided Missiles & Space Vehicles & Parts	376
Ship & Boat Building & Repairing	373

Appendix Table 2 (Continued)

Industry Name	**SIC Code**
Railroad Equipment	374
Motorcycles, Bicycles & Parts	375
Miscellaneous Transportation Equipment	379 (except 3795)
Ordnance Except Missiles	348, 3785
Aircraft & Parts	372
Professional & Scientific Instruments	38 (except 3825)

Figure One

THE RELATIONSHIP BETWEEN GROWTH IN R&D EXPENDITURES AND GROWTH IN LAGGED PACE

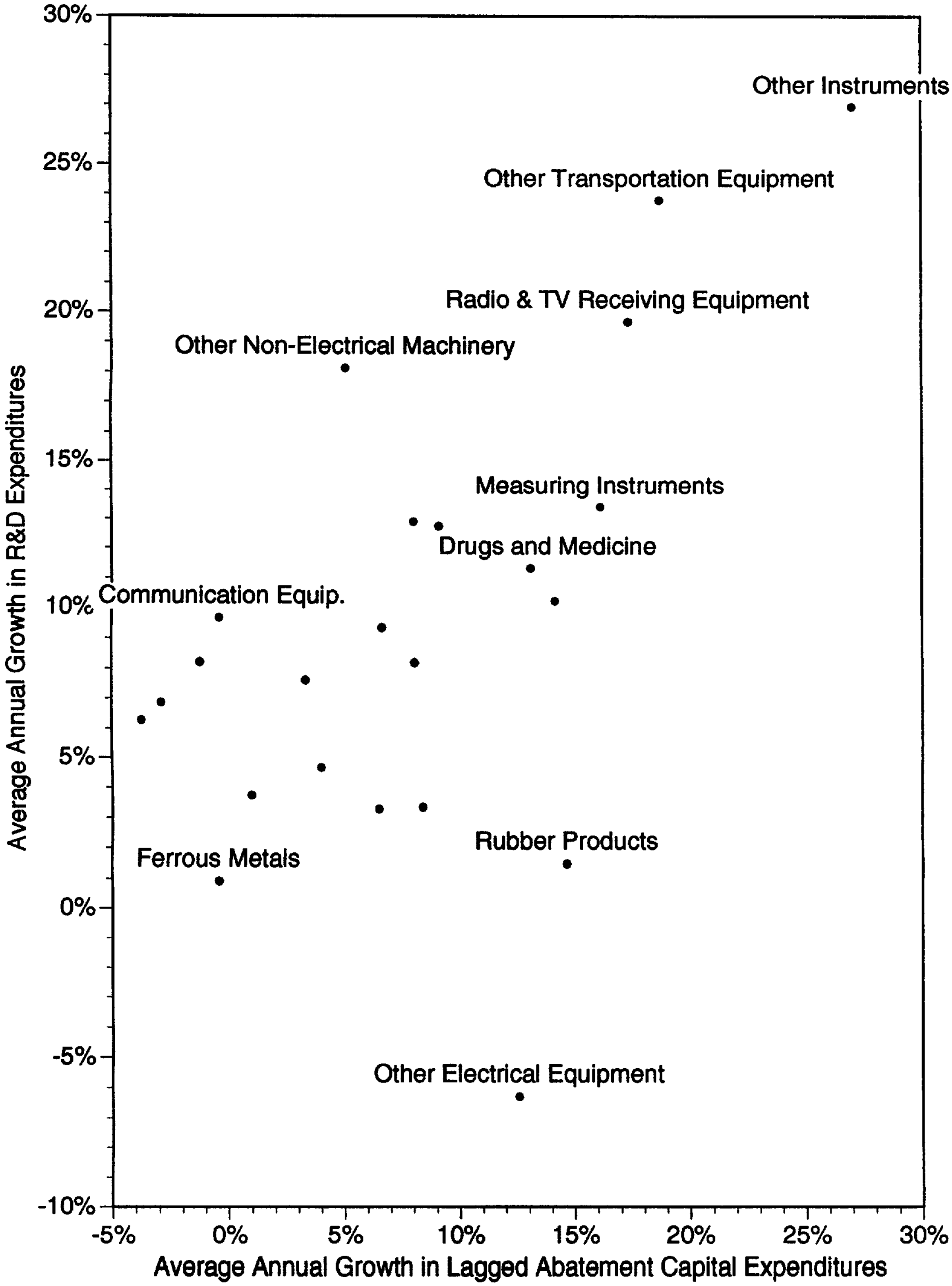

Figure Two

DISTRIBUTION OF R&D PACE COEFFICIENTS BY INDUSTRY