Do voluntary pollution reduction programs help reduce pollution levels?

Evidence from the Mexican Clean Industry Program.

Andrew Foster

Emilio Gutiérrez

Abstract

This paper evaluates the effectiveness of the Mexican Clean Industry Program, in which firms participate voluntarily if they are willing to meet the pollution emissions legal standards in exchange for a Clean Industry Certificate. It first develops a simple model with two groups of players, firms and the authorities. Firms can choose to be in compliance, non compliance or participate in the program. Authorities can set the cost of non compliance by changing the frequency with which they inspect different industrial sectors.

By imposing some structure to the cost of participation and the cost of compliance, we show evidence from aggregate data at the industrial sector level suggesting that firms with relatively low cost of compliance are the ones that participate in the Mexican Clean Industry Program. However, as authorities have the option to update the inspection intensity given the number of firms participating in the program, certification serves as a screening tool that reduces the cost of inspection in sectors with a high percentage of certified firms. According to our model, the reductions in pollution emissions levels are not only observed amongst participating firms, but also amongst non-certified firms in industrial sectors with a high percentage of certified firms.

The predictions of the model are further tested with firm level data. For each firm's exact geographic location (zip code), a monthly measure of particulate matter in the atmosphere obtained from satellite imagery is assigned for the period between March, 2000 and December, 2006. While particulate matter concentrations seem to lower significantly where certified firms are located, a significant reduction is also observed in places where non-certified firms in sectors with a high percentage of certified firms are. This last relationship is not observed for firms with less than 10 employees, which are not subject to inspections by the authorities.

JEL codes: Q52, Q56.

Introduction.

The evaluation of the pollution control policies in developing countries, especially those with high levels of trade with industrialized nations, is becoming increasingly necessary. The fear of the "pollution haven" hypothesis, on one hand, which claims that weak regulation in developing countries represents an incentive to high polluting industries to relocate in poorer regions when the barriers to trade are low and, on the other hand, the possibility of trade creating a "race to the bottom", in which competition between nations to attract or retain firms incentives them to relax their pollution control policies, suggest a high need to precisely assess countries' success at controlling pollution emissions. Given the high levels of trade between the US and Mexico, the potential differences in the effectiveness of law enforcement between the two countries and the decreasing trade barriers between them, a careful evaluation of the effectiveness of the Mexican authorities at controlling pollution emissions seems then of special relevance for the US, Mexican and international contexts.

This paper contributes to the literature evaluating the policies that the Mexican authorities have put in place in order to control pollution emissions by firms, focusing on the two main policy tools used by the Mexican Federal Environmental Protection Agency (Procuraduría Federal de Protección al Ambiente, PROFEPA). On one hand, this agency is responsible for inspecting firms in order to determine if they comply with the current legal pollution emission standards. Inspections are performed at random, assigning a higher probability of inspection to sectors with higher perceived risk of polluting. If a firm is found to be in non compliance, it is forced to pay a fine, which increases in case of relapse. Relatively small firms seem to be rarely subject to inspections. On the other hand, the same agency, in 1997, introduced the Mexican Clean Industry Program (Programa de Industria Limpia), also known as National Environmental Auditing Program (Programa Nacional de Auditoría Ambiental), the main voluntary pollution reduction program in Mexico. Firms participating in this program have to pay for an audit by an independent agency that determines the actions to be taken in order to comply with the pollution emissions standards and, after they succeed at meeting the pollution levels standards, they are granted a Clean Industry Certificate, which can be used for marketing purposes. If certified, firms are exempted from inspections for a given period of time (at least two years). Since 1997 until 2007, 2,568 firms had received this certification.

This paper argues that these two policies cannot be evaluated in isolation. In general, it makes two main contributions. On one hand, it suggests a simple framework, which models both the authorities' inspection policy and the firm's decision between participating in the Clean Industry Program, being in compliance with pollution emission standards and being in non compliance and subject to fines, that allows the researcher to test for the characteristics of firms that have been granted a Clean Industry Certificate without the need of detailed firm level data (which seems to be one of the limitations for empirical studies). On the other hand, it stresses the fact that, even if relatively clean firms are the ones participating in the program, its effectiveness, when only looking at participating firms, might be understated. If used together with an inspection policy, the introduction of voluntary programs can reduce the cost of inspections by revealing information to the authorities about participating and non participating firms' characteristics. Authorities (can) set a higher inspection rate for non participating firms at a lower cost when a high percentage of firms get certified, increasing the incentives for non participating firms to reduce their pollution levels. This last fact seems widely ignored in the empirical literature.

The paper is presented as follows. The next section briefly reviews the empirical literature trying to evaluate the effectiveness of programs of this kind, and motivates the need for a theoretical framework for its evaluation. Section III describes the simple setup that we develop in order to describe participation in the program and the authority's role in terms of its inspection policy. Section IV describes the aggregate data and discusses its implications in terms of the characteristics of participating firms. Section V returns to the model and explores how the authorities can use the information revealed by participation in the program to update the inspection policy and tests the model's predictions with the aggregate data. Section VI describes the firm level data set used to further test the predictions of our empirical model, and the empirical strategy. Section VII shows the empirical results. The last section concludes.

II. Motivation.

Voluntary pollution reduction programs, similar to the Mexican, are popular tool used by policymakers around the world as part of the instruments aiming to encourage firms to reduce their emissions levels (OECD, 1999, 2003). Their emergence has been followed by a growing body of literature trying to evaluate their effectiveness, generally studying these programs in isolation from other environmental protection actions. Given this, we believe that most of the empirical studies trying to evaluate voluntary pollution reduction programs fail at taking into consideration a more general equilibrium perspective on their effectiveness. By looking at these programs in isolation, they ignore the relevance of the information revealed in the process of certification, and how that information can be used by other actors and influence firm's behavior.

The existing literature seems especially concerned with testing if participating firms are those already in compliance with the emissions standards, or if firms invest in pollution reduction for reasons not related to the existence of the program (Vidovic and Khanna, 2007; Morgenstern and Pizer, 2007) and it has focused on industrialized countries. Specifically, the US Environmental Protection Agency 33/50 program has received most of the attention in the literature. Arora and Carson (1996), Gamper-Rabindran (2006) and Sam and Innes (2006), for example, do not find evidence that firms participating in the program were those who had reduced their emissions before the implementation of the Program.

However, Vidovic and Khanna (2007) find the opposite. According to them, a very small percentage of the total emissions by participating firms can be attributed to the program. Some of these studies also try to test if the firms with the lowest or highest emissions levels are the ones participating, with no conclusive results. The differences in the findings seem to come from differences in the sample used, the possibility for correction for selection into the participating sample, or the variable used to measure environmental compliance (Alberini and Segerson, 2002).

There exists one study trying to evaluate the Mexican Clean Industry Program (Blackman et al., 2007). It shows that firms that have been inspected or fined for not complying with pollution emissions standards in the past are more likely to participate. It argues that this is evidence that the program is contributing to reduce pollution, given that participating firms are more likely than average to be in non compliance before entering the program, and presumably in compliance with environmental regulations when they graduate from it. However, as we will see later, the positive correlation between the probability of being inspected by the authorities and participation in the program might prove that it is the relatively cleaner firms that decide to participate in the Clean Industry Program, contrary to what is argued by the mentioned study.

Both the empirical challenges faced when trying to determine if it is the cleanest firms that are getting certified, and the possibility for other actors' responses to participation, which can incentive non participating firms to change their behavior as a consequence of the existence of programs of this kind, motivate the need for a theoretical framework, which we develop in the following section. The model will allow us first to test if the cleanest firms are the ones participating in the program from aggregate data and it will help us argue that any paper trying to evaluate the overall impact of voluntary pollution reduction programs should not only focus on participating firms, but also on the authorities' and non participating firms' response to participation. We will show that it is possible to observe no reduction in pollution emissions for participating firms, but rather an increase in the incentives for non participating firms to improve their environmental performance.

