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# Voluntary Environmental Regulation in Developing Countries

*Mexico's Clean Industry Program*

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## **Abstract**

Because conventional command-and-control environmental regulation often performs poorly in developing countries, policymakers are increasingly experimenting with alternatives, including state-sponsored voluntary regulatory programs that provide incentives, but not mandates, for pollution control. Although the literature on this trend is quite thin, research in industrialized countries suggests that voluntary programs are sometimes ineffective because they mainly attract relatively clean participants seeking to free-ride on unrelated pollution control investments. We use plant-level data on more than 60,000 facilities to identify the drivers of participation in the Clean Industry Program, Mexico's flagship voluntary regulatory initiative. Our results suggest that the threat of regulatory sanctions drives participation in the program. Therefore, the program does appear to attract relatively dirty firms. We also find that plants that sold their goods in overseas markets and to government suppliers, used imported inputs, were relatively large, and were in certain sectors and states were more likely to participate in the program, all other things equal.

**Key Words:** voluntary environmental regulation, duration analysis, Mexico

**JEL Classification Numbers:** Q56, Q58, O13, O54, C41

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## Contents

<b>1. Introduction.....</b>	<b>1</b>
<b>2. Literature.....</b>	<b>4</b>
2.1. Past Environmental Performance.....	4
2.2. Regulatory Pressure .....	5
2.3. Nonregulatory Pressures .....	5
<b>3. Data and Variables .....</b>	<b>6</b>
3.1. Data .....	6
3.2. Independent Variables .....	8
<b>4. Empirical Model.....</b>	<b>11</b>
4.1. Duration Models .....	11
4.2. Modeling Regulatory Activity .....	13
4.3. Results.....	14
<b>5. Conclusion .....</b>	<b>17</b>
<b>References.....</b>	<b>20</b>
<b>Tables and Figures.....</b>	<b>23</b>

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## 1. Introduction

The conventional approach to industrial pollution control is to establish laws requiring firms to cut emissions. Voluntary regulation, by contrast, provides incentives, but not mandates, for pollution control. In industrialized countries, such regulation has become quite popular over the past two decades (OECD 1999, 2003).

Less well known is that environmental authorities in developing countries, particularly those in Latin America, also have embraced voluntary regulation and are rapidly putting new initiatives in place. For example, in Colombia, more than 50 voluntary agreements between environmental authorities and industrial associations were signed between 1995 and 2003 (Esterling Lara 2003). And in Mexico, 10 such agreements involving some 600 firms were signed during the 1990s (Hanks 2002).

Although environmental authorities in both industrialized countries and developing countries use voluntary regulation, the purposes differ. In industrialized countries, they typically use such regulation to encourage firms to overcomply with mandatory regulations or to cut emissions of pollutants for which mandatory regulations do not exist, such as greenhouse gases (Lyon and Maxwell 2002). In developing countries, by contrast, environmental authorities generally use voluntary regulation to help remedy rampant non-compliance with mandatory regulation resulting from, among other factors, limited public support for environmental protection, weak regulatory institutions, and a paucity of financial and technical resources in the private sector. In short, they use voluntary regulation to shore up weak enforcement of

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mandatory regulation (Blackman and Sisto in press; Jiménez 2007). Given this role, the stakes for the success of voluntary regulation in developing countries are high.

The question of whether voluntary regulation actually generates environmental benefits has stirred considerable debate. A particular concern involves one of the three main types of voluntary initiatives—programs administered by regulatory authorities that invite firms to meet pre-established environmental performance targets.<sup>1</sup> As discussed in the literature review presented in next section, empirical research in industrialized countries suggests that at least in some cases, the environmental benefits of these programs are limited because they mainly attract firms that are either already relatively clean or becoming cleaner for reasons unrelated to the program (Vidovic and Khanna 2007; Morgenstern and Pizer 2007). Such firms have clear incentives to join voluntary programs: the costs are relatively low because no additional pollution control investments are required to meet the voluntary program’s environmental performance goals, and the benefits, which may include positive publicity, pollution control subsidies, and preferential treatment by regulators, can be significant. Firms that join for these reasons are said to “free ride” on unrelated investments in pollution control (e.g., Lyon and Maxwell 2007; Alberini and Segerson 2002).

The growing popularity of voluntary programs has spurred a boom in economic research on them. Virtually none of the rigorous empirical research on these programs focuses on developing countries, however.<sup>2</sup> A key reason is that the firm- and facility-level data needed to analyze these programs are exceptionally rare. This gap in the literature is significant because the findings from industrialized countries may not apply to developing countries, where public voluntary programs have different aims and are implemented in a different sociopolitical context.

To help fill that gap, this paper analyzes Mexico’s flagship voluntary initiative, the National Environmental Auditing Program (*Programa Nacional de Auditoria Ambiental*), also known as the Clean Industry Program (*Programa Industria Limpia*). Created in 1992, this initiative is administered by the Federal Environmental Attorney General’s Office (*Procuraduría Federal de Protección al Ambiente*—PROFEPA). Plants volunteering to join the program pay for an environmental audit by an accredited third-party, private sector inspector. The audit

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<sup>1</sup> Prominent examples in the United States are the Environmental Protection Agency’s 33/50 and Climate WiSe programs. The two other main types of voluntary regulation are agreements negotiated between regulatory authorities and firms, and unilateral commitments undertaken by firms (OCED 1999).

<sup>2</sup> An exception is Rivera (2002).

determines what pollution control and prevention procedures the plant has in place and what additional procedures are required to achieve compliance with current environmental regulations. Following the audit, the plant agrees in writing to correct all violations or deficiencies by a specified date. PROFEPA, in exchange, agrees not to penalize the plant for the identified violations until that date has passed. If the plant abides by this agreement, it is awarded a “clean industry” certificate that exempts it from regulatory inspections for two years. Akin to a seal of good housekeeping, this certificate is commonly used in marketing campaigns. Hence, like many voluntary initiatives, the Clean Industry Program provides a basket of incentives for participation, including an official Clean Industry certificate that can be used as a marketing tool, enforcement amnesty, and the threat of enforcement of mandatory environmental regulations for plants not in the program. The popularity of the Clean Industry Program is evident in the number of participating plants, which grew from 77 in 1992 to roughly 3,500 in 2005.

To evaluate the Clean Industry Program, we construct a unique data set by merging plant-level registries compiled by the Ministry of Economics and PROFEPA. We use duration analysis to identify the drivers of participation in the program. We are particularly interested in understanding whether the plants that join the program do so to avoid formal regulatory sanctions. The answer has implications for the program’s effectiveness in improving participants’ environmental performance. If plants join the program to avoid regulatory sanctions, then presumably they are not in compliance when they join but are in compliance when they graduate from the program. In this case, the program may have a significant positive impact on participants’ environmental performance. If, on the other hand, the plants that join the program are not motivated by the threat of regulatory sanctions, then presumably they are already in compliance when they join and participation does little to improve their environmental performance. Rather, the program simply rewards them for pollution control investments they made prior to joining.

Our econometric analysis indicates that plants that were inspected and/or fined by PROFEPA were more likely to join the Clean Industry Program, all other things equal. This finding suggests that the threat of regulatory sanctions does drive participation—a result that echoes findings for voluntary regulatory programs in industrialized countries. We also find that plants that sold their goods in overseas markets and to government suppliers, used imported inputs, were relatively large, and were in certain sectors and states were more likely to participate in the Clean Industry Program, all other things equal.

