Do Voluntary Pollution Reduction Programs (VPRs) Spur Innovation in Environmental Technology?

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Abstract

In the context of the EPA's 33/50 program, we study whether a VPR can prompt firms to develop new environmental technologies that yield future emission reduction benefits. Because pollutant reductions generally require costly reformulations of products and/or production processes, environmental over-compliance – induced by a VPR – may potentially spur environmental innovation that can reduce these costs. Conversely, a VPR may induce a participating firm to divert resources from environmental research to environmental monitoring and compliance activities that yield short-term benefits in reduced emissions. We find evidence that higher rates of 33/50 program participation are associated with significant reductions in the number of successful environmental patent applications four to six years after the program ended; these results suggest a negative relationship between the 33/50 program and longer-run environmental innovation.

Keywords: Voluntary environmental programs, regulatory enforcement, environmental innovation, count panel models

JEL: Q28, K32, D62, L51, C33

I. Introduction

Voluntary pollution reduction programs have become an integral part of U.S. environmental policy; there are currently over 60 partnership programs sponsored by the Environmental Protection Agency (EPA). Participants in these programs commit themselves to reduce pollutant emissions that are not addressed by environmental laws, or exceed emission standards set forth by such laws when they exist. Current partnership programs include ``AgStar'' which promotes the use of biogas recovery systems to curb Methane emissions at confined animal feedlot operations and ``EnergyStar'' which seeks to reduce carbon dioxide emissions. Economists have put forth a number of theories to explain why profit-maximizing firms self-select into costly voluntary pollution reduction programs (VPRs). Empirical work has sought to determine the extent to which these theories have operated in practice to explain actual participation, most notably in the EPA's 33/50 program (e.g., see Arora and Cason, 1995, 1996; Videras and Alberini, 2000; Khanna and Damon, 1999; Sam and Innes, 2006). Empirical work has also documented the salutary effect of VPRs in reducing pollution (e.g., Khanna and Damon, 1999; Sam and Innes, 2004). However, to our knowledge, there has been no work to date identifying the mechanism by which VPRs may lead to emissions reductions, whether due to heightened management awareness and conscientiousness within given environmental systems and technologies or due to adoption of new environmental management systems (Anton, et al., 2004; Khanna, et al., 2005) or due to adoption of new environmental technologies.

In this paper, we study this last potential channel for beneficial effects of VPRs. In particular, VPRs could induce participant firms to innovate in their environmental technologies, thus lowering their costs of over-compliance. Pollutant reductions generally require costly reformulation of products or production processes, suggesting that over-compliance positively impacts environmental innovation. A limited number of theoretical (Milliman and Prince (1989), Fischer, and al. (2003)) and empirical (Jaffe and Palmer (1997), Brunnermeier and Cohen (2003), Carrion-Flores and Innes (2006)) papers study the impacts of various environmental policy instruments on technological innovation. While this work generally documents that higher pollutant abatement costs spur environmental R&D (the induced innovation hypothesis), none has explored the potential role of VPRs in promoting innovation.

We present an empirical study of the determinants of environmental innovation using a panel of 127 U.S. manufacturing industries defined by 3-digit SIC classifications over the 1989-2002 period. Following Brunnermeier and Cohen (2003) and Carrion-Flores and Innes (2006), we measure innovation by the number of successful environmental patent applications. The VPR that is our focus is the EPA's 33/50 program, the principal object of empirical work on VPRs to date. The 33/50 program was created in 1991 as the EPA's first formal effort to achieve voluntary pollution reductions by regulated firms. The program sought to reduce releases of seventeen toxic chemicals by a third by 1992 and by 50 percent by 1995, measured from 1988 baseline levels. At its inception, the program invited all firms releasing 33/50 pollutants in 1988 to participate (approximately 5000 companies). Although the 33/50 program was purely voluntary and its pollution reduction targets were not enforceable, there is ample anecdotal (EPA, 1999) and empirical evidence of the program's success. We measure 33/50 effects at a 3-digit SIC industry level using rates of industry participation in the program.

The reminder of the paper is organized as follows. In the next section we briefly describe the 33/50 program, followed by a description of competing empirical hypothesis that we test in this paper. In section IV, we describe our empirical model, followed by discussion of our data and econometric methods in section V. Section VI presents our estimation results. Finally, section VII concludes.