III. Modeling firms' participation in the Clean Industry Program.

III.1. The Firms' Problem.

A first glance at aggregate data at the sector level for inspections performed by PROFEPA, inspections resulting in non compliance and participation in the Clean Industry Program seems rather puzzling. As can be seen in Table 1, the correlation between the percentage of firms inspected in each industrial sector and the non compliance rate (for the whole 1992 to 2006 period) is very close to zero, while the percentage of firms in each sector that have received a Clean Industry Certificate and the same probability of inspection are strongly positively correlated. Our model will explain these relationships, arguing that the lack of correlation between inspections and non compliance can be evidence of the effectiveness of the Mexican inspection policy, which imposes higher incentives to potentially polluting firms to be in compliance, as they are assigned a higher inspection probability. On the other hand, as we will see, when imposing some structure to the cost of compliance and participation in the Program, the positive correlation between inspection intensity and certification rate can provide information about the types of firms within industrial sectors that get certified.

Table 1

Correlation between Inspection Intensity and other sector level variables

	Log % in non compliance before Certificates	Log % in non compliance after Certificates	Log % of firms certified
Log of % of firms inspected	-0.0405	0.0651	0.6766***

160 industrial sectors in the sample
*** Significant at 1% level

The model presented in this paper will abstract from the fact that in reality there is a continuum of pollution emissions (and possibly a continuum of possible fines imposed by the government given the emissions level of each firm when inspected and found in non compliance). The setup includes two types of players. Firms choose if they will invest in complying with the pollution emissions standards given the authorities' inspection strategy. Authorities set their inspection policy by maximizing the expected benefit from inspections, given the information they observe about firms' characteristics. Firms have a choice between three different options: Complying with pollution emissions standards without getting certified as clean firms; compliance with emissions standards and obtaining a "Clean Industry Certificate"; and non compliance. Note that all certified firms are assumed to be in compliance, but not all the non-certified firms are assumed to be in non compliance. Each of the options has a different cost for each firm, depending both on the types of goods they produce (industrial sector) and unobserved firm specific characteristics. Authorities do not observe the firm specific cost of compliance, but rather an average cost of compliance for firms of the same type, that we define as industrial sector.

The cost of compliance with pollution emissions standards without certification for firm i in sector j is:

$$C_{ij}^{c1} = C_j + d_{ij} \tag{1}$$

Where C_j is the sector j level cost, observed by the authorities and

d_{ij} is the firm specific cost, not observed by the authorities, with a distribution F.

The cost of certification is:

$$C_{ij}^{c2} = \alpha C_j + \beta d_{ij} \tag{2}$$

Where α and β are two constants, which for the moment we will assume as unknown, although common to all firms. As can be seen, α multiplies the industrial sector level cost of compliance, while

β multiplies the firm specific cost of compliance. We will discuss the economic meaning of different values of these two parameters later in this paper.

Finally, the cost of non compliance is given by:

$$C_{ij}^{nc} = P_j * M \tag{3}$$

Where P_j is the probability that the authorities will inspect a firm in sector j and M is the fine imposed if the firm is found to be in non compliance. M is assumed to be fixed. P_j is set at the sector level, given that authorities are unable to observe the firms' specific d_{ij}. As stated before, we assume that the firm specific component of the cost of compliance is only observed by the firm.

In the absence of certificates, it is clear from equation (1) and (3) that only firms with low d_{ij} will comply with pollution emissions standards. However, the values of α and β will determine who gets certified. While theoretically we do not impose any restrictions on the values of α and β, by imposing the restriction that there is an interior solution for this problem in each industrial sector, three general scenarios are possible[1], which we analyze in what follows. For this purpose, let's define *a* as the intersection between equation (1) and (2), *b* as the intersection between equations (1) and (3), and *c* as the intersection between equations (2) and (3).

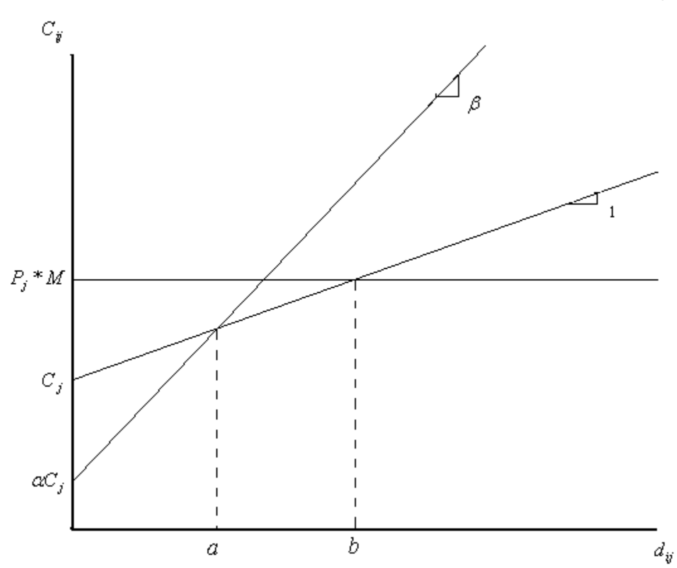
Figure 1 plots the cost of compliance, non compliance and compliance with certification when $\alpha < 1$ and $\beta > 1$ for different values of *d* when there is an interior solution to this problem. $\alpha < 1$ implies that most of the benefits from participating in the program are common to all firms within one industrial sector. $\beta > 1$ implies that the cost of participating in the program is higher for firms with

[1] This restriction is related to the value of MP_j. For cost schedules 1 and 2, it can be expressed formally as: $MP_j > \frac{(\beta - \alpha)}{(\beta - 1)} C_j$. For cost schedule 3, it is: $MP_j < \frac{(\beta - \alpha)}{(\beta - 1)} C_j$.

relatively high compliance costs. Firms will get certified if $d < a$. Firms for which $a < d < b$ will be in compliance and not certified, and firms with $d > b$ will be in non compliance.

This situation is what seems to be the biggest concern for in the literature trying to evaluate the impact of voluntary pollution reduction programs, and what most of the empirical work in the literature tries to test. In this situation, certified firms would be in compliance regardless of the existence of the program. Programs of this kind do not seem to directly push firms in non compliance to reduce their pollution emissions levels and, as a consequence, their impact is believed to be low.

Figure 1. Cost Schedule 1. $\alpha < 1, \quad \beta > 1$.



Figures 2 and 3 plot the same three hypothetic cost schedules, this time for $\alpha > 1$. In Figure 2, β is set to be lower than one but higher than zero, illustrating a situation in which firms with intermediate levels of d get certified. Figure 3 shows the extreme case, in which β is negative, implying that the firms who get certified are those with the highest levels of *d*. In both of these cases, at least some of the firms getting certified are firms who would be in non compliance in the absence of the program. As stated before, this is what the literature on the subject tries to test for.

Figure 2. Cost schedule 2. $\alpha > 1, \quad \beta < 1$.