The remainder of the paper is organized as follows. Section 2 provides a brief summary of relevant findings from the literature on voluntary regulation. Section 3 discusses our data.

Section 4 explains our econometric approach and presents regression results. The last section sums up the policy implications.

## 2. Literature

This section briefly reviews the empirical economics literature on the drivers of participation in voluntary programs, paying particular attention to past environmental performance and regulatory pressure.<sup>3</sup>

### 2.1. Past Environmental Performance

The evidence on whether firms that participate in voluntary programs are already relatively clean when they join—and therefore free-ride on past pollution control investments—is decidedly mixed. The bulk of empirical economic research on public voluntary programs has focused on the U.S. Environmental Protection Agency's 33/50 program. Launched in 1991, the program required participants to pledge to cut their emissions of 17 high-priority toxic chemicals by 33 percent by 1992 and by 50 percent by 1995.

An anomaly of the design of the 33/50 program created a seeming incentive for free-riding on past environmental performance. Emissions reductions were measured against a 1988 baseline. Therefore, any reductions made between 1988 and the launch of the program in 1991 were credited toward participants' emissions reductions targets. Arora and Cason (1996), Gamper-Rabindran (2006), and Sam and Innes (2006) all find that firms that made significant emissions reductions during these three years were not more likely to join. However, Vidovic and Khanna (2007) find the opposite. In fact, they attribute most of the well-publicized emissions cuts associated with the program to participants' free-riding on pollution control investments initiated before the program was launched.

In addition to examining the issue of preprogram emissions reductions, most studies of the 33/50 program also test whether firms that were relatively dirty were more likely to participate. Arora and Cason (1995), Khanna and Damon (1999), Gamper-Rabindran (2006), Sam and Innes (2006), and Vidovic and Khanna (2007) all find that firms with higher absolute levels of 33/50 emissions were more likely to join the program. However, the effect of emissions

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<sup>3</sup> For reviews of this literature, see Lyon and Maxwell (2002, 2007), Alberini and Segerson (2002), and Khanna (2001).

normalized by sales or number of employees is less clear. These ambiguous findings are consistent with results from evaluations of programs other than the 33/50 program. For example, Welch et al. (2000) examine participation by electric utilities in the U.S. Department of Energy's Climate Challenge Program and find no evidence that dirtier utilities were either more or less likely to join the program.

## **2.2. Regulatory Pressure**

Closely related to the question of whether past environmental performance drives participation in public voluntary programs is the question of whether regulatory pressure affects the likelihood of participation. Again, most of the empirical economic research focuses on EPA's 33/50 program, and again, the evidence is mixed. On the one hand, Khanna and Damon (1999), Videras and Alberini (2000), Sam and Innes (2006), and Vidovic and Khanna (2007) all find that firms named as potentially responsible parties at a higher-than-average number of Superfund sites were more likely to participate. Similarly, Videras and Alberini (2000) and Sam and Innes (2006) find that firms that were out of compliance with the Resource and Conservation Recovery Act or Clean Air Act were more likely to join. On the other hand, Arora and Cason (1996) and Gamper-Rabindran (2006) find that firms that violated Clean Air Act requirements were not more likely to participate. Finally, two papers examine the impact of inspection (versus confirmed noncompliance). Although Sam and Innes (2006) find that firms that were inspected for preprogram violations of the Clean Air Act were more likely to participate in some sectors, Gamper-Rabindran (2006) finds the opposite.

As for research on other public voluntary programs, Videras and Alberini (2000) find that firms named as potentially responsible parties at a higher-than-average number of Superfund sites were more likely to participate in EPA's Waste Wi\$e and Green Lights programs. They also find that the number of Clean Air Act fines levied does not explain participation in the Green Lights program. Finally, Welch et al. (2000) find that the amount electric utilities spend on regulatory expenses per year does not explain participation in the Department of Energy's Climate Challenge Program.

## **2.3. Nonregulatory Pressures**

Like regulatory activity, pressure brought to bear by consumers may also motivate participation in public voluntary programs. Arora and Gangopadhyay (1995) show that firms may overcomply with environmental regulations to attract "green" consumers. Some empirical evidence supports this proposition. For example, Arora and Cason (1996) and Vidovic and

Khanna (2007) show that firms with a higher ratio of advertising expenditures to sales were more likely to participate in EPA's 33/50 program, and Videras and Alberini (2000) show that firms selling directly to final consumers were more likely to participate in the Waste Wi\$e and Green Lights programs.

Finally, pressures generated by communities and nongovernmental organizations may create incentives for firms to join voluntary programs. Such pressures are the focus of the literature on so-called informal regulation, which mostly relies on cross-sectional, plant-level econometric analyses of environmental performance in developing countries (see World Bank 1999 for a review).<sup>4</sup> For example, Blackman and Bannister (1998) find that in the early 1990s, participation in a voluntary clean fuels initiative targeting small Mexican brick kilns was correlated with, among other factors, proxies for pressures applied by industry and neighborhood organizations.

### 3. Data and Variables

#### 3.1. Data

Unfortunately, official census data on Mexican plants are not available. We constructed a plant-level data set from three sources. The first is the July 2004 System of Mexican Business Information (*Sistema de Información Empresarial Mexicano*—SIEM). The Mexican Ministry of Economics compiles and maintains SIEM and uses it to promote Mexican commerce. By law, all private sector Mexican plants are required to provide basic data to SIEM. The database is constantly updated to include new entrants and omit plants that have exited the market. The data in SIEM are not time specific. For example, they do not include information on when plants provided their data to SIEM or whether this information has changed subsequently. SIEM contains basic information on more than half a million facilities throughout Mexico, over three-quarters of which are small-scale retail operations. The data include geographic location, sector, scope of market, gross sales, equity, and whether the facility exports, imports, and is a government supplier.

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<sup>4</sup> Whereas the voluntary regulation literature concerns overcompliance with *de jure* regulatory standards in industrialized countries, the informal regulation literature concerns overcompliance with lax *de facto* regulatory standards in developing countries.

Our SIEM data contain 528,618 records. However, to limit our subsample of nonparticipating facilities to those types of plants that had a proven history of participating in the Clean Industry Program, we dropped all plants in sectors (defined by CMAP codes, the Mexican equivalent standard industrial classification codes) that were not also represented in the PROFEPA Clean Industry database. This process eliminated approximately 80 percent of the plants in the SIEM data, leaving a sample of 77,197 plants.

The second data source is a PROFEPA registry of facilities that had participated or were participating in the Clean Industry Program (PROFEPA-CI) in September 2004. The registry includes plant name, location, and year of participation, among other variables, for 2,749 plants. However, 759 of these plants were government owned (and thus could not be matched with the SIEM data for privately owned firms) and were therefore dropped, leaving a sample of 1,990 participating plants.

Our third data source is a registry of PROFEPA monitoring and enforcement activity (PROFEPA-ME). It contains records of every PROFEPA inspection and fine between May 1987 and June 2004, including the date of inspection, the date of the fine, and the amount of the fine; 35,350 plants are represented in the data.

