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Abstract

Countries develop voluntary environmental incentive programs to complement traditional command-and-control regulations. However, the effect of these programs on environmental performance is often unclear. I examine the effects of Mexico's Clean Industry certificate program on firm performance by drawing on data from 2000 to 2018 and over 3,000 major toxic water polluters. About a quarter of these plants adopted or renewed Clean Industry certificates. I find that plants located in a municipality with higher amount fined on neighboring polluters are more likely to participate in the Clean Industry program. This is called regulator reputation effect, in the enforcement and monitoring literature. I find that plants with own toxic violations detected are less likely to enroll in the program. Plants are less likely to enroll if their neighbors are fined more often. I interpret this result as evidence on peer effects of enrollment in the program. I also find some evidence that Clean Industry participants are more likely to report pollution. The panel data results show that Clean Industry participants reduce their toxic releases by 1,204 kgs annually. From the counterfactual estimators' model, Clean Industry participants reduce their toxic releases by 56 percent in the third year, after graduating from the two-year certification period. Results are, however, not significant upon estimation within types of manufacturing facility. I conclude that the Clean Industry program has been an effective instrument for promoting compliance with the environmental regulation by increasing pollution reporting at the same time as reducing toxic releases.

JEL codes: K32, L51, Q28, Q52, Q53, Q58

Keywords: Voluntary environmental programs, Toxic Releases, Formal and informal regulation, Pollution control in developing countries, ISO14001

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1 Introduction

Voluntary environmental incentive programs are widely used in developed countries. Companies are often driven to participate in such programs to appeal to consumers who prefer “green” products or because of poor environmental track records (Videras and Alberini 2000). Most studies, however, find little evidence that these programs are effective in reducing industrial emissions (e.g., Vidovic et al. 2019; Kube et al. 2019; Vidovic and Khanna 2007, 2012; Gamper-Rabindran 2006). In the United States, the EPA’s 33/50 toxic releases disclosure program has been extensively studied with mixed evidence on effectiveness in reducing toxic releases (Zhou et al. 2020; Bi and Khanna 2012; Bui and Kapon, 2012; Khanna and Damon 1999; Innes and Sam 2008). Sam and Song (2022) find that ISO14001 certification leads to significant reductions in carbon dioxide emissions using a panel of Korean manufacturing firms.

In developing countries where formal monitoring and enforcement of pollution sources is weak, economists have proposed third-party environmental certificates to incentivize pollution control (Blackman, 2010; Shetty and Kumar 2017). Prior evidence on environmental performance of major toxic polluters from Mexico suggests that voluntary environmental programs may lead to short-term improvements in performance, but that participants do not perform systematically better than the nonparticipants in the long run (Blackman et al. 2010; Blackman 2012). However, the authors utilize fines as a proxy for environmental performance. In the absence of studies using actual pollution data, the effect of third-party environmental certificates on actual pollution levels remains an ongoing area of research.

In this paper, I investigate whether major water polluters in Mexico reduce their toxic releases following adoption or renewal of an environmental certificate. I draw on data from the federal government’s *Industria Limpia* or Clean Industry certificate program. I develop a panel database linking self-reported annual toxic waste discharges across 3,436 polluters, with cycles of Clean Industry certificates obtained by these polluters, over 2000-2018. I identified 848 major firms with reported annual toxic water pollutants that also signed up for this program at least once over the period studied. Previous studies on third-party certificates in developing countries do not explore the effects of certificates on pollution that is reported by the plants.

This paper makes three specific contributions to research on voluntary environmental programs. First, I model the Clean Industry adoption or recertification decision of a large sample of major toxic polluters over almost two decades. I use a rich set of regulatory activities data given the claim that most polluters obtain the certification or renewal to gain regulatory relief. Contrary to expectations, specific deterrence measures such as past toxic violations are associated with lower probability of participation in the program. On the other hand, general deterrence measures such as higher fined amount on toxic inspections of other plants in the same municipality increase participation of plants in the Clean Industry program. Second, I model pollution reporting as plants that get certified might report their annual pollution more regularly. I also find evidence of improvements in environmental performance by the Clean Industry program participants. I account for endogeneity of the treatment variable as plants self-select into getting certified. For robustness, I estimate average treatment effects by predicting counterfactuals for the treated plants from the pool of un-treated or control plants. Third, my

results can be applied to improve cost efficiency of environmental regulations as regulators can target major polluters that have not adopted voluntary incentives or renewed their certificates. From the panel data results, I show long term improvements in toxic releases, not statistically significant within different types of manufacturing facilities. Upon modeling the complex participation pattern of each polluter, I show improvements in the third year following completion of the certification period.