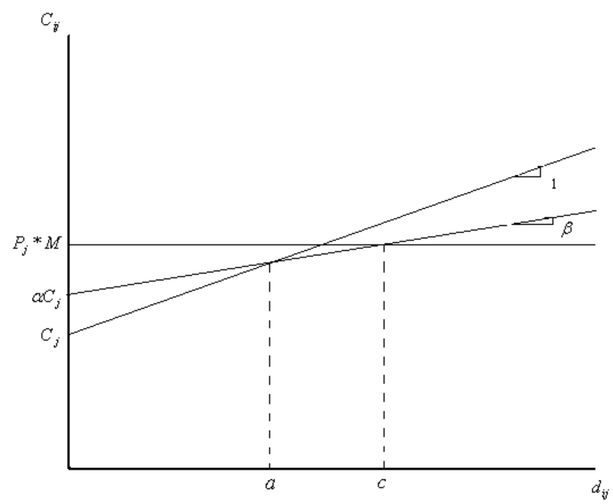
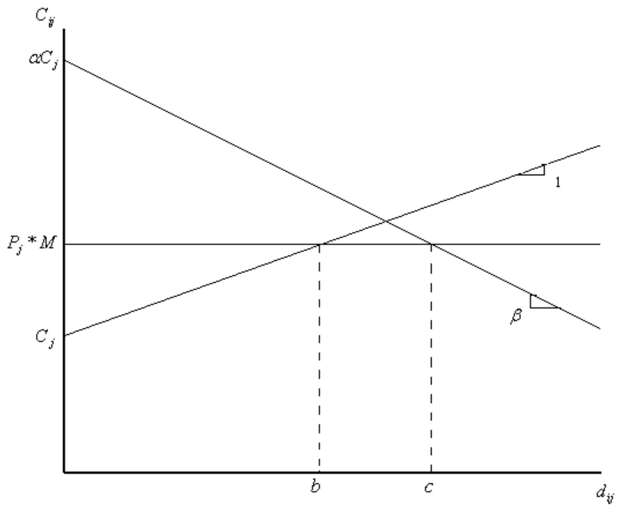


Figure 3. Cost schedule 3. $\alpha > 1, \quad \beta < 0$.



In what follows, we show how our model draws simple conclusions about the empirical relationships that should be found if each of the different cost schedules shown in Figures 1, 2 and 3 fit the data, if we assume that the values of α and β are common to all industrial sectors.

With this in mind, let's define first define D_j^k as the percentage of firms in sector *j* that should get certified under the cost schedule *k*.

$$D_j^1 = F(a) = F\left(\frac{(1-\alpha_1)}{(\beta_1 - 1)} C_j\right) \tag{4}$$

$$D_j^2 = F(c) - F(a) = F\left(\frac{MP_j - \alpha_2 C_j}{\beta_2}\right) - F\left(\frac{(1-\alpha_2)}{(\beta_2 - 1)} C_j\right) \tag{5}$$

$$D_j^3 = 1 - F(c) = 1 - F\left(\frac{MP_j - \alpha_3 C_j}{\beta_3}\right) \tag{6}$$

We assume that fines for non compliance are fixed. However, the authorities can decide to change the probability of inspection in each sector, P_j, which is likely to vary with C_j. Taking this into account, we can Compute the partial derivatives of D_j^k with respect to C_j:

$$\frac{\partial D_j^1}{\partial C_j} = f\left(\frac{(1-\alpha_1)}{(\beta_1-1)}C_j\right)\left(\frac{1-\alpha_1}{\beta_1-1}\right) \tag{7}$$

$$\frac{\partial D_j^2}{\partial C_j} = f\left(\frac{MP_j-\alpha_2 C_j}{\beta_2}\right)\left(\frac{M}{\beta_2}\frac{\partial P_j}{\partial C_j}-\frac{\alpha_2}{\beta_2}\right) - f\left(\frac{(1-\alpha_2)}{(\beta_2-1)}C_j\right)\left(\frac{1-\alpha_2}{\beta_2-1}\right) \tag{8}$$

$$\frac{\partial D_j^3}{\partial C_j} = -f\left(\frac{MP_j-\alpha_3 C_j}{\beta_3}\right)\left(\frac{M}{\beta_3}\frac{\partial P_j}{\partial C_j}-\frac{\alpha_3}{\beta_3}\right) \tag{9}$$

Given that, as stated, $\alpha_1 < 1$ and $\beta_1 > 1$, it is easy to see that the expression for $\frac{\partial D_j^1}{\partial C_j} > 0$.

The sign of the derivative of the percentage of firms certified in each sector with respect to the fixed cost of compliance in each sector under the two last cost schedules, depends on the derivative of the probability of inspection with respect to *C*, $\frac{\partial P_j}{\partial C_j}$.

In what follows, we show that adding some structure to the authorities´ behavior in terms of inspections can help us infer the value of this derivative. Moreover, we will also show that, if the structure of our model is correct, we can approximate the sector level fixed cost of compliance with the inspection probability in the absence of certificates, easier to obtain from real data.

III.2. The authorities’ problem in the absence of certificates.

In the absence of certificates, our model assumes that the only policy tool to enforce compliance with pollution emissions standards is the number of inspections performed by the authorities in each industrial sector. Authorities inspect a specific number of firms at random from each industrial sector.[2] Each inspection has a cost *B*. If a firm is in compliance with the pollution emissions standards, society wins a fixed amount *A*. As there are no certificates, a firm in sector *j* is in compliance when

$d_{ij} < MP_j - C_j$.

The government then maximizes the social welfare with respect to the probability of inspection in each sector, P_j. The objective function, in this simple framework, is defined as:

$$S = \sum_j N_j AF(MP_j - C_j) - \sum_j P_j N_j B \tag{10}$$

Where N_j is the total number of firms in sector *j*.

The first order conditions for the maximization problem are then:

$$f(MP_j - C_j) = \frac{B}{AM} \tag{11}$$

Using the implicit function theorem, we obtain $\frac{\partial P_j}{\partial C_j} = \frac{1}{M}$, and $C_j = \phi + \frac{1}{M} P_j$.

Substituting $\frac{\partial P_j}{\partial C_j} = \frac{1}{M}$ in equations (8) and (9), it can be seen that both $\frac{\partial D_j^2}{\partial C_j}$ *and* $\frac{\partial D_j^3}{\partial C_j}$ *< 0.*

Moreover, it is clear that the probability of inspection can be used as a proxy for the fixed cost of compliance at the sector level.

III.3. Testable predictions from the model.

The zero correlation shown in table 1 between the frequency of inspections by industrial sector and the percentage of firms in non compliance fits the predictions of our model (equation 11). The positive

[2] According to informal conversations with PROFEPA authorities, this assumption is in line with the actual Mexican inspections policy.

correlation between the frequency of inspections and the percentage of firms receiving a Clean Industry Certificate seem to support the hypothesis that it is the cleanest firms within industrial sector that are getting certified. In what follows, we present a more careful analysis of these relationships. To do so, we first obtained the total number of firms, employees and the value of production for each four digit NAICS (North American Industrial Classification System) sector from the 1999 Mexican Industrial Census. PROFEPA provided a list of all firms that were granted a Clean Industry Certificate since 1997 until 2006, as well as a yearly list of the total number of inspections performed since 1992 until 2007, by NAICS industrial sector. We also know how many of these inspections found the firms to be in non compliance each year. We restrict the sample to manufacturing sectors, excluding utilities (publicly owned) and services. We then deal with information since 1992 to 2007, for 160 four digit NAICS industrial sectors.

First, if the authorities' objective function stated in equation (10) holds, given the first order conditions, we should expect to observe no relationship between non compliance levels and the probability of inspection (before the introduction of the program) in each sector.

To test this, we combine both the information in the 1999 industrial census with the inspections and non compliance data provided by PROFEPA. We define the probability of inspection in each sector as the total number of inspections performed between 1992 and 1995 (the first certificate was granted in 1997), divided by the total number of firms in the Census in each sector. Between 1992 and 1995, 16,616 inspections took place, out of which 82 percent resulted in non compliance. However, some sectors seem then to face a much higher inspection probability than others. The inspection probability by industrial sector, defined as the total number of inspections between 1992 and 1995 divided by the total number of firms in each sector in the 1999 Mexican Industrial Census, fluctuates between 29 and 65 percent.