We merged information on plant characteristics from the SIEM database, program participation from the PROFEPA-CI database, and inspections and fines from the PROFEPA-ME database to create the plant-level data set used in the econometric analysis. Because the three databases did not have a common numerical code identifying individual plants, we merged them by nonnumerical identifiers—plant name, state, and *municipio* (county)—using a computerized approximate matching routine to account for differences across the three data sets in spelling and punctuation.<sup>5</sup> The nonnumeric identifiers did not uniquely identify plants. For example, in the SIEM data, multiple records have the same plant name, state, and *municipio*. To avoid incorrectly matching records, we dropped all records that were not uniquely identified. This resulted in a loss of 5 to 20 percent of the records in each data set. The end result was a sample of 61,821 plants, of which 541 participated in the program and 61,280 did not.

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<sup>5</sup> Using finer geographical identifiers (e.g., city) proved to be impractical because of a lack of uniformity across the databases.

### **3.2. Independent Variables**

This section first discusses the time-varying independent variables used in the regression analysis, and then the nontime-varying independent variables.

#### **3.2.1. Time-Varying Independent Variables: Inspections and Fines**

As discussed in the introduction, among the potential drivers of participation in the Clean Industry Program we are particularly interested in the threat of regulatory sanctions. Two independent variables proxy for this threat in our duration model: time-since-last-inspection and time-since-last-fine. These are the only two time-varying independent variables in our duration model.

We discuss how these variables enter into the model in Section 4.3 below. Here, we briefly present summary statistics on PROFEPA fines and inspections between 1987 and 2004 (Table 1). PROFEPA conducted 4,414 inspections during this time and issued 2,685 fines. In our entire sample of 61,821 plants, 4 percent were inspected and 3 percent were fined. Some plants were inspected and fined more than once. Of the 2,367 plants that were inspected, the average number of inspections per plant was 1.86. Of the 1,611 plants that were fined, the average number of fines was 1.5 per plant, and the average fine was 39,847 pesos (approximately US\$4,000). Sixty percent of inspections resulted in fines.

Table 1 shows that compared with nonparticipating plants, those that participated in the Clean Industry Program were inspected and fined far more often: 29 percent of the 541 participants in our sample were inspected versus only 3 percent for nonparticipants, and 20 percent of participants were fined versus only 4 percent for nonparticipants.

Hence, there appears to be a simple correlation between environmental regulatory activity and participation in the program. However, this correlation does not necessarily imply causation, for at least two reasons. First, it may have been generated by underlying differences in plant characteristics. For example, it could simply reflect a tendency for large plants to be inspected and fined and also to participate in the program. Second, the simple correlation between regulatory activity and participation does not take into account the intertemporal relationship between these events. For example, it lumps together cases where a fine was followed by participation 1 year later and cases where a fine was followed by participation 10 years later, even though the former are more likely to represent actual causation. Our econometric model addresses both of these issues: it controls for a variety of underlying plant characteristics and takes into account the intertemporal relationship between regulatory activity and participation.

### 3.2.2. Nontime-Varying Independent Variables

Table 2 lists the nontime-varying independent variables in the econometric analysis and presents sample means for the entire sample, for the subsample of participants, and for the subsample of nonparticipants.

EXPORT is a dummy variable that identifies plants that export their products. Of the sample plants, 13 percent export, and this percentage is considerably higher among participants (55 percent) than nonparticipants (12 percent). We expect EXPORT to be positively correlated with the probability of participation for at least two reasons. First, almost 90 percent of Mexican exports are sold in the United States (Clifford 2001). U.S. consumers, including buyers of intermediate products, may be more concerned about the environmental performance of Mexican firms than are domestic consumers. Second, in Mexico, a significant share of exporters are *maquiladoras*—assembly plants owned by foreign multinational corporations. Such plants are often required to meet company-wide international standards for environmental performance (Garcia-Johnson 2000; Hutson 2001).

IMPORT is a dummy variable that identifies plants that use imported inputs. Of the sample, 18 percent use imported inputs. This percentage is also considerably higher among participants (62 percent) than nonparticipants (18 percent). Notwithstanding these summary statistics, we do not have a hypothesis about the likely effect of IMPORT on the probability of participation.

GSUPPLIER is a dummy variable that identifies plants that sell their products to the Mexican government. Of the sample plants, 11 percent are government suppliers; 18 percent of participants are suppliers versus 11 percent of nonparticipants. We expect GSUPPLIER to be positively correlated with the probability of participation because the government may be more concerned about whether its suppliers have Clean Industry certificates than are private sector buyers.

Four dummy variables indicate the scope of the plant's market. SCOPE\_LOC corresponds to a local market, SCOPE\_REG to a regional market, SCOPE\_NAT to a national market, and SCOPE\_INT to an international market. Of the plants in our sample, 63 percent have a local market, 6 percent a regional market, 6 percent a national market, and 2 percent an international market. As Table 2 indicates, a greater share of plants that participated in the Clean Industry Program had a scope that extended beyond a local market than did nonparticipants. Presumably, the correlation between the scope of the market and the probability of participation depends on, among other things, differences in demand for “green” goods among the plant's

local, regional, and national markets. These differences obviously depend on the location of the plant and differ across plants. Therefore, we do not have strong expectation about the signs of these variables.

We have two sets of dummy variables—on sales and capitalization—that measure plant size. SA\_0\_50 is a dummy variable indicating that the gross revenue of the plant falls between zero and 50,000 pesos (approximately \$US 5,000). The remaining nine sales dummies have a similar interpretation. Fully 30 percent of plants in the sample have gross revenues less than 50,000 pesos. A much lower percentage of participants have gross revenues in the bottom category (7 percent) than do nonparticipants (30 percent), and a much higher percentage of participants have gross revenues in the top category (6 percent) than do nonparticipants (9 percent).

CAP\_0\_300 is a dummy variable indicating that the capitalization of the plant falls between zero and 300,000 pesos (approximately \$US 30,000). The remaining six capitalization dummies have a similar interpretation. Fully 49 percent of the plants have a capitalization of less than 300,000 pesos. As with the sales dummies, a much lower percentage of participants have capital in the bottom category (16 percent) than do nonparticipants (49 percent), and a much higher percentage of participants have gross revenues in the top category (56 percent) than do nonparticipants (11 percent).

Both the sales and the capitalization dummies measure plant size. Empirical research suggests that large plants are usually more likely to participate in voluntary regulatory programs (Lyon and Maxwell 2002). Participation in voluntary regulatory programs inevitably involves fixed transactions costs that arise from, among other things, meeting new bureaucratic requirements. These fixed costs generate economies of scale (Blackman and Mazurek 2001).

We include 17 dummy variables for the plants' type of economic activity. The three sectors with the greatest number of sample plants are commercial retail (SECTOR D3, 26 percent), industrial manufacturing (SECTOR D6, 20 percent), and commercial wholesale (SECTOR D2, 16 percent). Together, these three sectors constitute 62 percent of the sample. Presumably, plants in some sectors have stronger incentives to join the Clean Industry Program than others. These may be sectors that are particularly dirty and sell to consumers who are particularly concerned about environmental performance.

Finally, we include 30 dummy variables for the federal entity (state or delegation) where each plant is located. Only three entities contain more than 3 percent of the sample plants: the Federal District (STATE\_DIF, 23 percent), Jalisco (STATE\_JAL, 11 percent), and Nuevo León

(STATE\_NUL, 7 percent). Together, these sectors account for 42 percent of the sample plants. Presumably, plants in some locations have stronger incentives to join the program than others. For example, these may be locations where consumers are particularly concerned about environmental performance.