This current study addresses environmental performance of Clean Industry participants using panel data on plant-level toxic releases of major polluters. I create a unique dataset over close to two decades (2000-2018) for which I obtained participation status of major toxic polluters. Next, I match these plants with frequent toxic releases into water that are reported by the plants to the Environment Secretariat. Last, I match the annual self-reported pollution to the regulatory actions database. I estimate a probit model of participation in the Clean Industry program based on a rich set of regulatory activities variables such as inspections, fines, and amount fined, and local community characteristics. Second, I model the reporting decision of these polluters upon adopting Clean Industry certificates as plants face regulatory actions if they do not implement monitoring and reporting protocols. Third, I use the predicted values of participation from a linear probability model in a panel data estimation of plant-level toxic releases. Mandatory reporting of pollution started in 2004 with a two-year lag in publicly available data. Identification comes from within plant variation in participation in the Clean Industry program. Last, I estimate a Counterfactual Estimator model to address staggered adoption and entry exit from the program.

I find that manufacturing plants belonging to the beverages and tobacco, concrete, petroleum and petrochemicals, and electricity generating plants are more likely to obtain Clean Industry certificates. I find some evidence that higher toxic fined amount on nearby plants lead to increased participation in this voluntary incentive program. I find that participation lead to increase in pollution reporting 24 percentage points. I find that participation in the Clean Industry program also leads to a decline in annual pollution by 1,204 kgs. Upon accounting for dynamic treatment effects that capture the interactions between the participating plant and time dummies indicating the period pre and post intervention for each participation cycle, I continue to find negative coefficients of participants on toxic releases. For policy, my findings imply that the role of voluntary pollution control mechanisms is significant in emerging economies. This is contrary to prior studies that establish dirtier industries and recent fines trigger participation in ISO14001 certification in Mexico (Blackman, 2012).

2 Background and Conceptual Framework

2.1 The Clean Industry program of Mexico

The *Procuraduria Federal de Proteccion al Ambiente* (PROFEPA), the federal agency responsible for enforcing Mexico's environmental laws, developed the National Environmental

Audit Program in 1992. The program began issuing Clean Industry certificates in 1997, with 80 certificates. The Clean Industry certificate program targets major industrial polluters, particularly in the high-risk industries such as chemical and metal manufacturing, and energy sectors. Certification uses third-party audits to verify that a facility's emissions meet federal law. In 2008, 405 industrial plants obtained Clean Industry certificates, with 115 in the Mexico City Metropolitan Area and 75 in Veracruz (PROFEPA 2008). Prominent companies that obtained these certificates were PEMEX, Coca Cola, Grupo Bimbo, Walmart, Cemex, and Danone. In 2018, PROFEPA issued 137 certificates and renewed 414 Clean Industry certificates.

There are two levels of Clean Industry certificates awarded. Level 1 requires plants to comply with all relevant environmental regulations and identify action plans for specific regulation types (such as air, water, land), which can involve installing new equipment, improved monitoring and reporting protocols, and improved handling of toxic materials to reduce pollution. Level 2 typically recognizes plants that are renewing their certificate with well-established environmental management systems and continued improvement in pollution control, including improvements in at least two environmental performance indicators (such as air emissions, or toxic release into water). In 2018, PROFEPA awarded Level 2 certificates to 99 plants.

Despite mixed evidence on effectiveness of voluntary environmental programs at reducing pollution, PROFEPA reports that the Clean Industry program has improved natural resource use efficiency and reduced environmental impacts. For example, a recent estimate (PROFEPA 2018) states energy savings of 2,887 million kilowatt per year, water withdrawals savings of 44.9 million cubic meter per year, emissions reduction of 5.9 million tons of CO₂ equivalent, and toxic release reductions of 1.7 million tons annually.

Prior studies find mixed evidence on the impact of voluntary incentive programs on environmental performance. Foster and Gutierrez (2013) find that plants with the least compliance costs sign up for this program. The authors highlight the role of this certification program in revealing information about firms that can help regulators target more monitoring resources on non-participants. Blackman & Guerrero (2012) examine ISO 14001 certification in Mexico and find that regulatory fines increase the probability that polluters will participate in the certification program. Henriques et al. (2013) examine pollution levels per worker associated with Clean Industry and ISO 14001 certification in 2004-2007 and report that plants more likely to adopt the Clean Industry certificate are associated with fewer toxic pollution emissions. The authors highlight stringent sanctioning mechanisms in the case of Clean Industry, when discontinuation with the program exposes the facilities to frequent visits by the regulators. By contrast, ISO 14001 does not implement any sanctions and establishes only a commitment to comply with government regulations. On the other hand, Martinez Hernandez (2021) surveyed 225 Clean Industry certified plants to determine what factors lead to adoption of these certificates and whether there are any self-perceived improvements in environmental performance. The author finds that perceptions of peer pressure, environmental awareness, compliance with regulation, PROFEPA recognition and publicity are associated with

environmental performance, but do not find any significant evidence that Clean Industry certificate adoption improves their environmental performance.