In order to better control for other variables that are likely to drive the (lack of) correlation between inspections and non compliance, we also construct a set of sector level variables from the Census data (log of employees per firm and the log of the percentage of production exported). The regression run will be thus the following:

$$NC_j = \phi_0 + \phi_1 P_j + \sum_s \lambda_s X_{sj} + \varepsilon_j$$

Where NC_j is the percentage of inspections resulting in non compliance in sector j (in logs); P_j is the log of the percentage of firms inspected in each sector in the period between 1992 and 1995; and the X_s are a set of s sector level characteristics. As stated, the coefficient of interest is ϕ_1, which we expect to be close to zero.

Regression results are shown in Table 2. Column 1 shows the coefficient of the regression when including no controls. Column 2 includes the log of the employees per firm and the percentage of the production exported in each sector, and Column 3 adds a 2 digit sector level fixed effect. The coefficient for the log of the probability of inspection is close to zero and insignificant for all three specifications. This is consistent with our hypothesis that authorities are assigning a higher inspection probability to sectors that face high compliance costs, imposing on them a higher incentive to invest in reducing pollution emissions.

Table 2

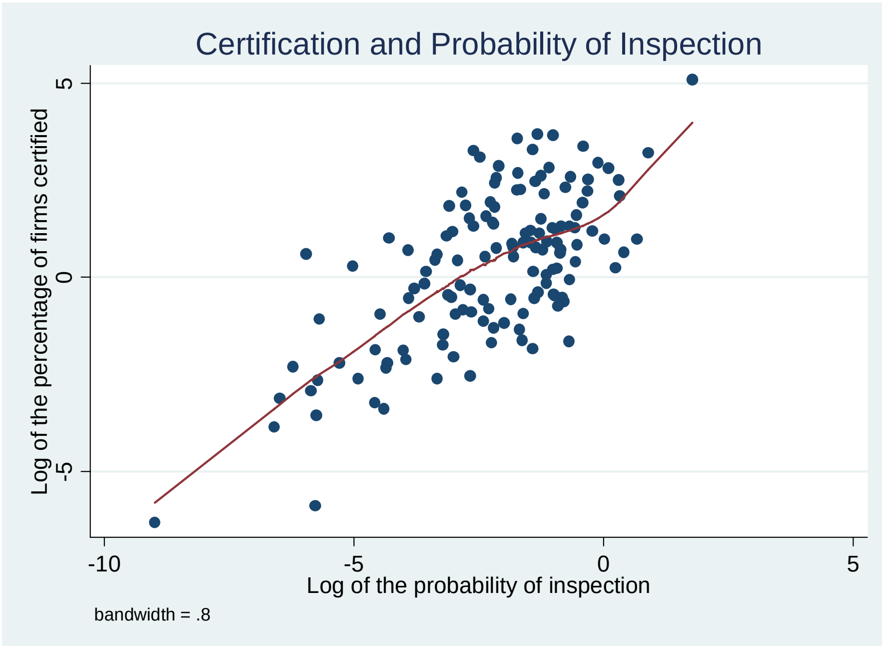
Determinants of non Compliance at the sector level Dependent variable: Log of the percentage of inspections resulting in non-compliance			
Log % Inspected (92-95)	-0.00338	-0.00435	-0.00081
	[0.00663]	[0.00828]	[0.00842]
Log Employees per firm		-0.00041	-0.00411
		[0.01215]	[0.01217]
% production exported		0.00014	0.00009
		[0.00011]	[0.00012]
Constant	-0.21166	-0.22002	-0.17073
	[0.01937]***	[0.05648]***	[0.06107]***
Observations	160	160	160
R-squared	0	0.01	0.05

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

If this is the case, we can estimate the sign of $\frac{\partial D_j}{\partial C_j}$, by simply computing $\frac{\partial D_j}{\partial P_j}$, as a way of testing which firms are the ones getting certified within sectors. Below, we test for this.

Figure 4 then plots the log percentage of firms that have received a Clean Industry Certificate since its introduction in 1997 until December, 2007, against the probability of inspection between 1992 and 1995. As can be seen, the correlation between these two variables is strong and positive. If the structure imposed on the cost of compliance and certification outlined in the previous section holds, it is the firms with the lowest cost of compliance that are getting certified.

Figure 4



In order to explore this relationship in better detail, Table 3 shows the results of a set of linear regressions with the log of the percentage of firms certified as the dependent variable, and the probability of inspection as the explanatory variable. Column 1 does not include any controls. Column 2 includes the log of the number of employees per firm and the percentage of the production exported as controls and, finally, Column 3 also includes 2 digit NAICS sector fixed effects. While the magnitude of the coefficient goes down with the introduction of control variables, the relationship between the probability of inspection and the percentage of firms certified is always positive and significant. If the structure of our model holds, it is the relatively cleaner firms that are getting certified. Certified firms are in compliance with the pollution emissions standards regardless of the existence of the program.

Table 3

Determinants of Certification Dependent variable: Log of the percentage of firms certified			
Log % Inspected (92-95)	0.75164	0.30488	0.25081
	[0.07014]***	[0.05796]***	[0.05697]***
Log Employees per firm		1.14113	1.1957
		[0.08737]***	[0.08362]***
% production exported		-0.00292	-0.0022
		[0.00084]***	[0.00085]**
Constant	1.97504	-3.031	-3.67436
	[0.19940]***	[0.40507]***	[0.42746]***
Observations	138	138	138
R-squared	0.46	0.76	0.79

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

So far, this paper has presented a simple theoretical framework which, from aggregate data, argues that it is in fact the cleanest firms that voluntarily participate in this voluntary pollution reduction program. This fact seems one of the main concerns in the empirical literature evaluating the effectiveness of programs of this kind. As stated before, it is believed that if the firms with lowest compliance costs are the ones getting certified, voluntary pollution reduction programs are likely to have a very low impact on the quality of the environment. In what follows, this paper argues that this is not necessarily the case.

If authorities perform inspections given the average compliance cost level observed within each industrial sector, then the program serves as a screening mechanism within sectors, where clean firms self-select themselves to participate. Given that the authorities exclude certified firms from the inspection pool, non-certified firms might face higher inspection probabilities. This imposes on them a higher incentive to reduce pollution levels. To illustrate this, we go back to the model presented in the previous section, and recalculate the optimal inspection probabilities set by the authorities. This time, we include the level of participation in the program, and the fact that it is now known that participating firms come from the lowest tail of the distribution of the cost of compliance within each sector.

V. Authorities' reaction to participation in the Program.

Let's recall the authorities' objective function from section III (equation 10).

$$S = \sum_j N_j AF(MP_j - C_j) - \sum_j P_j N_j B$$

The first term of this objective function is simply the product of what society gains for each firm in compliance and the total number of firms in compliance in each sector: $N_j F(MP_j - C_j)$. The second term is the cost of inspections, which is equal to the total number of inspections performed, multiplied by its cost. Note, however, that we wrote the total number of inspections as $P_j N_j$. Where P_j is the total number of inspections performed in each sector *j*, divided by the number of firms, assumed to be the probability of being inspected observed by firms.

When certificates are introduced, in a situation where the firms with the lowest cost of compliance participate, as shown in the previous section, the first element of this objective function does not change. All certified firms are firms that, in the absence of the program, for any given P_j, would be in compliance anyway.

However, the second term does change. Participation in the program is public. All certified firms are given a diploma that they publicize and use as a marketing tool. Moreover, they are taken out of the authorities' inspection pool. Then, the observed probability of being inspected is not the total number of inspections divided by the total number of firms in the sector, but the total number of inspections divided by the total number of non-certified firms in the sector. Each inspection still has a cost B.

Therefore, the second term of this equation becomes $\sum_j P_j (N_j - N_j^c) B$, where N_j^c is the total number of certified firms, and the authorities' objective function can be rewritten as:

$$S = \sum_j N_j AF(MP_j - C_j) - \sum_j P_j (N_j - N_j^c) B \tag{12}$$

Given that in this case the probability of inspection is defined as the total number of firms inspected divided by the total number of non-certified firms (strictly lower than the total number of firms), it is easy to see that the outcome in a situation with no certificates can be attained at a lower cost. The certificates, even if not directly pushing any firm into compliance, seem to be useful at reducing the cost of inspections.