#### 4. Empirical Model

This section discusses our modeling framework, explains how we model regulatory activity, and presents our regression results.

##### 4.1. Duration Models

We use a duration model to analyze participation in the Clean Industry Program. Such models are used to explain intertemporal phenomena, such as the length of time that patients with a life-threatening disease survive, and the length of time industrial facilities operate before adopting a new technology.<sup>6</sup> Duration models estimate a hazard rate,  $h$ , which may be interpreted as the conditional probability that a phenomenon occurs at time  $t$  given that it has not already occurred and given the characteristics of the unit of analysis (patient, plant) at time  $t$ . The hazard rate is defined as

$$h(t, \mathbf{X}_t, \boldsymbol{\beta}) = f(t, \mathbf{X}_t, \boldsymbol{\beta}) / (1 - F(t, \mathbf{X}_t, \boldsymbol{\beta})) \quad (1)$$

where  $F(t, \mathbf{X}_t, \boldsymbol{\beta})$  is a cumulative distribution function that gives the probability that the phenomenon (death, adoption of a technology) has occurred prior to time  $t$ ,  $f(t, \mathbf{X}_t, \boldsymbol{\beta})$  is its density function,  $\mathbf{X}_t$  is a vector of explanatory variables related to the characteristics of the unit of analysis (which may change over time), and  $\boldsymbol{\beta}$  is a vector of parameters to be estimated. In this paper, to analyze participation in the Clean Industry Program, the hazard rate, simply put, is the conditional probability that a plant in our data set joins the program at time  $t$ , given that it has not already joined and given the characteristics of the plant at time  $t$ .

In duration models, the hazard rate is typically broken down into two components. The first is a baseline hazard,  $h_0(t)$  that is a function solely of time (not of any explanatory variables)

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<sup>6</sup> For an introduction, see Keifer (1998).

and that is assumed to be constant across all plants. The baseline hazard captures any effects not captured by explanatory variables (such as the diffusion of knowledge about the Clean Industry Program or changes in macroeconomic conditions). The second component of the hazard rate is a function of the explanatory variables. Combining these two components, the hazard rate  $h(t)$  is written

$$h(t) = h_0(t)\exp(\mathbf{X}_t'\boldsymbol{\beta}). \quad (2)$$

The vector of parameters,  $\boldsymbol{\beta}$ , is estimated using maximum likelihood.

A duration framework is appropriate for analyzing the effect of regulatory activity (inspections and fines) on participation in the program for two reasons. First, it explicitly accounts for the intertemporal relationship of these phenomena, which (as discussed above) helps determine whether regulatory activity actually causes participation. Second, it avoids the problem of “right censoring” that would arise in a simple cross-sectional probit or logit model because some of the plants that were not participating in September 2004, when the PROFEPA-CI data were collected, could join subsequently. A duration model circumvents this problem by estimating the conditional probability of participation in each period.

We use a Cox (1975) proportional hazard model. There are two broad approaches to specifying duration models. One is to make parametric assumptions about the time-dependence of the probability density function,  $f(t, \mathbf{X}_t, \boldsymbol{\beta})$ . Common assumptions include exponential, Weibull, and log-logistic distributions. Each assumption implies a different shape for the baseline hazard function,  $h_0(t)$ .<sup>7</sup> A second general approach is to use a Cox (1975) proportional hazard model which does not require a parametric assumption about the density function. This feature accounts for the broad popularity of the Cox model among economists, and it is the reason we choose it. We use years as our temporal unit of analysis. Although we know the day

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<sup>7</sup> For example, an exponential probability density function generates a flat hazard function,  $h_0(t)$ . The implication is that the probability of joining the Clean Industry Program (apart from the influences of regulatory activity and plant characteristics) stays the same over time. A log-logistic probability density function, on the other hand, generates a hazard function that rises and then falls.

on which plants were inspected and fined, we know only the year in which plants joined the program.<sup>8</sup>

#### **4.2. Modeling Regulatory Activity**

Because the inspections and fines are highly correlated, we cannot include them in the same model. Instead, we include inspection variables in one model and fines variables in a second. The remaining covariates are included in both sets of models.

We use an eight-year third-order polynomial to fit the relationship over time between the occurrence of a regulatory event (fine or inspection) and the probability of joining the Clean Industry Program. After eight years have passed, we assume the effect of a regulatory event is constant (and likely zero). We therefore include four inspection variables in the model: T\_INSP, defined as the number of years since the most recent inspection; T\_INSP\_2, defined as the square of the number of years since the most recent inspection; and T\_INSP\_3, defined as the cube of the number of years since the most recent inspection. All these variables are set equal to zero if the most recent inspection occurred more than eight years earlier, or if an inspection never occurred. We also include a dichotomous dummy variable T\_INSP\_P set equal to one if the inspection occurred more than eight years earlier. Together, the estimated coefficients for the four inspection variables map out the effect on the conditional probability of joining the program (hazard rate) as a function of the time since the most recent inspection. We use a similar

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<sup>8</sup> As a result, in some years multiple plants join the program in the same year. Such “ties” create a complication because estimating the duration model requires identifying the number of plants still at risk of joining the program each time a plant joins. If more than one plant joins the program in the same period, the size of the risk pool in each period is not clear. We use the Breslow (1974) method for ties. In addition, our use of years as a temporal unit of analysis raises questions about whether time aggregation bias is a problem, and whether a discrete-time representation might be more appropriate. In general, however, time aggregation bias is only a problem when hazard rates are high and/or the periods of measurement are long, that is, when a large number of failure events in a given interval begin eroding the underlying population of units at risk of failure (Petersen 1991). This is not the case in our sample, where the number of plants joining the program in any given year is always quite small relative to the number of nonparticipating plants.

approach for fines: we specify a second model with analogous variables called T\_FINE, T\_FINE\_2, T\_FINE\_3, and T\_FINE\_P.<sup>9</sup>

### 4.3. Results

We discuss results for the time-varying and nontime-varying independent variables separately.

#### 4.3.1. Time-Varying Explanatory Variables: Inspections and Fines

Table 3 presents regression results for the Cox proportional hazard model (Model 1) that includes the inspection variables. Because the hazard function given by equation (2) is nonlinear, the estimated coefficients do not have a simple interpretation (technically, they can be interpreted as the effect on the log hazard rate of a unit change in the explanatory variable at time  $t$ ). Exponentiated coefficients, however, can be interpreted as the hazard ratio—that is, the ratio of the hazard rate given an increase in an explanatory variable at time  $t$  (a unit increase in a continuous variable or a change from 0 to 1 of a dichotomous dummy variable) relative to the baseline hazard rate at time  $t$ . A hazard ratio greater than 1 indicates that an increase in the explanatory variable increases the hazard rate relative to the baseline. For example, a hazard ratio of 2 means that an increase in the explanatory variable doubles the hazard rate relative to the baseline.