2.2 Conceptual Framework

Conceptually, plants decide whether to obtain the Clean Industry certificate based on the expected benefits and the costs of certification. At a given point in time, a plant will get certified if its benefits exceed the costs of certification. A plant that obtains the Clean Industry certificate gains potential benefits through national recognition and increases in sales due to consumer preferences for environmental stewards. A plant that participates in the Clean Industry program gets regulatory relief implying the regulator does not visit the plant to inspect, detect violations or impose fines (if found in violation for a longer period). I focus on the benefits due to regulatory relief for the period of validity of each certificate. According to PROFEPA (2013), during inspection visits the inspector checks on emission sampling and measurement records and report violations as outcome of visits for the plants that have failed to adhere to pollution measurement protocols. Since 2004, the environmental regulation in Mexico required mandatory reporting of toxic releases by major polluters on an annual basis. Polluters can either obtain the Clean Industry certificate and get back into compliance or pay the fine when it is imposed on subsequent visits by the inspector. For the period of validity of the certificate, typically two years, the plant is not inspected or fined by the regulator. Hence, participation in the program reduces the expected costs of non-compliance with pollution measurement and reporting protocols.

H1: Increase in specific violations detected against the plant during the past three years is associated with a lower probability of the plant obtaining the Clean Industry certificate in the current year. This is expected as an initial violation either three or two years ago means that the plant would have been enrolled in the program for two years. After two years of completion, the costs of certification are higher as the plant needs to apply for a higher level of certification with more stringent pollution reduction strategies. Hence, the plant is less likely to renew its certificate one or two years immediately after participation.

H2: Participation in the Clean Industry program will lead to an increase in the annual frequency of pollution reporting. This is expected as a plant obtains the Clean Industry certificate to get back into compliance with reporting and measurement protocol of the regulation. In other words, a violation can be reported if the plant does not maintain its pollution records for the past three years. Obtaining the Clean Industry certificate requires compliance with outcome based environmental management system. Hence, plants are more likely to report pollution.

H3: Participation in the Clean Industry program will lead to a decline in toxic releases reported. Plants that complete a cycle of the Clean Industry certificate fulfill criteria on strict environmental management and hence are more likely to report pollution numbers lower than before its certification or renewal cycle. Plants that get certified for the first time need to comply with the metrics of the program by installing new technology or upgrading personnel training in environmental management. Hence, toxic releases are likely to go down. Plants that get certified

more than once qualify for more stringent outcome-based criteria and need to implement plans to further reduce their pollution from earlier periods.

3 Data

Our sample consists of 3436 facilities that reported toxic discharges into water. I focus on water pollution as plant-level data on toxic air emissions is scarce while greenhouse gas emissions were not regulated (Henriques et al. 2013). Of these facilities, 848 received the Clean Industry certificate at least once during 2000 to 2018. Due to data limitations, it is not possible to determine which facilities may have received the Clean Industry certificate before 2000, so I treat the first year of adoption or recertification after 2000 as equivalent to the first date of adoption. Given that I exploit within-plant variation in participation status, any bias from missing certification data before 2000 should be minimal, because Clean Industry certificates expire after two years, at which time plants need to be recertified with updated environmental management practices. Observed reductions in pollution emissions after recertification as opposed to first time adoption are likely the result of specific measures adopted by the plant in each cycle of renewal of its certificate.

The top industrial sectors for adopters are chemicals and allied products (24 percent), metals processing (16 percent), food, beverages, and tobacco (11 percent), automotive (10 percent), petroleum and petrochemicals (9 percent), energy (7 percent), electronics (5 percent), and others including services (18 percent). Of the non-adopters, the top industrial sectors are chemicals and allied products (28 percent), metals processing (16 percent), automotive (10 percent), electronics (6 percent), food, beverages, and tobacco (6 percent), petroleum and petrochemicals (4 percent) and others including services (30 percent). Plants in the food, beverages, and tobacco sector, energy sector, and petroleum and petrochemicals sector are more likely to enroll in the Clean Industry program.

By location, the adopters are mainly located in Nuevo Leon (11 percent), Tamaulipas (8 percent), Jalisco (7 percent), Queretaro, Mexico City, and State of Mexico (6 percent), and Coahuila, Veracruz, and Puebla (5 percent). By location, the non-adopters are mainly located in State of Mexico (20 percent), Tamaulipas (11 percent), Nuevo Leon (10 percent), Mexico City (9 percent), Jalisco (7 percent), and Coahuila, Queretaro, and Veracruz (4 percent). Plants located in the State of Mexico (and Tamaulipas and Mexico City to some extent) are less likely to enroll in the Clean Industry program.