II. The 33/50 Program

Started in 1991, the 33/50 program was the EPA's first formal effort to achieve voluntary pollution reductions by regulated firms. The program sought to reduce releases of seventeen toxic chemicals by a third by 1992 and by 50 percent by 1995, measured from 1988 baseline levels. Roughly seventy percent of the 33/50 chemicals (by 1988 weight of releases) were air pollutants (AC). Two of the chemicals (carbon tetrachloride and 1,1,1-trichloroethane) depleted the stratospheric ozone layer and, hence, came under the Montreal Protocol's provisions for the phase-out of such substances; however, these two chemicals represented less than fifteen percent of total 33/50 releases (in 1988).

The EPA initiated the 33/50 program shortly after creating the Toxic Release Inventory (TRI), a database compiling information on toxic releases of all firms with ten or more employees producing one or more of 320 targeted pollutants. In early 1991, the EPA invited the 509 companies emitting the largest volume of 33/50 pollutants to participate in the program; these companies were responsible for over three-quarters of total 33/50 releases as of 1988. In July 1991, the 4534 other companies with reported 33/50 releases in 1988 were asked to participate as well. With additional enrollments through 1995, the EPA invited a total of 10,167 firms to join the 33/50 program, and 1294 firms accepted. The latter program participants accounted for 58.8 percent of 33/50 releases in 1990.

The 33/50 program was purely voluntary and its pollution reduction targets were not enforceable. Despite the absence of apparent regulatory teeth, the EPA (1999) cites some aggregate statistics as indicators of the program's success. Among reporting firms, total 33/50 releases declined by over 52 percent between 1990 and 1996, and net 33/50 releases, excluding the two ozone-depleting compounds, declined by over 45 percent. In contrast, non-33/50 TRI releases fell by 25.3 percent over this period. Moreover, rates of 33/50 release reductions were greater for program participants (down 59.3 percent between 1990 and 1996) than for non-participants (down 42.9 percent over the same interval). Of course, these numbers may mask other hidden determinants of firms' pollution; for example, participating firms may have been more apt to reduce pollution, regardless of participation in the 33/50 program. However, recent work finds that, even controlling for other relevant explanators of pollution and potential selection bias in 33/50 program participation, the program led to significant reductions in participant emissions during the later program years of 1993-1995 (Sam and Innes, 2006; Khanna and Damon, 1999).

The question posed in this paper is whether these short-term emission reduction benefits of the 33/50 program spurred or impeded environmental research.

III. Empirical Hypotheses

To the extent that firms take seriously any voluntary pollutant reduction commitments that they make (as is suggested by extant empirical evidence on the 33/50 program), such commitments may implicitly elevate the potential cost-reduction benefits of new environmental technologies, thus spurring more environmental R&D:

> *Hypothesis 1*. Higher rates of participation in the 33/50 program yield increased incentives for environmental R&D and, hence, more environmental patents.

Hypothesis 1 is essentially the "induced innovation" hypothesis as it applies to VPRs.

However, this logic may not reflect the true nature of the dynamic trade-offs that confront firms. For example, firms may have to decide how many resources to invest, alternately, in (i) environmental monitoring and compliance efforts that reduce short-run emissions, and (ii) research that may potentially yield new environmental compliance technologies. In principle, a VPR might spur a diversion of resources from the latter (R&D) to the former (monitoring and compliance). If so, we would instead have the competing hypothesis:

> *Hypothesis 2*. Higher rates of participation in the 33/50 program yield a redirection of resources away from environmental R&D and, hence, fewer environmental patents.

IV. The Empirical Model

Following Carrion-Flores and Innes (2006), we posit an underlying structural model that determines environmental patent outcomes as a function of anticipated emission standards, 33/50 participation rates, and other observable exogenous variables. This model takes the following simple form:

(1) $$P_{it} = a^*_{pit} + b^*_p E_{t-1}(Q_{it}) + c^*_p Q_{it-1} + d^*_p PR_{it-1} + f^*_p X_{pit} + \varepsilon^*_{pit}$$