Moreover, if the authorities are maximizing some social welfare function, they should update the inspection probabilities set in the absence of the program, to take into account that they are identifying firms in compliance without needing to inspect them. Assuming that equation (12) is the new authorities' objective function, the maximization first order conditions are then:

$$f(MP_j - C_j) = \frac{B}{AM} \frac{(N_j - N_j^c)}{N_j} = \frac{B}{AM}(1 - D_j) \tag{13}$$

It is easy to see that, for a higher number of certified firms, the lower the value of *f* should be in order to satisfy the first order conditions. If fines and sector level fixed costs of compliance are fixed, and if the authorities respond to certification, the probability of inspection in sectors with a high number of certified firms should increase. For comparison purposes with the theoretical relationship between the probability of inspection and the sector level fixed cost of compliance in the absence of certificates, we can calculate $\frac{\partial P_j^c}{\partial C_j}$ for a situation in which certificates are available:

Formally, from the implicit function theorem,

$$\frac{\partial P_j^c}{\partial C_j} = \frac{1}{M} - \frac{B}{AM^2} \frac{f\left(\frac{(1-\alpha)}{(\beta-1)} C_j\right)}{f'(MP_j - C_j)} \frac{(1-\alpha)}{(\beta-1)} \tag{14}$$

It is easy to see that,

$$\frac{\partial P_j^c}{\partial C_j} - \frac{\partial P_j^{nc}}{\partial C_j} = -\frac{B}{AM^2} \frac{f\left(\frac{(1-\alpha)}{(\beta-1)} C_j\right)}{f'(MP_j - C_j)} \frac{(1-\alpha)}{(\beta-1)} > 0 \tag{15}$$

V.2. Empirical Evidence.

Our model predicts that, if the authorities actually obtain information about firms' cost of compliance given certification, they should update the inspection probabilities. The derivative on the probability of inspection with respect to the sector level fixed cost of compliance should be higher in a context in which certificates are available.

In our industrial sector level data, we have information about the number of inspections performed since 1992 until 2007. If certificates were introduced in 1997, we can compare the calculated inspection probabilities before and after the introduction of the program. It is worth noting that, as stated in our model, the probability of inspection observed by firms after the introduction of the Clean Industry Program is not equal to the total number of inspections performed by the authority divided by the total number of firms. In our model, and our regressions, we define the probability of inspection after the introduction of the certificates as the total number of inspections performed, divided by the total number of non-certified firms.[3] The total number of non-certified firms was calculated by simply subtracting the total number of firms granted a Clean Industry Certificate from the total number of establishments in each sector in the 1999 Mexican Industrial Census.

For this section, it is worth recalling that we are using the probability of inspection as a proxy for the fixed cost of compliance in each sector. If the probability of inspection is a noisy measure of the sector level fixed cost of compliance, correlating the probability of inspection in the 1992-1995 period against the change in the probability of inspection before and after the introduction of the certificates will produce a downward biased estimate of the derivative of the inspection probability with respect to the fixed cost of compliance. The error in the inspection probability in the 1992-1995 period is clearly correlated with the change in the inspection probability.

Equation (7) suggests a correlation between D_j, the percentage of firms certified in each sector and both the fixed cost of compliance and the probability of inspection. However, in order for the percentage of firms certified in each sector to be a good instrument for the fixed cost of compliance within sectors, it is necessary that the increases in the inspection intensity do not translate into a higher rate of participation in the Clean Industry Program. As shown in section IV, firms getting certified seem to be the cleanest within industrial sectors. According to our theory, if this is the case, an increase in inspections should only affect the number of firms in compliance, having no effect on the certification intensity. Given this, in order to obtain consistent estimates of the coefficient of interest, we use this variable, as well as the inspection probabilities in the United States, as our instruments for the probability of inspection in Mexico during the 1992-1995 period.

If the US inspection policy is well represented by the model presented in section III.2 of this paper, for the probability of inspection in the US to be a valid instrument, some assumptions have to hold. First,

[3] All regressions were run also defining the inspection probability as the total number of inspections divided by the total number of firms. The results keep the sign observed in the results presented in this paper, although the significance level of the coefficients is slightly lower.

there must be a positive correlation between the fixed cost of compliance by sector in the US and Mexico. Second, the change in the probability of inspection after the introduction of the Clean Industry Certificates in Mexico should not be correlated with the US inspection policy through other channels other than the fixed cost of compliance.[4]

The US Environmental Protection Agency (EPA) publishes the Enforcement and Compliance History Online (ECHO). ECHO is a Web-based tool that provides public access to compliance and enforcement information for approximately 800,000 EPA-regulated facilities. ECHO gives access to permit, inspection, violation, enforcement action, and penalty information covering the past five years in the United States. The site includes facilities regulated as Clean Air Act stationary sources, Clean Water Act direct dischargers, and Resource Conservation and Recovery Act hazardous waste generators/handlers. From this system, we obtained the number of pollution emission inspections conducted in each industrial sector in the US, since 2002 until 2007.

The probability of inspection in the United States will be then defined as the total number of inspections reported in ECHO, divided by the total number of establishments in the US Industrial Census, for each 4 digit NAICS industrial sector.

Table 4 shows the results of our first stage regressions, for the probability of inspection in the 1992-1995 period, against both of our instrumental variables: the log of the percentage of firms certified and the log of the probability of inspection in the US. We drop 22 sectors in which no firms have received a Clean Industry Certificate.[5] Column 1 includes no additional regressors, while Column 2 adds the

---

[4] All regressions presented in this section were also run using only the probability of inspection in the US, on one hand, and only the percentage of firms certified, on the other, as instrumental variables. The sign of the relevant coefficients does not change considerably with respect to the results shown in this paper.

[5] All regressions were run using the level in the dependent and independent variables, instead of their logs. In this case, we kept the 160 observations for all regressions. The sign of the coefficients did not differ from the ones when using the logs of the variables. However, the fit of the regressions was poor.

log of the employees per firm and the percentage of the production exported, and Column 3 adds 2 digit sector level fixed effects.

The regression coefficients for both of our instruments are positive. The F statistics for the test with the null hypothesis that the sum of both coefficients is equal to zero is always above ten, although decreasing with the inclusion of controls.

Table 3

First Stage Dependent Variable: Log of % Inspected between 1992 and 1995			
Log of % Certified	0.53349	0.40868	0.41259
	[0.08019]***	[0.13789]***	[0.14352]***
Log % Inspected USA	0.17001	0.23693	0.16596
	[0.12753]	[0.13698]*	[0.14378]
Log Employees per firm		0.17287	0.17502
		[0.18428]	[0.19586]
% production exported		0.00063	0.0001
		[0.00119]	[0.00126]
Constant	-2.15062	-2.68327	-3.11797
	[0.22675]***	[0.60661]***	[0.71495]***
Observations	138	138	138
R-squared	0.46	0.47	0.48
F test (for instruments)	60.17	30.66	19.82

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4 shows the second stage results. Column 1 shows the results of an OLS regression of the change in the probability of inspection against the inspection probability between 1992 and 1995. Columns 2, 3 and 4 show the instrumental variable estimates for this same coefficient, increasing the control variables as in all the regressions previously shown.

As can be seen, in Column 1, a simple OLS regression shows a negative and significant relationship between the probability of inspection between 1992 and 1995 and the change in the inspection probability before and after the introduction of the Clean Industry Certificates. We believe this is due to the error in the measurement of the pre-certificates probabilities of inspection. In Column 2, our instrumental variable estimate shows a positive coefficient, as suggested by our model. In Columns 3 and 4, while the coefficient of interest is not significant, it still shows the expected sign.