On average, only 6 percent of major toxic plants enroll in the Clean Industry program annually. Over time, the share of plants enrolled in the Clean Industry program increased from close to 3 percent in 2000 to more than 7 percent in 2012 with a subsequent decline in the share to less than 5 percent in 2018. Table 1 below shows the frequency table of the number of plants participating in the Clean Industry program annually.

The data show that about 22 percent of certified facilities are enrolled in the program only once. Plants that recertified once were 14 percent, recertified twice were 11 percent, recertified three times were 15 percent, and four and five times were 12 and 10 percent, respectively. So, most of the participants did not renew their certificates frequently. In fact, only

two plants have renewed their certificates throughout the entire study period. This contrasts with the studies that discuss incentives for plants to renew these certificates as a cost-effective strategy in contrast to facing regulatory scrutiny (Henriques et al. 2013).

Table 1 Year of Adoption, Annual participation (%) in the Clean Industry program (2000-2018)

Year	New adoptions	Annual participation	Share of plants
2000	108	108	3.14
2001	71	72	2.10
2002	90	118	3.43
2003	57	126	3.67
2004	37	153	4.45
2005	40	132	3.84
2006	50	153	4.45
2007	65	200	5.82
2008	52	191	5.56
2009	47	174	5.06
2010	44	219	6.37
2011	39	206	5.99
2012	44	254	7.39
2013	42	252	7.33
2014	8	182	5.30
2015	16	211	6.14
2016	14	188	5.47
2017	14	182	5.30
2018	10	155	4.51

Share of plants is the number of plants participating annually in the Clean Industry program as a percentage of the plants reporting toxic pollution each year.

Table 2 presents summary statistics of the variables by participation status of plants. On average, annual toxic releases into water were higher for participants in the Clean Industry program in contrast to non-participants. This is consistent with previous studies that document historically dirtier plants enrolling in the Clean Industry program (Blackman et al. 2010). On average, participants were in less dense municipalities and more likely to be in municipalities with poorer socioeconomic status than non-participants. This is likely because large industries tend to locate in peri-urban areas with worse socioeconomic indicators than urban centers and large cities.

Next, I collect data on formal regulatory activities on both participants and non-participants. I separate out the inspections, fines, and fines amount by toxic and non-toxic programs. I adopt this classification as the environmental performance variable is plant-level toxic pollutants discharged into water. Inspection protocols for manufacturing facilities fall under six programs: high-risk activities; toxic waste management; environmental impact; land; air (fixed sources); and water pollution. Table 2 shows that fewer inspections of participants occurred under the toxics program than of non-participants. This is expected as one of the incentives, discussed in the literature, to enroll in environmental certifications programs in Mexico is reduced monitoring by regulators. By contrast, participants faced higher inspections

under non-toxic programs compared to non-participants.¹ On average, participants had more toxic violations detected in contrast to non-participants but faced fewer toxic fines and smaller fine amounts. Upon adoption of the third-party certified requirements on measures to control pollution, plants can get back into compliance with reporting and measurement protocols. Regulatory pressure under the toxic program was also lower on other plants in the same municipality as the participants, relative to non-participants.

Table 2 Summary Statistics, by participation in the Clean Industry program (2004-2018)

¹ Most of the non-toxic inspections were under high-risk activities, air, and land contamination programs.

Variable	Participants (848 plants)	Non- participants (2588 plants)	Participants vs non-participants
Toxics pollution, kg per year	109.0223	85.9437	23.0785**
Population density ('000), per sq. km.	1.6502	3.0914	-1.4412***
Population, over 15, illiterate (%)	5.1073	4.3859	0.7214***
6 to 14-year-olds not attending school (%)	4.6773	4.4105	0.2669***
Population, over 15, primary education incomplete (%)	39.9883	37.6074	2.3808***
Population without access to health services (%)	34.9123	35.1119	-0.1997
Households with mud floor (%)	5.6641	4.3644	1.2997***
Households without sewage connection (%)	6.5230	5.9033	0.6197***
Households without piped water (%)	7.8763	6.8482	1.0281***
Households without adequate drainage (%)	9.0610	6.8907	2.1704***
Households without electricity (%)	3.1295	2.7101	0.4193***
Households without washing machine (%)	32.3179	30.1902	2.1277***
Households without refrigerator (%)	16.9514	15.7905	1.1609***
Past 3 yr. toxic inspections	0.0772	0.0844	-0.0072*
Past 3 yr. non-toxic inspections	0.0957	0.0732	0.0225***
Past 3 yr. toxic inspections, on others	2.8643	3.3700	-0.5057***
Past 3 yr. non-toxic inspections, on others	2.4045	2.3396	0.0649*
Past 3 yr. toxic violations	0.0242	0.0203	0.0039***
Past 3 yr. toxic fines	0.0268	0.0341	-0.0073***
Past 3 yr. non-toxic fines	0.0281	0.0256	0.0025
Past 3 yr. toxic fines, on others	1.1659	1.4100	-0.2441***
Past 3 yr. toxic fines amount, 2010 USD	0.9565	3.7966	-2.84
Past 3 yr. toxic fines amount, on others, 2010 USD	101.8875	129.2292	-27.3417**
Past toxic inspections on others (accidents & citizen complaints)	0.0054	0.0053	0.0001
Past non-toxic inspections on others (accidents & citizen complaints)	0.0133	0.0102	0.0032**