where P_{it} is time t environmental patents in industry i, Q_{it} is time t emissions in industry i, $E_{t-1}(Q_{it})$ is its time $t-1$ expectation, PR_{it-1} is the appropriately lagged measure of the 33/50 participation rate in industry i, the X_{pit} represent exogenous variables, and e_{it} represent random errors. This structure gives rise to three types of joint endogeneity: (1) the observable regressor, Q_{it}, is jointly endogenous in the usual sense, with technological change potentially prompting revisions in emission standards; (2) the true regressor, $E_{t-1}(Q_{it})$, is measured with error; and (3) there is potential selection correlation between 33/50 participation rates and innovation because more innovative industries (ceteris paribus) may be more likely to participate in the VPR. Under perfect foresight, the second "endogeneity" problem evaporates and all we need are instruments that are highly correlated with emissions and 33/50 participation, but uncorrelated with patents. Without perfect foresight, but with rational expectations, we also need such identifying instruments, while also requiring that *all* instruments be lagged (see Carrion-Flores and Innes, 2005). In this paper, we estimate under both premises. We use enforcement variables to jointly identify the two jointly endogenous variables (emissions and participation), as there is ample evidence that strict enforcement in the form of more inspections and enforcement actions, spurs emission reductions (Gray and, Deily 1996; LaPlante and Rilstone, 1995) and 33/50 participation (Sam and Innes, 2004), but has no discernable effect on innovation (Carrion-Flores and Innes, 2005; Brunnermeier and Cohen, 2003). Standard instrument and over-identifying restriction tests (Bound, et al., 1995; Wooldridge, 2002) provide statistical evidence in support of these instrument choices.

In estimating (1), there a number of determinants of innovative activity for which we need to control, in addition to the evident role of anticipated emissions and the key 33/50 participation effects of interest. First, spillovers in research activity may lead to environmental patent successes; we use non-environmental patent counts and overall industry R&D investments to control for these effects. Second – and unlike prior work – we seek to measure potential impacts of environmental pressure groups on environmental R&D. We do so by including an industry measure of Sierra Club strength. Third, we control for industry size using a measure of real sales. Fourth, we control for the nature of industry assets, both age and capital intensity. We expect industries with older assets and more capital intensive production to have more scope for cost-reducing environmental R&D. Fifth, more rapidly growing industries may have either more or less incentive to innovate, whether because they have already modernized and hence have less scope for innovation or because they are more innovative by nature and hence more likely to innovate in the environmental realm as well. Finally, more concentrated industries may be prone to either more or less environmental R&D. On one hand, concentration gives rise to "raising rivals costs" motives for heightened research (Innes and Bial, 2002); on the other, concentrated industries may collectively recognize the costs of higher R&D in spurring tightened environmental regulations, leading to a research deterrent (Carrion-Flores and Innes, 2005). We control for such effects by including a measure of industry concentration in our estimations.

V. Data and Empirical Estimation

Our sample is an unbalanced panel of 127 manufacturing industries defined by 3-digit SIC classifications (SIC codes 200-399) over the period 1989 – 2002. Total toxic emissions data are available from the EPA's Toxic Release Inventory (TRI) for 1989-2002.[4] Using the TRI, we construct industry level total toxic releases (***TRI-REL***) by aggregated weight by year. Facility releases reported in the TRI are assigned to the primary industry of the parent company. Using data on 33/50 chemical releases obtained under a Freedom of Information Act request from the EPA, we also construct total 33/50 chemical releases (***33/50-REL***) by industry by year.

Following previous studies (c.f., Jaffe and Palmer, 1997; Brunnermeier and Cohen, 2003 and Carrion-Flores and Innes, 2006), we use successful environmental patent applications as a proxy for environmental innovation. Using data from the U.S. Patent and Trademark Office, we construct successful patent application counts by year, by industry, environmental and non-environmental, obtained by U.S. companies. Environmental patents are determined by patent classifications that relate to air or water pollution, hazardous waste prevention, disposal and control, recycling and alternative energy (***ENV-PAT***). Non-environmental patents are those in all other patent utility classes (***NONENV-PAT***).

[4] Because the first year of TRI release reports are considered incomplete and suspect, we only rely on post-1988 TRI data.

The EPA's Office of Environmental Information Records provided data on 33/50 participation, as well as Federal and State enforcement activity under the Clean Air Act (CAA).[5] We measure 33/50 effects at a 3-digit SIC industry level using rates of industry participation in the program. Specifically, for each year of the 33/50 program (1991-1995), we measure the industry participation rate (***PR***) as the proportion of reported industry 33/50 emissions attributable to program participants in that year.

From our enforcement data, we construct three measures of enforcement stringency: (1) counts of Federal and State enforcement actions (***ACTIONS***), (2) the numbers of facilities out of compliance with clean air laws (***OUTCOMP***), and (3) the numbers of reported self-inspections (***SELFINSPECT***). We use these enforcement variables to jointly identify emissions and participation rates (with three lags due to plausible lags in effects and because such lags avoid any potential for joint endogeneity).