Table 4

Second Stage Dependent Variable: Change in the log of inspection Probability 9295 and 03-06				
	OLS	IV	IV	IV
Log % Inspected (92-95)	-0.23121	0.25893	0.18502	0.23829
	[0.05787]***	[0.11092]**	[0.20213]	[0.26172]
Log Employees per firm			0.09668	0.06905
			[0.20192]	[0.24063]
% production exported			-0.00115	-0.00085
			[0.00126]	[0.00141]
Constant	-1.01835	0.24691	-0.21058	0.19073
	[0.16838]***	[0.28187]	[1.13467]	[1.57850]
Observations	137	137	137	137
R-squared	0.09			

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

This result is consistent with the idea that authorities are able to screen between firms with high and low costs of compliance within sectors as a result of the introduction of the Clean Industry Certificates. Our results are then evidence that the authorities updated their inspection policy after the introduction of the Program, increasing the probability of inspection in sectors with higher fixed costs of compliance. Contrary to what is widely believed in the literature, if this is the case, all the reductions in pollution emissions levels as a result of the program will not only be observed amongst participating firms, but also amongst non-certified firms in industrial sectors with a high percentage of certified firms. This fact questions the appropriateness of any comparison group for measuring the impact of voluntary pollution reduction programs when only looking at the changes in pollution emissions by participating firms, which are likely to be biased downwards.

VI. Testing the predictions of the model with firm level data.

So far, we have presented a simple model which, given the aggregate level data at the sector level, seems to suggest that firms participating in the program are the relatively cleanest firms within industrial sectors. However, the authorities seem to have updated their inspection probability given ceritification, increasing inspection intensity for non-certified firms in sectors with high levels of certification. If this is the case, we should expect to observe a reduction in pollution emissions amongst non certified firms in sectors with a high number of certified firms.

in what follows, we test these predictions empirically with firm level data containing a measure of pollution concentrations around the firm's exact geographic location. This will allow us, on one hand, to precisely estimate the effects of the program in reductions in pollution concentrations, as well as to isolate the causal impact of certification on the reduction of emissions by non-certified firms. In particular, we will provide some evidence suggesting that it is only non-certified firms that are subject to an increase in inspection given certification in their sector that are reducing their pollution emissions. Firms with less than 10 employees in sectors with a high percentage of firms certified, which are usually not subject to inspections from PROFEPA, do not show the same decreasing trend in their pollution emissions given certification.

VI.1. Firm level data

For this purpose, we constructed a firm level data set from different sources. The main one is SIEM (Sistema de Información Empresarial Mexicano), administered by the Mexican Ministry of Economics. The data contains information on 34,433 firms in the industrial sector. It includes each firm's name, exact address (including zip code), NAICS industrial sector, number of employees and dummy variables indicating whether the firm exports or imports. SIEM does not include government owned firms. The geographic coordinates of each of the firm's zip code was obtained from Postal Code World©, which provides geographic coordinates for 32,332 of the zip codes in SIEM. 11,255 of these zip codes are excluded from the analysis, as the geographic coordinates for their location is imprecise.

The second data set is a list of facilities that have received a Clean Industry certificate, provided by PROFEPA. 1,266 Clean Industry certificates have been granted in the industrial sector. The list of certificates includes each firm's name and the municipality in which it is located. We matched the names of the firms with the SIEM database. 394 of the 1,266 certified firms were found in the SIEM database.[6] The percentage of firms certified in each sector calculated previously in this paper is also assigned to each firm, given their declared NAICS sector in SIEM.

VI.2. Air quality.

Data from Moderate Resolution Imaging Spectroradiometer (MODIS onboard the Terra Satellite), acquired from the NASA's Goddard Space Flight Center Earth Sciences Distributed Active Archive Center (DAAC), provided us with daily measures of Aerosol Optical Depth (AOD) at a 5km spatial resolution for cloud-free images, for the whole Mexican territory for the period between February 1st 2000 to December 31st 2006.

Aerosols are liquid and solid particles suspended in the air. AOD can be described as the extinction of beam power caused by the presence of these particles in the atmosphere. It has been shown to be a very good predictor of levels of suspended particles in the atmosphere.[2] For the Mexican context, within municipality changes in AOD levels have been shown to be highly correlated with infant

---

[6] No sector level characteristics in the Mexican census are correlated with the percentage of certificates matched between the two databases.

mortality levels (Gutierrez, 2008). It is worth noting, however, that while AOD is likely to provide a measure of air quality, it does not allow us to carefully distinguish between different kinds of particles. An estimated measure of average AOD monthly levels for each zip code was constructed.

To do so, a 5km diameter area around each of zip codes exact geographic location was constructed. Using GIS technology, the observed measures of AOD from the satellite images were overlapped with the area around each of the zip codes. Daily measures of AOD were first calculated for each of the areas (an unweighted average of all AOD measures in the area in each given day), and then the estimated AOD daily value for each zip code was averaged for each month in the sample, only considering those days for which we had at least one AOD measure.

However, given what has been shown in previous studies about the relationship between AOD and suspended particles in the atmosphere, for this paper, some precautions should be taken when trying to relate AOD to pollution levels.

Weather conditions can easily influence the observed measures of AOD and its relationship with suspended particles. Also, the empirical relationship between the ground measurements of suspended particles and AOD can vary regionally, given that the composition of aerosols is different in each geographic region. While the positive relationship between AOD and suspended particles is usually observed, comparisons across regions are hard to make, given the great variety in geographic and weather characteristics of each of location, especially when dealing with an area of the extension of Mexico. The empirical strategy will take this issue into account, by estimating the impact of changes in AOD levels within zip codes, and adding monthly measures of the temperature and dew point in each zip code in the regressions.

VI.3. Weather conditions.

Weather data was obtained from the US National Climatic Data Center, which publishes the Global Surface Summary of Day Data providing daily information for the 2000-2006 period for over one hundred weather stations spread around the Mexican territory. An average monthly value of the temperature and dew point were calculated for each weather station. Then, these values were interpolated using an inverse distance weight technique for the whole Mexican territory using GIS (Geographic Information System) technology.

This technique calculates a weighted average of a variable for each point in the map, assigning a weight that is a function of the inverse distance between each of the points for which a measure of the variable exist (in this case, each of the weather stations) and the location for which it is being calculated. The mean monthly temperature and dew point for each zip code were the estimated value from the interpolated data at each zip code's exact geographic location.

VI.4 Empirical strategy.

As stated, our empirical strategy will try to estimate the impact of certification on pollution concentrations in the atmosphere from firm level data. Our model predicts that a high percentage of firms certified in an industrial sector will incentive non-certified firms to reduce their pollution emissions, given the authorities' response in terms of inspection intensity.

Small firms are rarely subject to inspections. PROFEPA prioritizes firms, first by industrial sector, assigning a higher inspection probability to sectors with high polluting potential, but then assigning a much higher likelihood of inspection to larger firms.[7] Moreover, the inspection probability seems to discretely increase at some level at which firms start being classified as "medium sized". Relatively small firms, as a result, seem to be rarely inspected, mainly due to the high cost of inspection and the

[7] www.profepa.gob.mx

very high number of small firms in the economy. Unfortunately, the inspections data provided by PROFEPA does not include information on the size of inspected firms. Given this, we will classify firms by size, according to their distribution in the SIEM data.

Figure 5 shows a kernel density estimate for the size of firms restricting the sample to firms with less than 100 employees. As can be seen, there seems to be a very high concentration of firms with a small number of employees, and the density seems to flatten considerably after 10 or 15 employees. We believe that the high concentration of firms with less than ten employees corresponds to micro enterprises, not subject to inspections by the authorities. As the actual threshold is likely to be somewhere around 5 and 15, we will then simply classify firms as having less than ten employees, having between eleven and 100 employees, and having more than 100 employees. We believe that firms with less than 10 employees are likely to face a probability of inspection very close to zero.