Toxic pollution is the sum of arsenic, cadmium, chromium, cyanide, lead, mercury, and nickel releases into water

*** p<0.01, ** p<0.05, * p<0.1

4 Empirical Strategy

In this section, I investigate the determinants of participation in the Clean Industry program. I test a second hypothesis on the impact of Clean Industry participation on pollution reporting decisions. We know that reporting of toxic releases data in a developing country is not fully complied with despite the environmental law requiring mandatory reporting by major toxic polluters. I hypothesize that plants that obtain Clean Industry certificates adopt environmental management practices to reduce their pollution amounts; hence, they are more likely to measure and report their pollution records. Next, I test the hypothesis that Clean Industry participants improve their environmental performance, as evidenced by reductions in toxic water releases.

The literature mentions that participation in the program is influenced by regulatory scrutiny, informal or community pressure, type of industry, and benefits of public recognition. Final manufacturing plants might be more likely to self-select into this program to reap consumer benefits from higher sales and revenue.² Previous studies have focused on fines and plant specific factors such as multinational enterprises, government suppliers, or size, driving participation (Blackman et al. 2010; Henriques et al. 2013). I consider a rich set of potential explanatory variables including regulatory stringency and proxies for community pressure.

4.1 Participation in the Clean Industry program

I estimate a probit model to predict the likelihood of annual participation in the Clean Industry program. Equation (1) below presents the underlying annual decision (latent model) to adopt or renew Clean Industry certificates by each plant i and in year t . I utilize detailed information on plant-specific regulatory actions, F_{it} includes the total number of toxic and non-toxic fines imposed on the plant, the total number of toxic violations as an outcome of inspections of the plant, and the log of total monetary fines amount imposed on the plant. My hypothesis is that increased regulatory stringency results in a higher likelihood of the plant enrolling or renewing its Clean Industry certificate. I consider a lag of three years as certification or renewal status gives the plant inspections amnesty. I include regulatory stringency experienced by other plants in the same municipality, to determine participation that is influenced by general regulatory pressure. F_{-it} includes the total number of toxic and non-toxic fines imposed on other plants in the same municipality, the log of the total fines amount on the other plants in the same municipality, and the total number of accidents and citizen complaints triggering toxic and non-toxic inspections of others in the same municipality.

In equation (1), X_{it} is a vector of twelve lagged socioeconomic, demographic variables, including population density of the municipality for plant i , and is drawn from the 2000 and 2010 censuses, the 2005 count, and the 2015 intercensal databases. I consider the lagged variables as socioeconomic variables do not change dramatically in short time spans and the plant's knowledge when it makes the participation decision depends on experience with community pressure from the affected population. I include yearly dummy variables to capture

² Such as increased sale of final manufacturing products such as food, beverage, and tobacco, energy, and petroleum industries rather than intermediate production of chemicals and metals processing.

general trends in other factors that might influence the decision to participate. For example, changes in overall perception of consumers, general changes in regulatory agency budget going through different administrations, etc. I also include the state in which each plant is located to control for factors such as state-specific differences in regulatory stringency, and long term, location specific variations such as economic, and industrial production activities by each state. I include the type of manufacturing facility to control for chemicals and metals manufacturing as opposed to final goods.

$$Clean_{it}^* = BF_{it'} + AF_{-it'} + \Phi X_{it} + \chi_i state_i + \tau_i type_i + \mu_t year_t + \varepsilon_{it} \quad (1)$$

Where participation in the Clean Industry program is observed, i.e., $Clean_{it} = 1$ only if $Clean_{it}^* > 0$; zero otherwise.

4.2 Impact of Clean Industry certificates on reporting of toxic releases

The second empirical question is to find evidence of the impact of Clean Industry certificates on reporting of toxic releases. I hypothesize that participation in the Clean Industry program might incentivize polluters to regularly measure and report pollution. In addition, I hypothesize that reporting frequency depends on specific regulatory actions taken against the plant in the recent past, but it also depends on general regulatory pressure captured by formal actions on other plants in the same municipality. To capture regulatory pressure, I include inspections, fines, and amount fines under the toxic and non-toxic programs R_{it} in equation (2). I include a vector of general regulatory pressure captured by inspections, fines, and fined amounts on other plants in the same municipality R_{-it} in equation (2). To capture informal regulatory pressure, I include a vector of socioeconomic variables X_{it} of the municipality in which the plant is located. Yearly dummy variables would capture general policy changes such as shifts in federal administration and state regulatory budgets. I include plant level dummy variables to capture plant specific factors that determine pollution reporting. It subsumes all time invariant factors such as state specific differences in regulatory stringency and industry specific trends in pollution reporting.