The Sierra Club provided us a panel of its state membership. To obtain a measure of environmental group influence on each industry, we obtain the weighted average annual Sierra Club membership for the industry (***SIERRA***), weighting each state's membership by the proportion of the industry's regulated facilities operating in the state.

Financial and employment data was obtained from the Standard and Poor's Compustat Dataset. Deflators are obtained using producer price indexes reported in the Economic Report of the President (2004). For controls, we include (deflated) industry sales volume (***SALES***) in order to account for potential effects of industry size on patents; a measure of capital intensity (***CAP-INT***), namely, the level of new capital and equipment expenditures divided by sales volume; the industry's total lagged level of research and development expenditures per-unit-sales (***R&D***) in order to capture effects of overall industry research activity on environmental innovation; a measure of asset age (***AGE***), obtained by dividing total assets of an industry by its gross assets (as in Khanna and Damon, 1999); and a sales growth measure (***SALESGR***). To measure industry concentration, we construct a four-firm Herfindahl index (***CONCENT***) using annual sales data reported in Compustat. [6]

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[5] Because the 33/50 program primarily relates to air releases, we focus on enforcement activity under the CAA.

[6] Initially, we also included an exogenous variable measuring each industry's export intensity (ratio of exports to total sales). However, as this variable was not statistically significant in any estimated equation

Merging all of our datasets fives us 127 industries for the 1989-2002 period for a total of 1778 observations over the 14 year period. If we incorporate two year lags in emissions, we have an unbalanced panel of 127 industries over 1991-2002 for a total of 1397 observations. Summary statistics are presented in Table 1.

Our measure of innovation takes a count form with a relatively large number of zero's and a mean count of approximately 20. As noted above, we also have endogeneity issues with respect to both emissions and participation rates. With regard to emissions, we measure the "true regressor," $E_{t-1}(Q_t)$, using actual emissions. Due to both joint endogeneity and measurement error, we instrument in order to avoid bias and inconsistency. Due to serial correlation in our emissions data, endogeneity bias also attaches to our lagged emission regressor; hence, we also instrument this variable using appropriately lagged exogenous data.

To estimate our count panel model with endogenous regressors, we follow Windmeijer and Silva (1997) and estimate a Poisson fixed effects structure by the Generalized Method of Moments (GMM). Testing for fixed time effects, we find none of significance and hence estimate without.

Effects of 33/50 participation on patent applications occur at least with the lag required for research to produce patentable outcomes (which we assume to be at least two years). Indeed, these effects may potentially take several years to manifest themselves. We attempt to capture lag-specific effects of participation by constructing year-specific participation rate variables. With a minimum of two-year lags in potential effects, we measure participation impacts in each of years 1993 (two years after the 33/50 program's inception) and 1997 by constructing year-specific two-year-lagged participation rate variables. For years 1998-2002, we measure participation impacts with year-specific variables for the most recent (1995) participation rates. These variables permit us to estimate year-specific participation effects (with variables $\boldsymbol{PR_t}$, t=1993,…2002).[7]

(regardless of the model), and its inclusion compromised model performance, we do not include it in our reported model estimations.

[7] To identify the year-specific participation variables, we construct year-specific counterparts to our lagged enforcement variables.

VI. Empirical Estimation and Findings

To judge the strength of our identifying (enforcement) instruments, we first estimate relevant "first stage" models of emissions and participation rates (per standard practice, Bound, et al., 1995). Because emissions are continuous, the relevant first-stage is a fixed effects linear panel estimation with all exogenous data, as reported in Table 2; as indicated, the three enforcement variables are highly correlated with emissions, with predicted signs. In particular, enforcement actions and heightened regulatory scrutiny due to out-of-compliance status both spur emission reductions; conversely, self-inspections – by potentially preempting regulatory scrutiny – are associated with higher emissions.

For our 33/50 participation rate data, the appropriate "first stage" procedure is complicated by the non-continuous and truncated nature of the data (with all rates in the unit interval and a number of zeros). To account for this data structure, we perform a "first stage" Tobit estimation using the participation odds ratios (***PR***/(1-***PR***)) (which are truncated at zero and otherwise continuous on R^+). Results are reported in Table 3. As required, the enforcement instruments are highly correlated with our participation variable (see, for example, the chi-square test statistic for the null of zero coefficients on our three enforcement variables).

Tables 4A-4C report estimations of our perfect foresight model. The first estimation includes year-specific participation rate effects. The second groups participation rate effects for the earlier post-program years (1993-1998) and the later years (1999-2002). And the third again groups participation rate effects; however, because 33/50 participation may have effects on research with more than a two year lag, this third estimation uses three-year lags in participation rate data (rather than two) for the early post-program years (1994-1998).