Figure 5

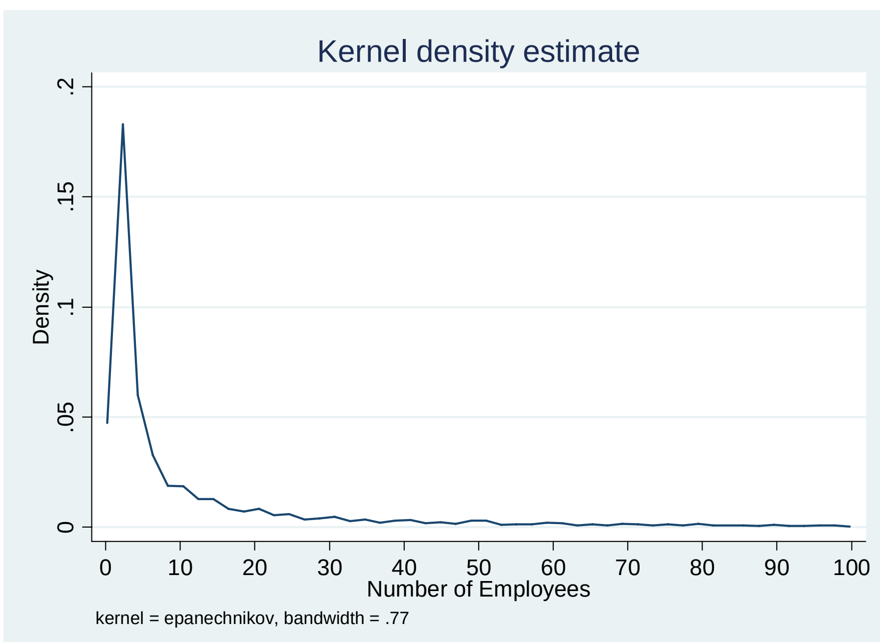


Table 6

Distribution of firms in SIEM by size and certificartion status		
Firm's size	Total	% certified (matched)
Less than 10 employees	21949	0.10
11 to 100 employees	7675	0.94
More than 100 employees	2708	11.04
Total	32332	1.22

Table 6 shows the distribution of firms in the SIEM database by size and certification status. In our sample, 68 percent of the firms listed in SIEM declare having less than 10 employees. Out of all of them, 0.1 percent was matched with the certificates list. 24 percent of firms have more than 10 and less than 100 employees, and the matching rate with the certificates list is nearly ten times higher than for the smallest firms in the sample. 8 percent of firms have more than 100 employees, and 11 percent of them are matched with the certificates list.

As stated, we suspect that, given the way firms are classified and assigned different inspection priorities, In our estimation strategy, we will exploit this change in the probability of inspection in order to isolate the effect of certification on the emissions of non-certified firms as a result of increases in inspections from sector specific trends in pollution emissions, not related to the authorities' inspection policy.

If the reductions in emissions are actually related to an increase in the inspection probability given certification, firms with less than ten employees should not be reducing their emissions as a result of certification. The following equation describes the specification that would identify the impact of the program on pollution emissions given certification at the firm level.

$$\Delta Poll_i = \alpha + \beta_1 C_i + \beta_2 * M_i * CI_i + \beta_3 CI_i + \beta_4 M_i + \sum \gamma_k X_{ki} + \varepsilon_i \qquad (16)$$

Where $\Delta Poll$ is the change in pollution emissions by firm *i*.

C_i is a dummy variable equal to 1 if the firm has received a Clean Industry certificate.

M_i is a dummy variable equal to 1 if the firm has more than 10 employees, which will isolate the difference in emissions for firms with more than ten employees, regardless of the certification intensity.

The X_{ki} are a set of *k* control variables, including the log of the size of the firm, a dummy variable indicating if the firm exports, a dummy variable indicating if the firm imports, and the interaction of these variables with *CI*.

CI_i is the percentage of firms certified in firm *i*'s industrial sector which, along with its interaction with the log of the firms size (included as one of the X_{ki}), will control for the changes in emissions correlated with certification, but uncorrelated with the inspection probability. The interaction between the size of the firm and the percentage of firms certified in the sector will control for differences in pollution emissions by different sized firms in sectors with different percentages of certified firms, but that are unrelated to the increases in the inspection probability given certification.

Our coefficient of interest is the one of the interaction between the percentage of firms certified in the firm's industrial sector (*CI*) and the dummy variable indicating if the firm has more than 10 employees, and thus is subject to an increase in inspections given certification.

Given that our data do not measure pollution emissions by firms, but rather pollution concentrations around firms' zip codes (and that more than one firm are usually located in each zip code), we will assume that the pollution concentrations in each county are a weighted average of the pollution emissions by each firm.

A weighted average of each of the variables in equation (16) will be then calculated for each zip code, using the total number of employees declared by each firm divided by the total number of employees in each zip code (the sum of the employees of all firms in the SIEM database in each zip code) as the weight for each of the observation. The dependent variable will be the change in AOD between 2000 (the first point in time for which we have information on the pollution concentration) and 2006. The regressions will then be run at the zip code level. Given that we constructed a measure of monthly AOD in each zip code from our data, we pool all calendar months (from March through December), and run the regression including calendar month fixed effects and clustering the standard errors of the coefficients at the zip code level. Controls for the differences in the temperature and dew point in each zip code between 2000 and 2006 are also included.

Relatively strong assumptions have to be made in order for the zip code level regressions to be correctly estimating the impact of the Clean Industry Program on particulate matter concentrations. In particular, one of the main concerns is the location of firms not included in the SIEM database. As stated before, SIEM does not list government owned firms. Also, if not all the listed certificates were matched with the SIEM database, there are other private firms that are not included in the data. For our regressions to correctly estimate the impact of the Clean Industry Program on pollution concentrations, we need the the geographic location of firms not included in our sample to be uncorrelated with the industrial composition of each zip code calculated from the SIEM database.

The results are presented in Table 7. Column 1 is the regression output for the change in AOD at the zip code level against the weighted percentage of firms certified in each zip code, and the weighted certification intensity given the sector composition of each zip code, as well as the weighted average size of the firms. As can be seen, the coefficient on certification is negative and highly significant, suggesting that certified firms actually do experience a reduction in their pollution emission levels.

While our theory predicts no necessary reduction in certified firm's emissions, we believe this could be evidence that certification requires a higher level of compliance than the one required to avoid being fined if inspected. However, the coefficient on the certification intensity given the industrial composition of each zip code seems close to zero and insignificant. At first sight, this could seem to be contradicting our theoretical predictions.