In our model, the hazard ratio for time-since-last-inspection is given by

$$\text{HR}(t) = \exp(\beta_{T\_INSP\_P} + \beta_{T\_INSP} t + \beta_{T\_INSP\_2} t^2 + \beta_{T\_INSP\_3} t^3). \quad (3)$$

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<sup>9</sup> We experimented with using dummy variables (instead of third-order polynomials) to capture the relationship between regulatory activity and participation in the Clean Industry Program. Specifically, we used dummies indicating whether an inspection or fine had occurred within the past year, dummies indicating whether an inspection or fine had occurred in the past two years, and so forth, for eight years. The results mirrored those summarized in Figures 1 and 2, with the exception of inspections that had occurred six years earlier. This exception turned out to be due to an anomaly in our data: among the 100 plants for which six years elapsed between an inspection and either a decision to join the program or the end of our panel, an unusually high percentage joined the program. The third-order polynomial smoothes out this data anomaly. In addition, it allows us to generate the intuitive response functions in Figures 1 and 2.

Figure 1 is a graph of this “response function” polynomial along with 95% confidence intervals. The hazard ratio,  $HR(t)$ , is positive and significantly different from unity (i.e., no difference from baseline hazard rate without an inspection) for  $t$  between 1 and 4. The appropriate interpretation is that a PROFEPA inspection raised the probability that a plant would join the program for four years following the inspection. To be more specific, when  $t = 1$ , the estimated hazard ratio is approximately 3. This means that a PROFEPA inspection within the past year roughly tripled the conditional probability of joining the program. Figure 1 shows that, on average, an inspection more than doubles the likelihood of joining the program for four to five years after the inspection.

The graph of the response function indicates that, surprisingly, the probability that a plant participated is actually greater in the second year after an inspection than in the first year. However, the effect tails off sharply after the second year. The variable  $T\_INSP\_P$ , an indicator variable for inspections that occurred more than eight years ago, is insignificant. This result suggests that such inspections had no discernible effect on the probability of participation, a finding that matches the trend depicted in Figure 1.

Table 4 presents regression results for the Cox proportional hazard model that includes the fines variables (Model 2). Analogous to the inspections model, the four fines variables— $T\_FINE$ ,  $T\_FINE\_2$ ,  $T\_FINE\_3$  and  $T\_FINE\_P$ —define a third-order polynomial that maps the relationship between the hazard ratio and the time-since-last-fine. Figure 2 presents this polynomial along with 95 percent confidence intervals. The polynomial is positive and significantly different from unity for  $t$  between one and three years. As in the case of inspections, the results suggest that fines have a positive effect on the probability of joining the Clean Industry Program but for a shorter period of time—three to four years instead of four to five years. Also, in contrast to the inspection effect, the graph of the polynomial indicates that the probability that a plant participated is monotonically lower each year after the fine rather than peaking and then decreasing at two years.

In general, the similarities in the two response functions in Figures 1 and 2 suggest that the effects of inspections and fines on the probability of participation are closely related. Further investigation supports this hypothesis. The simple correlation coefficient between  $INSPECTED$  (a dummy variable indicating that the plant was inspected) and  $FINED$  (a dummy variable indicating that the plant was fined) is 91 percent. In 60 percent of the cases in our sample, an inspection was followed by a fine, and in no cases was a fine levied without having been preceded by an inspection. Figure 3 shows the relationship between the timing of an inspection and a fine. Almost exactly half of fines were levied within one year of an inspection.

Hence, the appropriate interpretation of the results of the inspections and fines variables in Models 1 and 2, as reflected in Figures 1 and 2, is that inspections and fines are closely related elements of the same regulatory action and, therefore, have a joint impact on the probability of participation. Plants are inspected and often fined within the same 12-month period. This joint regulatory action increases the probability of participation for four to five years after the inspection that initiates the regulatory action. If one measures the effect on the probability of participation one year after the initiation of the action (when fines are levied), then not surprisingly, the action affects the probability of participation for three to four years. The fact that Figure 1 indicates that the probability of participation increases one year after an inspection may be due to the fact that fines typically are levied one year after inspections.<sup>10</sup>

A potential concern about our analysis is that the inspections and fines variables could, in principle, be endogenous if they are both correlated with unobserved plant characteristics that affect participation.<sup>11</sup> Although such endogeneity cannot be ruled out, it is unlikely to be driving the observed correlation between regulatory activity and participation. The reason is that endogeneity would not generate response functions with the shape of those in Figures 1 and 2—namely, a response that diminishes in magnitude over time. Instead, endogeneity would generate a response that did not change over time.

Hence, taken together, the results summarized in Figures 1 and 2 suggest a causal relationship between regulatory activity and participation in the program. In particular, the fact that the positive and significant effect of regulatory on the hazard ratio diminishes over time suggests that regulatory activity causes participation.

#### **4.3.2. Nontime-Varying Explanatory Variables**

Among the nontime-varying explanatory variables, not surprisingly, the results are virtually identical for Model 1 and Model 2. As expected, EXPORT and GSUPPLIER are both positive and significant (although GSUPPLIER is significant only at the 10 percent level),

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<sup>10</sup> Surprisingly, however, the variables T\_FINE\_P, an indicator variable for fines that occurred more than eight years in the past, is significant at the 5 percent level. This result is likely due to the fact that our sample has very few observations in which a fine is not followed within eight years by either a second fine or the end of the data set.

<sup>11</sup> For example, aside from our sector dummies, our covariates do not include a precise measure of the complexity of the production process, so complexity is partly unobserved. It could be that complex plants are more likely to be inspected and fined because they have a higher potential for violating environmental regulations and are also more likely to participate in the program because they tend to employ educated and sophisticated managers. If this were actually true, then inspections and fines would be endogenous.

indicating that plants that sold their goods in overseas markets and to the government were more likely to join the Clean Industry Program, all other things equal. IMPORT was also positive and significant.

The sales and capitalization dummies provide some evidence that, as expected, larger plants are more likely to join the program. The reference groups for these dummies are plants with less than 50,000 pesos in sales and those with less than 300,000 pesos in capital. SA\_30KPLUS is positive and significant, indicating that compared with the reference group, plants with more than 30,000 pesos in sales are more likely to join. Somewhat surprisingly, none of the other sales dummies are significant. Three of the capital variables are significant: CAP\_301\_600, CAP\_901\_3K, and CAP\_10KPLUS. These results suggest that plants with capital between 301,000 and 600,000 pesos, between 901,000 and 3,000,000 pesos, and more than 10,000,000 pesos are more likely to participate than plants in the reference group, all other things equal. These results comport with previous studies of voluntary programs that generally find larger facilities are more likely to join.

For the sector fixed effects, the reference sector is agriculture, livestock, forestry, fish, and hunting (SECTOR1). Compared with plants in this sector, those in the following sectors were less likely to join: commercial and wholesale (SECTOR2), construction (SECTOR4), information and mass media (SECTOR7), and waste management and remediation (SECTOR11). Only plants in one sector—mining (SECTOR8)—were more likely to join than those in the reference sector.

For the state fixed effects, the reference state is Aguascalientes (STATE\_AGU). Compared with this state, plants in the following states were more likely to join: Chihuahua (STATE\_CHI), Coahuila (STATE\_COA, in Model 1 only), Michoacan (STATE\_MIC), Morelos (STATE\_MOR), Oaxaca (STATE\_OAX), Puebla (STATE\_PUE, in Model 1 only), Queretaro (STATE\_QUE), Sonora (STATE\_SON, in Model 2 only), Tabasco (STATE\_TAB), Tlaxcala (STATE\_TLA), Veracruz (STATE\_VER), Yucatan (STATE\_YUC), and Zacatecas (STATE\_ZAC). Plants in only one state—the Federal District (STATE\_DIF)—were less likely to join than those in the reference state.