Several results should be stressed. First and foremost, in all models, we find significant negative long-run effects of 33/50 participation on successful environmental patents, broadly supporting Hypothesis 2. In Table 4A, for example, we have statistically significant negative effects of 33/50 participation rates on successful patents in years 1994, 1996, 1999, 2000, and 2002. With three-year participation lags (Table 4C), this conclusion is tempered by significant positive short-run effects of participation on environmental innovation. A possible explanation for differing short and long run effects is that participating firms are diverting resources from more ambitious longer term environmental R&D projects to both monitoring/compliance efforts and less ambitious shorter-term R&D. Both of the latter investments promise dividends in meeting the shorter-term objectives of the 33/50 program.

Second, as in Carrion-Flores and Innes (2005), the anticipation of tightened emission standards spurs more environmental R&D (with significant negative coefficients on ***TRI-REL***. Third, environmental innovation is positively associated with industry scale (***SALES***), research spillovers (***R&D*** and ***NONENV-PAT***), capital intensity (***CAPINT***), and older assets (with ***AGE*** measuring "newness" of assets), all as expected. Concentration (***CONCENT***) is found to decrease innovation, consistent with the view that concentrated industries recognize regulatory responses to improved technologies and circumscribe their R&D investments accordingly. More rapidly growing industries are also found to be the source of less environmental innovation (with negative effects of the ***SALESGR*** variable), perhaps because they are already quite modern and hence lesser scope for technological improvement.

Finally, we should also stress our test of instrument performance. For all models, the implicit (Sargan) test of zero correlation between our identifying instruments and the equation error is not rejected at reasonable levels of significance.

Forthcoming are estimations of our rational expectations model.

VII. Conclusions

Our tentative conclusion from this paper is that VPRs may potentially have costs that have not before been recognized or anticipated by scholars or policy-makers. In particular, we find preliminary evidence that participation in the 33/50 program may have diverted resources away from longer-term environmental R&D investments, leading to longer-run reductions in our patent count measure of successful environmental research. This outcome requires further study to determine its robustness to different lags of 33/50 program effects on patent outcomes and different models of expectations formation. It also suggests the need for more work to determine any long-run effects of VPRs on ultimate environmental performance.[1] However, if these results withstand further scrutiny and to the extent that environmental R&D is considered the engine of environmental improvement, this paper suggests that VPRs may potentially have an important environmental cost that may or may not outweigh the short-run emission reduction benefits identified in prior work.

[1] Extant studies of 33/50 effects on emissions have focused only on years before the program ended (pre-1996) and hence have not measured any long-run effects, potentially via research channels.

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Table 1. Summary Statistics

Variable	Mean	Std. Dev.
ENV-PAT	19.69	17.45
TRI-REL	3.9474	14.5074
SIERRA	79.5417	94.0778
SALES	31.1121	103.5474
SALESGR	-0.0347	-0.2642
AGE	0.7046	0.1430
CAPINT	0.0834	0.0523
R&D	0.6070	-0.2652
NONENV-PAT	13.1232	62.8939
CONCENT	0.0958	0.2198
ACTIONS	86.34	169.63
OUTCOMP	112.81	178.34
SELFINSPECT	5.17	13.43
PR (1991-1995)	0.4212	0.3478

Table 4A

Environmental Patent Equation with Year-Specific Participation Effects

	coeff	rob se	t-ratio	p-value
TRI-REL	**-0.0081**	**0.0032**	**-2.5168**	**0.0118**
TRI-REL_2	-0.0055	0.0042	-1.2912	0.1966
SIERRA	0.0010	0.0011	0.8775	0.3802
SALES	**0.0108**	**0.0030**	**3.6442**	**0.0003**
SALESGR	**-1.7364**	**0.2593**	**-6.6964**	**0.0000**
AGE	**-8.1314**	**1.0830**	**-7.5084**	**0.0000**
CAPINT	**10.8309**	**1.5094**	**7.1757**	**0.0000**
R&D	**2.9258**	**0.3999**	**7.3164**	**0.0000**
NONENV-PAT	**0.0082**	**0.0006**	**13.9695**	**0.0000**
CONCENT	**-4.6847**	**1.1910**	**-3.9335**	**0.0001**
PR1993	-2.2089	2.5743	-0.8581	0.3909
PR1994	**-1.9601**	**0.8161**	**-2.4019**	**0.0163**
PR1995	0.0754	0.2753	0.2739	0.7841
PR1996	**-1.2520**	**0.7147**	**-1.7519**	**0.0798**
PR1997	-0.0224	0.7417	-0.0301	0.9759
PR1998	-1.1398	0.7767	-1.4675	0.1422
PR1999	**-1.8599**	**0.9577**	**-1.9421**	**0.0521**
PR2002	**-2.2563**	**1.2478**	**-1.8083**	**0.0706**
PR2001	**-4.5495**	**0.6676**	**-6.8151**	**0.0000**
PR2002	0.1693	3.5286	0.0480	0.9617