Table 7

OLS Regression Results
Dependent variable: Difference in log AOD between 2000 and 2006

% Certified	**-0.0917**	**-0.0712**	**-0.0719**	**-0.0749**	**-0.0293**
	[0.0316]* **	**[0.0332]****	**[0.0335]****	**[0.0343]****	**[0.0442]**
Medium*Log Cert. Intensity wt		**-0.0931**	**-0.0964**	**-0.0964**	**-0.0972**
		[0.0343]***	**[0.0344]*****	**[0.0347]*****	**[0.0347]*****
Log Size* Log Cert. Intensity wt		0.01	0.0114	0.0062	0.0073
		[0.0077]	[0.0077]	[0.0078]	[0.0081]
Log Cert. Intensity wt	0.0066	0.0285	0.028	0.0259	0.0248
	[0.0083]	[0.0131]**	[0.0132]**	[0.0133]*	[0.0135]*
% Medium		0.0652	0.0589	0.0569	0.0593
		[0.0337]*	[0.0336]*	[0.0335]*	[0.0337]*
Log Size wt	0.0149	0.0051	0.0124	0.0158	0.0145
	[0.0031]***	[0.0082]	[0.0084]	[0.0085]*	[0.0087]*
Cert. * Log Cert. Intensity wt					-0.0292
					[0.0263]
Exporting*Log Cert. Intensity				0.0059	0.0034
				[0.0244]	[0.0245]
Importing. * Log Cert. Intensity				0.0446	0.0471
				[0.0226]**	[0.0228]**
Log AOD 2000	-0.2991	-0.3002	-0.3015	-0.3025	-0.3027
	[0.0111]***	[0.0111]***	[0.0111]***	[0.0111]***	[0.0111]***
Constant	-0.6674	-0.6729	-0.6763	-0.6777	-0.6769
	[0.0274]***	[0.0279]***	[0.0280]***	[0.0279]***	[0.0279]***
Weather Controls	Yes	Yes	Yes	Yes	Yes
Month fixed Effects	Yes	Yes	Yes	Yes	Yes
Exporting and Importing dummies			Yes	Yes	Yes
Observations	20445	20445	20445	20445	20445
R-squared	0.18	0.18	0.18	0.18	0.18

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

However, the next four columns include the full specification, with an increasing number of control variables. The zero coefficient on the certification intensity in Column 1 seems to be driven from the fact that it is only firms that are subject to inspection that seem to reduce their pollution emissions as a result of other firms in their sector getting certified. Our coefficient of interest, that of the interaction between the dummy variable indicating if the firm is big enough to be subject to inspections by PROFEPA and the certification intensity given the zip code's industrial composition is negative and highly significant.

The positive and slightly significant coefficient on the certification intensity seems to suggest that it is not sectors that are reducing their pollution for reasons different from an increase in inspections that are getting certified. It seems that sectors with high certification intensity, when not subject to inspections, seem to actually increase their emissions.

We believe these results to be stronger evidence supporting our theory. Firms in sectors with a high percentage of certified firms are reducing their pollution emissions given the increase in the observed probability of being inspected resulting from other firms getting certified.

Both the theoretical and empirical results shown in this paper suggest that the Mexican Clean Industry Program is contributing to a reduction in pollution emissions through different channels than the reduction in emissions by participating firms. Aggregate data at the sector level show that authorities inspect more intensively firms in sectors with a high percentage of firms certified, probably as a result of a decrease in the cost of inspection. Data at the firm level show that pollution concentrations in the atmosphere go down in zip codes where certified firms are located, but also seem to go down in zip codes where non certified firms in sectors with a high percentage of certified firms are located. Moreover, this last relationship is not observed for firms with less than ten employees, which we believe are usually not subject to inspections by the authorities.

Conclusions.

The increasing popularity of voluntary pollution reduction programs has motivated research papers trying to evaluate their effectiveness at reducing firms' emissions levels. However, most of the empirical literature seems to focus on measuring the changes in pollution emissions for participating firms, and finding the appropriate comparison group in order to test its effectiveness. On the other hand, it seems especially concerned to prove if it is firms that would anyway be in compliance the ones participating in the program. Little attention seems to be put understanding the general equilibrium effects of programs of this kind. This paper contributes to this literature by evaluating the effectiveness of the Mexican Clean Industry Program, considering the possibility that authorities are using the program as a tool to screen between dirty and clean firms. It first develops a simple model with two groups of players, firms and the authorities, where firms can choose to be in compliance, non compliance or participate in the program, and where the authorities can set the cost of non compliance by changing the frequency by which they inspect different industrial sectors.

By doing this, although imposing some structure to the cost of participation and the cost of compliance, we show evidence suggesting that firms with relatively low cost of compliance are the ones that participate in the Mexican Clean Industry Program. However, contrary to what is widely believed in the literature, when authorities have the option to update the inspection intensity given the number of firms participating in the program, certification serves as a screening tool that reduces the cost of inspection and, as a result, increases compliance rates.

We believe our theory and our empirical results provide evidence supporting that the general equilibrium effects of voluntary pollution reduction programs are likely to be high. According to our model and our results, the reductions in pollution emissions levels are not only observed amongst participating firms, but amongst non-certified firms in industrial sectors with a high percentage of certified firms. This last relationship is not observed for firms with less than 10 employees, which are usually not inspected by the authorities.

This questions the appropriateness of any comparison group when trying to measure the impact of voluntary pollution reduction programs by only looking at participating firms' emissions. If non-participating firms experience an increase in the incentives to reduce their emissions levels as a result of other firms getting certified, the empirical literature measuring the effectiveness of programs of this kind has understated their potential impact.

VII. References.

Alberini, A., and K. Segerson. 2002. Assessing Voluntary Programs to Improve Environmental Quality. *Environmental and Resource Economics* 22(1–2): 157–84.

Arora, S., and T. Cason. 1995. An Experiment in Voluntary Regulation: Participation in EPA's 33/50 Program. *Journal of Environmental Economics and Management* 28: 271–86.

Blackman A, Lahiri B, Pizer W, Rivera Planter M and Munoz Pina, Carlos. 2007. Voluntary Environmental Regulation in Developing countries: The Mexican Clean Industry Program. Discussion Paper. Resources for the Future. July 2007. RFP DP 07-36.

Chu DA. Analysis of the relationship between MODIS aerosol optical depth and PM2.5 over the summertime US. Proceedings of SPIE 2006.

_______,Gllobal monitoring of air pollution over land from EOS-Terra MODIS. Journal of Geophysical Research 2003;108(D21):1-18.

Gamper-Rabindran, S. 2006. Did the EPA's Voluntary Industrial Toxics Program Reduce Emissions? A GIS Analysis of Distributional Impacts and by Media Analysis of Substitution. *Journal of Environmental Economics and Management* 52(1): 391–410.

Gupta P, et al. Satellite remote sensing of particulate matter and air quality assessment over global cities. Atmospheric Environment 2006;40:5880-5892

Gutierrez, Emilio. Can Satellite Imagery be used to measure the relationship between Air Quality and Infant Mortality? 2008. mimeo.

Jiménez, O. 2007. Voluntary Agreements in Environmental Policy: An Empirical Evaluation for the Chilean Case. *Journal of Cleaner Production* 15: 620–37.

Khanna, M. 2001. Economic Analysis of Non-Mandatory Approaches to Environmental Protection. *Journal of Economic Surveys* 15(3): 291–324.

Khanna, M., and L. Damon. 1999. EPA's Voluntary 33/50 Program: Impact on Toxic Releases and Economic Performance of Firms. *Journal of Environmental Economics and Management* 37:1–25.

Kumar N, Chu AD, Foster A. An empirical relationship between PM2.5 and aerosol optical depth in Delhi Metropolitan. Atmospheric Environment 2007;41:4492–4503.

Organization for Economic Cooperation and Development (OECD). 1999. *Voluntary Approaches for Environmental Policy: An Assessment.* Paris: OECD Environment Directorate.

———. 2003. *Voluntary Approaches for Environmental Policy: Effectiveness, Efficiency and Usage in Policy Mixes.* Paris: OECD Environment Directorate.

Sam, A., and R. Innes. 2006. Voluntary Pollution Reductions and the Enforcement of Environmental Law: An Empirical Study of the 33/50 Program. Working Paper. Columbus: Ohio State University Department of Agricultural, Environmental, and Development Economics.

Videras, J., and A. Alberini. 2000. The Appeal of Voluntary Environmental Programs: Which Firms Participate and Why? *Contemporary Economic Policy* 18(4): 449–61.

Vidovic, M., and N. Khanna. 2007. Can Voluntary Pollution Control Programs Fulfill Their Promises? Further Evidence from EPA's 33/50 Program. *Journal of Environmental Economics and Management* 53: 180–95.