## 5. Conclusion

We have used data on some 60,000 industrial facilities and other business in Mexico to identify the drivers of participation in the Clean Industry Program, Mexico's flagship voluntary regulatory program. We have used duration analysis because it explicitly accounts for the timing

of the dependent variable (participation) and the main independent variable of interest (regulatory activity) and because it controls for right censoring. Our results strongly suggest that PROFEPA inspections and fines do motivate participation in the program. Furthermore, inspections and fines are likely closely related elements of the same regulatory action and therefore have a joint impact on the probability of participation. Most inspections are followed by a fine, typically within 12 months. Together, the inspection and fine increase the probability of participation in the program for four to five years after the inspection and three to four years after the fine. The magnitude of the effect is significant: the probability of participation more than doubles for four to five years after an inspection. We also find that, all other things equal, plants are more likely to participate if they sell their goods in overseas markets and to government suppliers, use imported inputs, are large (as measured by gross revenues or capitalization), and are in certain sectors and states.

Our results suggest that the Clean Industry Program is not simply comprised of already-clean firms. Rather, it has attracted a significant number of dirty firms under pressure from formal regulatory authorities. Presumably, the dirty firms that joined the program and were awarded a Clean Industry certificate ultimately improved their environmental performance. However, without reliable plant-level data on environmental performance, which to our knowledge are simply not yet available, we are not able to gauge the relative importance of the Clean Industry Program versus other factors as a driver of these improvements. For example, it could be that some of the dirty plants that joined the program would have improved their environmental performance even if they had not joined because they were being inspected and/or fined by PROFEPA and wished to avoid new sanctions. Hence, by demonstrating that fines and inspections are driving dirty firms into Clean Industry program, our analysis can be interpreted as a positive preliminary indication—but by no means proof—that the program itself has generated environmental benefits.

What are the broad policy implications of our findings? The results provide limited evidence that voluntary regulation in developing countries may have environmental benefits. But even if these preliminary findings are borne out and reinforced by subsequent research, they will not necessarily imply that voluntary regulation can substitute for poorly performing mandatory regulation. In fact, our study suggests that the Clean Industry Program depends to some extent on the effectiveness of conventional mandatory regulation: plants join the program to escape regulatory sanctions. In other words, our results suggest that effective mandatory regulation—a strong “background threat”—drives the success of voluntary regulation. This conclusion echoes the literature on voluntary regulation in industrialized countries.

Finally, this paper highlights at least two interesting questions that could be addressed by future research. Is it possible to confirm that the Clean Industry Program generates environmental benefits by using data on environmental performance? If so, what design features and other factors are responsible for the apparent success of the program? Given the gaps in Mexico's environmental performance data, survey research would likely be the best means of addressing these questions.

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## Tables and Figures

Table 1. PROFEPA Inspections and Fines, 1987–2004

<i>Sample →</i> ↓		<i>Clean Industry participants &amp; non-participants</i>	<i>Clean Industry participants</i>	<i>Clean Industry non-participants</i>
<i>All plants</i>	Inspected	(n = 61,821) 3.83%	(n = 541) 29.02%	(n = 61,280) 3.61%
	Fined	3.17%	20.15%	3.02%
<i>Plants that were inspected</i>	Total no. inspections	(n=2,367) 4,414	(n=157) 301	(n=2,210) 4,113
	Avg. no. inspections/plant	1.86	1.92	1.86
<i>Plants that were fined</i>	Total no. fines	(n= 1,611) 2,658	(n = 98) 155	(n= 1,513) 2,503
	Average no. fines/plant	1.50	1.43	1.50
	Inspections resulting in fine	60.22%	51.50%	60.86%

**Table 2. Nontime-Varying Independent Variables and Sample Means**

<i>Variable</i>	<i>Explanation</i> (all 0/1 dummies)	<i>Entire sample</i> (n=61,821)	<i>Clean Industry participants</i> (n=541)	<i>Clean Industry nonparticipants</i> (n=61,280)
EXPORT	exporter	0.1263	0.5471	0.1226
IMPORT	importer	0.1849	0.6155	0.1811
GSUPPLIER	government supplier	0.1100	0.1756	0.1094
SCOPE_LOC	scope market local	0.6274	0.1608	0.6315
SCOPE_REG	scope market regional	0.0639	0.0721	0.0639
SCOPE_NAT	scope market national	0.0580	0.0758	0.0579
SCOPE_INT	scope market international	0.0229	0.0499	0.0226
SA_0_50	gross revenue 0-50K pesos	0.2976	0.0739	0.2996
SA_51_100	gross revenue 51K – 100K pesos	0.0881	0.0222	0.0887
SA_101_200	gross revenue 101K-200K pesos	0.0824	0.0277	0.0829
SA_201_500	gross revenue 201K-500K pesos	0.0888	0.0277	0.0894
SA_501_1K	gross revenue 501K - 1000K pesos	0.0906	0.0314	0.0911
SA_1001_3K	gross revenue 1001K-3000K pesos	0.0898	0.0665	0.0900
SA_3001_6K	gross revenue 3001K-6000K pesos	0.0636	0.0462	0.0638
SA_6001_12K	gross revenue 6001K-12,000K pesos	0.0579	0.0647	0.0578
SA_12001_30K	gross revenue 12,001K-30,000K pesos	0.0478	0.0665	0.0476
SA_30KPLUS	gross revenue 30,001K+ pesos	0.0933	0.573	0.0891
CAP_0_300	accounting capital 0-300K pesos	0.4863	0.1553	0.4892
CAP_301_600	accounting capital 301K-600K pesos	0.1382	0.0628	0.1388
CAP_601_900	accounting capital 601K-900K pesos	0.0782	0.0388	0.0786
CAP_901_3K	accounting capital 901K-3,000K pesos	0.0932	0.0887	0.0932
CAP_3001_5K	accounting capital 3,001K-5,000K pesos	0.0471	0.0462	0.0471

CAP_5001_10K	accounting capital 5,001K-10,000K pesos	0.0424	0.0462	0.0424
CAP_10KPLUS	accounting capital 10,001K+ pesos	0.1146	0.5619	0.1106
SECTORD1	ag., livestock, forestry fish and hunting	0.0036	0.0092	0.0035
SECTORD2	commercial wholesale	0.1596	0.0222	0.1608
SECTORD3	commercial retail	0.2642	0.1072	0.2656
SECTORD4	construction	0.056	0.0037	0.0564
SECTORD5	elec., water and gas	0.0052	0.0129	0.0051
SECTORD6	industrial manufacturing	0.1982	0.719	0.1936
SECTORD7	information and mass media	0.0542	0.0037	0.0546
SECTORD8	mining	0.005	0.024	0.0048
SECTORD9	other services except government activities	0.0191	0.0203	0.0191
SECTORD10	temp. lodging, food and beverage prep.	0.0577	0.0185	0.0581
SECTORD11	waste management and remediation	0.0321	0.0037	0.0323
SECTORD12	entertainment, culture, sports	0.0033	0.0000	0.0033
SECTORD13	health and social assistance	0.0188	0.0129	0.0189
SECTORD14	educational services	0.0120	0.0018	0.0121
SECTORD15	real estate services	0.0115	0.0074	0.0116
SECTORD16	professional, scientific and technical	0.0594	0.0092	0.0599
SECTORD17	transport, mail and services	0.0401	0.0240	0.0403
STATE_AGU	Aguascalientes	0.0125	0.0333	0.0123
STATE_BCA	Baja California	0.0345	0.0536	0.0343
STATE_CAM	Campeche	0.0037	0.0018	0.0037
STATE_CHS	Chiapas	0.0057	0.0037	0.0057
STATE_CHI	Chihuahua	0.0395	0.1109	0.0389
STATE_COA	Coahuila	0.0246	0.0425	0.0244
STATE_COL	Colima	0.0039	0.0055	0.0039
STATE_DIF	Distrito Federal	0.2332	0.0462	0.2348
STATE_DUR	Durango	0.0066	0.0092	0.0065
STATE_GTO	Guanajuato	0.0365	0.0259	0.0366
STATE_GUE	Guerrero	0.0032	0.0037	0.0031
STATE_HID	Hidalgo	0.0113	0.0092	0.0113
STATE_JAL	Jalisco	0.1146	0.0776	0.1149
STATE_MIC	Michoacan	0.0142	0.0240	0.0141