SARGAN TEST STATISTIC (P VALUE): 8.3633 (0.7561)

TESTS for SERIAL CORRELATION and P-VALUES

M1	-0.9401	0.3472
M2	-2.0639	0.0390

The dependant variable is ENV-PAT. The estimation is by GMM, Poisson fixed effects, following Windmeijer and Silva (1997). Year specific PR variables have two-year lags for 1993-1997 and the most recent lag (1995 participation rates) for 1998-2002. A two-year lag in TRI-REL is denoted with "_2." Statistically significant coefficients (at the 10 percent level) are denoted in bold.

Table 4B

Environmental Patent Equation with Grouped Participation Effects

	coeff	rob se	t-ratio	p-value
TRI-REL	-0.0074	0.0058	-1.2664	0.2054
TRI-REL_2	-0.0022	0.0019	-1.1602	0.2460
SIERRA	-0.0004	0.0006	-0.6686	0.5038
SALES	**0.0028**	**0.0017**	**1.6207**	**0.1051**
SALESGR	**-0.9779**	**0.1001**	**-9.7705**	**0.0000**
AGE	0.1902	0.6290	0.3023	0.7624
CAPINT	**7.0412**	**0.6788**	**10.3735**	**0.0000**
R&D	0.0512	0.2477	0.2066	0.8363
NONENV-PAT	**0.0115**	**0.0003**	**33.5502**	**0.0000**
CONCENT	**-2.3049**	**1.0992**	**-2.0969**	**0.0360**
PR1993-98	-0.8042	0.7034	-1.1433	0.2529
PR1999-02	**-0.9610**	**0.1504**	**-6.3882**	**0.0000**

SARGAN TEST STATISTIC (P VALUE): 24.8701 (0.1285)

TESTS for SERIAL CORRELATION and P-VALUES

M1	-1.2935	0.1959
M2	-1.5370	0.1243

The dependant variable is ENV-PAT. The grouped PR variables have two-year lags for 1993-1997 and a three-year lag for 1998 (to construct PR1993-98) and the most recent lag (1995 participation rates) for 1998-2002 (to construct PR1999-02). Statistically significant coefficients (at the 10 percent level) are denoted in bold.

Table 4C

Environmental Patent Equation with Grouped Participation Effects

	coeff	rob se	t-ratio	p-value
TRI-REL	**-0.0090**	**0.0009**	**-9.4501**	**0.0000**
TRI-REL_2	**-0.0067**	**0.0004**	**-16.5678**	**0.0000**
SIERRA	0.0000	0.0005	-0.0932	0.9258
SALES	**0.0093**	**0.0026**	**3.6185**	**0.0003**
SALESGR	**-0.5720**	**0.0499**	**-11.4608**	**0.0000**
AGE	-0.5078	0.3433	-1.4790	0.1391
CAPINT	**5.1906**	**0.4656**	**11.1475**	**0.0000**
R&D	**0.6653**	**0.1956**	**3.4009**	**0.0007**
NONENV-PAT	**0.0118**	**0.0003**	**39.9738**	**0.0000**
CONCENT	**-4.9717**	**1.0022**	**-4.9608**	**0.0000**
PR1994-98	**0.8001**	**0.2202**	**3.6343**	**0.0003**
PR1999-02	**-0.7374**	**0.3138**	**-2.3498**	**0.0188**

SARGAN TEST STATISTIC (P VALUE): 23.2322 (0.1818)

TESTS for SERIAL CORRELATION and P-VALUES

M1	-0.5253	0.5994
M2	-1.2971	0.1946

The dependant variable is ENV-PAT. The grouped PR variables have three-year lags for 1994-1998 (to construct PR1994-98) and the most recent lag (1995 participation rates) for 1998-2002 (to construct PR1999-02). Statistically significant coefficients (at the 10 percent level) are denoted in bold.