$$Report_{it} = \alpha_i + \delta \widehat{Clean}_{it} + BR_{it'} + \Sigma R_{-it'} + KX_{it} + \zeta_t year_t + \epsilon_{it} \quad (2)$$

4.3 Impact of Clean Industry certificates on amount of toxic releases

A third hypothesis that I test is the impact of Clean Industry participation on the environmental performance of these plants, i.e., on toxic releases of each plant. I match each Clean Industry participant with its corresponding self-reported toxic releases. I account for potential endogeneity in participation in the Clean Industry program as it is likely determined with toxic pollutants

release decisions of each plant. I utilize the predicted values of participation using a linear probability model. I include plant fixed effects in the linear participation model to control for all time-invariant plant specific factors that capture the plants more or less likely to participate. I lag the likelihood of participation in the toxic releases model as actions taken by the plant upon obtaining these certificates might be observed as decline in toxic releases with a lag.

Equation (3) below presents the panel data model for toxic releases. I aggregate across the most frequently reported seven toxic substances released into water each year. I adopt this approach because I am interested in plant-level environmental performance rather than exploring variations across toxic pollutants reported by each plant. For plant i , in year t , I regress the log of toxic pollutants discharged into the water on the predicted values of participation lagged three years, a set of regulatory activity variables and socioeconomic controls that can influence pollution levels. This empirical strategy exploits the annual variation in pollution depending on participation in voluntary incentives program.

I include total number of toxic and non-toxic inspections of the plant, total number of toxic violations as an outcome of inspections at the plant, the total number of toxic and non-toxic fines imposed on the plant, and the log of the sum of monetary fines imposed on the plant. I include general regulatory actions such as total number of inspections under both toxic and all other non-toxic programs conducted on other plants in the same municipality, total number of toxic and non-toxic fines imposed on other plants in the same municipality, total toxic fines amount imposed on other plants in the same municipality, and total number of toxic and non-toxic inspections arising out of accidents or citizen complaints of other plants in the same municipality. I consider the same lag length of the past three years as the participation model for the variables capturing regulatory activities.³

Lagged socioeconomic variables X_{it} capture any differences in plant-level pollution based on community characteristics. I include plant fixed effects that would capture all time-invariant plant-specific and location-specific factors (e.g., type of manufacturing facility, political jurisdiction, state, distance to large metropolitan cities). Year fixed effects control for annual changes in toxics releases not specific to a plant.

$$aggtox_{it} = \beta_i + \gamma \widehat{Clean}_{i(t-3)} + \Psi R_{it'} + \Pi R_{-it'} + \Delta X_{it} + \omega_t year_t + \theta_{it} \quad (3)$$

5 Results

Table 3 presents the results of the participation model for the Clean Industry certificates by each plant. Column (1) presents the probit estimation of the annual participation model of equation (1). Column (1) presents the marginal effects calculated at mean values. Almost all regulatory

³ Results are much smaller in magnitude upon considering past two years lag length for the variables related to regulatory activities.

finances and amount fined on the plant lead to a decline in participation. This is expected as Clean Industry participants get regulatory relief during the period when its certificate is valid. I find that a higher frequency of violations under the toxic inspections program reduces the likelihood of annual participation decisions of these plants. The coefficients can be interpreted as one more detection of violation during the past three years, lowering the probability of participation in the voluntary program by 2.4 percentage points. In terms of general regulatory pressure, higher amounts fined under the toxics inspection program on others have a positive sign i.e. encouraging participation in voluntary incentives. The coefficients can be interpreted as an increase in fines amount on others result in a higher likelihood of participation in the Clean Industry program by 0.4 percentage points. I interpret this result as evidence of regulator reputation effects (as described in Shimshack and Ward, 2005) as a potential channel to encourage participation and renewal of these certificates is to avoid regulatory scrutiny. However, one more toxic fine imposed on others lowers the probability of participation by 0.2 percentage points. I interpret this as peer effects as neighbors are likely to face fewer fines if they are signed up for the certificate (Zhang et al. 2026).

Among types of plants, beverages and tobacco, concrete, electricity generating plants and petroleum and petrochemicals participate more in the Clean Industry program.⁴ Among the community factors, denser areas, less educated and mud floors seem to reduce the likelihood of annual participation in the Clean Industry program. Higher illiterate population on the other hand increases participation in the voluntary program. State level controls are highly significant, implying that location is important for annual participation decisions. For example, state level variations in long-term regulatory stringency and industrial composition might explain participation in the program.