STATE_MOR	Morelos	0.0069	0.0222	0.0068
STATE_NAY	Nayarit	0.0083	0.0074	0.0083
STATE_NUL	Nuevo Leon	0.0748	0.0665	0.0749
STATE_OAX	Oaxaca	0.0079	0.0166	0.0078
STATE_PUE	Puebla	0.0424	0.0536	0.0423
STATE_QUE	Queretaro	0.0151	0.0462	0.0148
STATE_QUI	Quintana Roo	0.0428	0.0166	0.0431
STATE_SLP	San Luis Potosi	0.0091	0.0203	0.009
STATE_SIN	Sinaloa	0.0172	0.0277	0.0171
STATE_SON	Sonora	0.0193	0.0111	0.0194
STATE_TAB	Tabasco	0.0043	0.0092	0.0043
STATE_TAM	Tamulipas	0.0238	0.0555	0.0235
STATE_TLA	Tlaxcala	0.0061	0.0388	0.0058
STATE_VER	Veracruz	0.0378	0.0407	0.0378
STATE_YUC	Yucatan	0.0228	0.0277	0.0227
STATE_ZAC	Zacatecas	0.005	0.0111	0.0049

**Table 3. Regression Results for Cox Proportional Hazard Model  
of Participation in Clean Industry Program, 1992–2004  
[Model 1: Inspections; n = 61,821]**

<i>Variable</i>	<i>Coefficient</i>	<i>S.E.</i>	<i>Variable</i>	<i>Coefficient</i>	<i>S.E.</i>
T_INSP	0.7732	0.7683	SECTOR17	-0.2692	0.5826
T_INSP_2	-0.2614	0.2395	STATE_BCA	0.1103	0.2394
T_INSP_3	0.0187	0.0209	STATE_CAM	0.7768	1.0138
T_INSP_P	0.5491	0.6834	STATE_CHS	0.607	0.7232
EXPORT	0.5812**	0.1426	STATE_CHI	0.7379**	0.1999
IMPORT	0.454**	0.1481	STATE_COA	0.4646 <sup>§</sup>	0.2602
GSUPPLIER	0.2311 <sup>§</sup>	0.1294	STATE_COL	0.031	0.7221
SCOPE_REG	0.6102**	0.2208	STATE_DIF	-1.2523**	0.2497
SCOPE_NAT	0.1973	0.2026	STATE_DUR	-0.058	0.5242
SCOPE_INT	-0.2426	0.2178	STATE_GTO	-0.0756	0.3217
SA_51_100	-0.3022	0.3687	STATE_GUE	0.7913	0.7228
SA_101_200	-0.4547	0.3729	STATE_HID	-0.0142	0.5194
SA_201_500	-0.491	0.3521	STATE_JAL	0.0148	0.2115
SA_501_1K	-0.3785	0.3223	STATE_MIC	1.2039**	0.3121
SA_1001_3K	0.1101	0.2743	STATE_MOR	1.1229**	0.3354
SA_3001_6K	-0.0301	0.301	STATE_NAY	-0.4888	1.0113
SA_6001_12K	0.2494	0.2746	STATE_NUL	-0.1545	0.2306
SA_12001_30K	0.1275	0.2813	STATE_OAX	1.0691*	0.4418
SA_30KPLUS	0.9878**	0.2412	STATE_PUE	0.449 <sup>§</sup>	0.2404
CAP_301_600	0.5783**	0.2327	STATE_QUE	0.793**	0.2487
CAP_601_900	0.4073	0.2849	STATE QUI	0.3139	0.4435
CAP_901_3K	0.7301**	0.2203	STATE_SLP	0.3393	0.3794
CAP_3001_5K	0.3211	0.2775	STATE_SIN	0.5586	0.3545
CAP_5001_10K	0.3245	0.2679	STATE_SON	-1.1668	0.7236
CAP_10KPLUS	1.1052**	0.1934	STATE_TAB	1.3866**	0.4717
SECTOR2	-2.1327**	0.6205	STATE_TAM	0.372	0.2357
SECTOR3	-0.7508	0.5164	STATE_TLA	1.2043**	0.2589
SECTOR4	-2.5052**	0.8662	STATE_VER	0.7599**	0.2658
SECTOR5	0.3217	0.6743	STATE_YUC	0.6153*	0.314
SECTOR6	0.742	0.4848	STATE_ZAC	1.4558**	0.44
SECTOR7	-2.2595*	1.1163			
SECTOR8	1.731**	0.5705			
SECTOR9	0.5794	0.5955			
SECTOR10	-0.5925	0.6223			
SECTOR11	-1.8425 <sup>§</sup>	1.1173			
SECTOR12	-42.0108	1.45E+09			
SECTOR13	0.2396	0.6415			
SECTOR14	-1.1122	1.1154			
SECTOR15	0.2409	0.7028			
SECTOR16	-1.0888	0.7041			

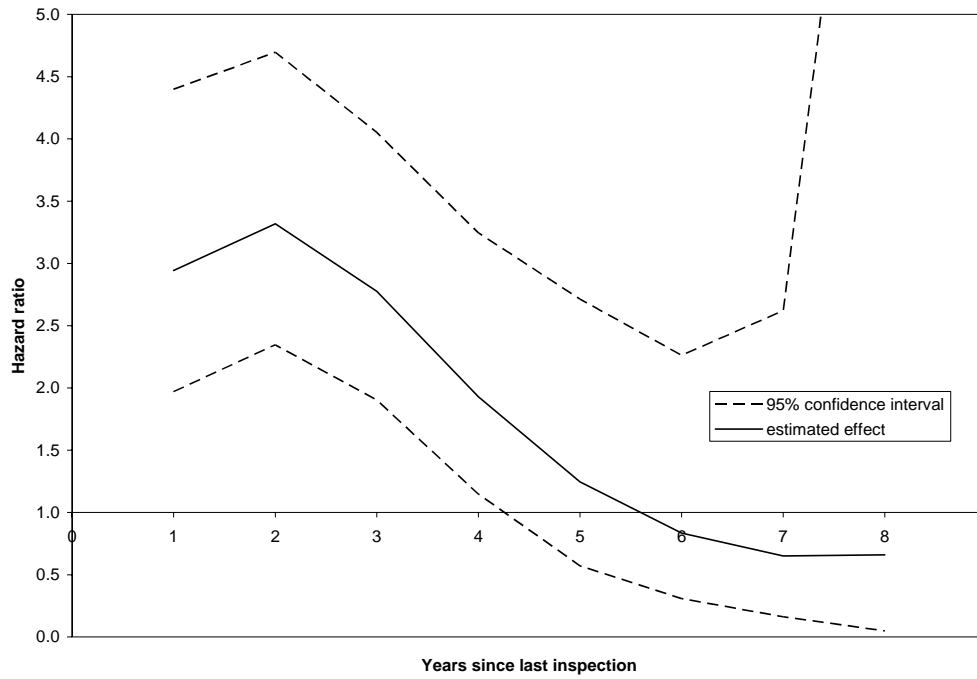
\*\*Significant at 1% level; \*significant at 5% level; <sup>§</sup>significant at 10% level.

**Table 4. Regression Results for Cox Proportional Hazard Model  
of Participation in Clean Industry Program, 1992–2004  
[Model 2: Fines; n = 61,821]**

<i>Variable</i>	<i>Coefficient</i>	<i>S.E.</i>	<i>Variable</i>	<i>Coefficient</i>	<i>S.E.</i>
T_FINE	-0.8960	1.1283	SECTORD17	-0.2621	0.583
T_FINE_2	0.2221	0.3697	STATE_BCA	0.0153	0.2357
T_FINE_3	-0.0205	0.0343	STATE_CAM	0.6708	1.0128
T_FINE_P	1.8032*	0.9272	STATE_CHS	0.5031	0.7218
EXPORT	0.6043**	0.1425	STATE_CHI	0.6742**	0.1955
IMPORT	0.4579**	0.1481	STATE_COA	0.3621	0.2566
GSUPPLIER	0.2144 <sup>§</sup>	0.1293	STATE_COL	0.0271	0.7212
SCOPE_REG	0.6231**	0.2206	STATE_DIF	-1.2785**	0.2469
SCOPE_NAT	0.2131	0.2027	STATE_DUR	-0.1703	0.5221
SCOPE_INT	-0.2302	0.2177	STATE_GTO	-0.1802	0.3189
SA_51_100	-0.3062	0.3686	STATE_GUE	0.678	0.7213
SA_101_200	-0.4544	0.3729	STATE_HID	-0.0816	0.5181
SA_201_500	-0.4924	0.3521	STATE_JAL	-0.1004	0.2066
SA_501_1K	-0.3855	0.3221	STATE_MIC	1.0909**	0.3088
SA_1001_3K	0.1023	0.2741	STATE_MOR	0.9843**	0.3321
SA_3001_6K	-0.0364	0.3007	STATE_NAY	-0.5574	1.0106
SA_6001_12K	0.2554	0.2745	STATE_NUL	-0.3323	0.2419
SA_12001_30K	0.1348	0.2813	STATE_OAX	0.9498*	0.4397
SA_30KPLUS	1.0046**	0.2408	STATE_PUE	0.3527	0.2367
CAP_301_600	0.5803**	0.2325	STATE_QUE	0.6537**	0.2443
CAP_601_900	0.4079	0.2847	STATE_QUI	0.2219	0.4411
CAP_901_3K	0.7445**	0.2201	STATE_SLP	0.269	0.3773
CAP_3001_5K	0.3446	0.2774	STATE_SIN	0.4452	0.352
CAP_5001_10K	0.3353	0.2681	STATE_SON	-1.289 <sup>§</sup>	0.722
CAP_10KPLUS	1.1266**	0.1931	STATE_TAB	1.2718**	0.4695
SECTORD2	-2.1319**	0.6208	STATE_TAM	0.3506	0.2322
SECTORD3	-0.7455	0.5168	STATE_TLA	1.2472**	0.2552
SECTORD4	-2.4828**	0.8663	STATE_VER	0.6413**	0.2616
SECTORD5	0.3943	0.6751	STATE_YUC	0.5699*	0.3117
SECTORD6	0.7827	0.4851	STATE_ZAC	1.3667**	0.4385
SECTORD7	-2.2476*	1.1165			
SECTORD8	1.7321**	0.5710			
SECTORD9	0.5946	0.5958			
SECTORD10	-0.592	0.6225			
SECTORD11	-1.8411 <sup>§</sup>	1.1173			
SECTORD12	-44.3538	.			
SECTORD13	0.2724	0.6416			
SECTORD14	-1.1256	1.1155			
SECTORD15	0.2397	0.703			
SECTORD16	-1.085	0.7042			

\*\*Significant at 1% level; \*Significant at 5% level; <sup>§</sup>Significant at 10% level

**Figure 1. Hazard Ratio (Hazard Rate with Inspection/Hazard Rate without Inspection) as Function of Time since Last Inspection**



**Figure 2. Hazard Ratio (Hazard Rate with Fine/Hazard Rate without Fine) as Function of Time since Last Fine**

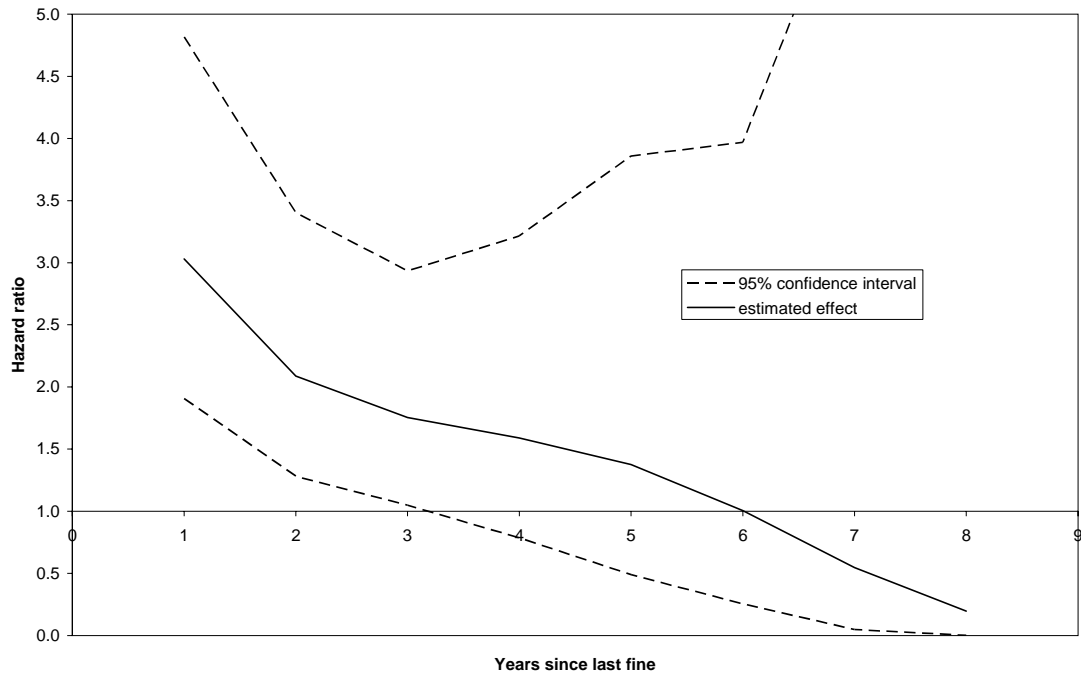


Figure 3. Histogram of Gap (in Years) between Inspection and Fine