Table 3 Participation in the Clean Industry program

⁴ Results not presented in Table 3.

VARIABLES	(1) Probit	(2) Linear Probability Model
Past toxic fines	-0.0160 (0.0176)	-0.0146* (0.00764)
Past non-toxic fines	-0.0157 (0.00961)	-0.00776 (0.00624)
Past toxic fines amount	-0.0108 (0.00782)	0.00167 (0.00361)
Past toxic violation	-0.0239* (0.0129)	-0.0183* (0.00966)
Past toxic fines on other plants	-0.00168* (0.000984)	4.62e-07 (0.000540)
Past non-toxic fines on other plants	0.00274 (0.00310)	-0.00108 (0.00131)
Past toxic fines amount on other plants	0.00376* (0.00194)	-0.000792 (0.00150)
Past toxic inspections on others (accidents & citizen complaints)	-0.0249 (0.0202)	-0.0150 (0.0102)
Past non-toxic inspections on others (accidents & citizen complaints)	-0.00763 (0.0128)	-0.0115** (0.00560)
State FE	X	
Year FE	X	X
Type of manufacturing FE	X	
Plant FE		X
Observations	63,584	64,610

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Column (2) in Table 3 presents the linear probability model of participation in the Clean Industry program including plant level dummy variables. Results are overall similar to the probit estimation but somewhat smaller in magnitude. Past toxic fines and violations lead to lower participation in the voluntary program by 1.5 and 1.8 percentage points respectively. On the other hand, non-toxic inspections following accidents and citizen complaints not directed at the plant result in lower participation in the program by 1.2 percentage points.

In the reporting model presented in Table 4, participation in the Clean Industry program increases the probability of annual reporting by 24 percentage points in the probit estimation. Upon inclusion of plant level dummy variables in the linear probability model, the coefficient increases to 33 percentage points but is not statistically significant. Regulatory variables are overall important in determining reporting frequency. Increase in past toxic inspections lead to higher reporting by 3 percentage points (column (1)). Increase in past non-toxic inspections lead to an increase in the probability of reporting by 5.9 percentage points. Higher fined amount result in an increase in reporting by 1.8 percentage points. Past non-toxic inspections on other plants in the same municipality leads to an increase in reporting by 0.2 percentage points. Finally, one more toxic fine on others leads to an increase in the probability of reporting by 0.2 percentage points. On the other hand, one more toxic fine lead to a decline in reporting by 2.7 percentage

points. Higher fined amounts on other plants in the same municipality leads to a decrease in the probability of reporting by 0.5 percentage points.

Coefficients are smaller in magnitude in the linear probability model (column (2)) with plant level dummy variables. Higher past non-toxic inspections lead to an increase in pollution reporting by 2.5 percentage points. Increase in the amount fined leads to an increase in the probability of reporting by 2.6 percentage points. Higher non-toxic inspections lead to an increase in reporting by 0.4 percentage points. Past toxic fines on others lead to an increase in probability of reporting by 0.5 percentage points. On the other hand, one more toxic fine imposed result in a lower probability of reporting by 3 percentage points. And, higher fined amounts on others also result in a decline in polluting reporting by 0.5 percentage points.

Table 4 Pollution reporting models

VARIABLES	(1) Probit	(2) Linear Probability Model
Adoption/Renewal of the Clean Industry certificate	0.242*** (0.00985)	0.333 (0.411)
Past Toxic Inspections	0.0295*** (0.00895)	0.00779 (0.00785)
Past non-toxic inspections	0.0593*** (0.00757)	0.0247*** (0.00769)
Past toxic fines	-0.0272* (0.0165)	-0.0313** (0.0140)
Past non-toxic fines	0.00353 (0.0144)	0.0186 (0.0124)
Past toxic fines amount	0.0178*** (0.00664)	0.0263*** (0.00638)
Past toxic violation	-0.00507 (0.0108)	0.00767 (0.0171)
Past toxic inspections on other plants	-0.000380 (0.000700)	-0.00123 (0.000754)
Past non-toxic inspections on other plants	0.00238*** (0.000902)	0.00349*** (0.000961)
Past toxic fines amount on other plants	-0.00535*** (0.00133)	-0.00461*** (0.00162)
Past toxic fines on other plants	0.00233* (0.00128)	0.00225* (0.00126)
Past non-toxic fines on other plants	-0.00221 (0.00210)	0.000237 (0.00177)
Past toxic inspections on others (accidents & citizen complaints)	0.0289 (0.0257)	0.0214 (0.0239)
Past non-toxic inspections on others (accidents & citizen complaints)	0.00353 (0.0122)	-0.000642 (0.0135)
State FE	X	X
Year FE	X	X
Type of manufacturing FE	X	X
Observations	51,010	64,610

Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5 presents the panel data results on annual toxic releases, accounting for participation in the Clean Industry program, using the predicted values of the linear participation model. This model includes plant fixed effects. Identification comes from within plant variation in participation and renewal of certificates on pollution levels reported by the same plant. For example, if voluntary approaches are effective mechanisms of pollution control, the coefficient on lagged participation status would have a negative sign. I can establish that as plants adopted and subsequently renewed their certificates, they reduce pollution from baseline levels i.e. from levels prior to adoption. In column (1), we can see that indeed the effect of predicted participation status three years prior leads to a significant reduction in toxic releases for a typical adopter. The coefficient can be interpreted as participation in the Clean Industry program lagged three years results in a reduction in current toxic releases by 1,204 kgs annually. This coefficient can be interpreted as the impact of the effect of the Clean Industry program on plant level toxic discharges into water.

Table 5 Panel Data Estimates of toxic releases

VARIABLES	(1) Annual toxic releases	(2) Annual toxic releases, Automotive	(3) Annual toxic releases, Chemicals	(4) Annual toxic releases, Metals
Adoption/Renewal of the Clean Industry certificate	-1,204* (726.2)	-1,194 (2,660)	-2,611 (2,216)	1,958 (1,714)
Past Toxic Inspections	43.32 (32.67)	12.11 (33.51)	120.6 (79.61)	49.08 (64.74)
Past non-toxic inspections	-40.59* (23.91)	-12.94 (39.68)	-67.24 (56.12)	50.83 (61.93)
Past toxic fines	-44.11 (42.67)	-41.76 (70.29)	-94.99 (68.57)	67.76 (179.5)
Past non-toxic fines	13.93 (33.23)	145.4 (110.8)	60.56 (48.21)	-105.7 (71.45)
Past toxic fines amount	-2.561 (17.59)	14.17 (25.42)	-14.19 (14.54)	-62.31 (76.17)
Past toxic violation	8.074 (39.86)	-108.0 (130.1)	60.39 (59.75)	-33.92 (52.14)
Past toxic inspections on other plants	4.541 (4.125)	10.51* (5.650)	21.39 (32.22)	16.40 (14.26)
Past non-toxic inspections on other plants	-8.813* (4.992)	-16.15 (15.64)	-22.44* (13.50)	-0.575 (8.480)
Past toxic fines amount on other plants	-4.376 (6.367)	4.756 (13.18)	-8.648 (13.82)	-8.124 (8.536)
Past toxic fines on other plants	-6.745 (5.167)	-29.94** (13.98)	-13.98 (22.64)	0.863 (8.731)
Past non-toxic fines on other plants	6.928 (8.175)	2.167 (14.52)	4.254 (11.35)	-12.24 (14.11)
Past toxic inspections on others (accidents & citizen complaints)	-84.90 (61.27)	-11.32 (31.35)	-193.0 (144.5)	-80.84 (106.7)
Past non-toxic inspections on others (accidents & citizen complaints)	6.919 (63.60)	81.82 (52.81)	52.44 (94.85)	-144.9 (206.5)
Year FE	X	X	X	X
Plant FE	3,400	342	782	393
Observations	13,084	1,409	3,261	1,720

Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Controlling for endogenous participation in the Clean Industry program, only non-toxic inspections on itself and on others have a significant impact on toxic releases. One more inspection under the non-toxic programs leads to a plant reducing its toxic releases by 40.6 kgs annually. One more inspection under the non-toxic program on others in the same municipality leads to a decline in toxic releases by 8.8 kgs annually. Higher proportion of households without mud floors are linked to lower toxic releases.⁵

In columns (2) through (4), I report the results of the panel data estimation for the sub-samples of the automotive sector, the chemicals sector, and the metals processing sector. Plants in the chemicals sectors reduce their toxic releases by 2,611 kgs annually. Plants in the automotive sector reduce their toxic releases by 1,194 kgs annually. On the other hand, plants in the metals processing sector increase toxic releases by 1,958 kgs per year, following participation in the Clean Industry program. Results are, however, not statistically significant due to smaller sample sizes upon considering plants from each of three types of manufacturing facility.

In sum, I find evidence that past toxic violations reduce the likelihood of participation while higher fined amounts on others increase the likelihood of participation in the Clean Industry program. I also find evidence that Clean Industry participants increase their annual pollution reporting. I find that participants significantly reduce their pollutants discharges over time. This is the first such evidence utilizing actual measures of reported pollution discharges, specific and general regulatory activities and local community features. However, smaller sample sizes for the within industry models might be driving the statistical insignificance of the coefficient on Clean Industry participation.

5.2 Causal Inference

Since Clean Industry participants are distinct from the non-participants as seen in Table 2, I adopt a counterfactual estimator model to address sample selection bias. Blackman (2012) and Blackman et al. (2010) utilize propensity score matching to compare the participants with their matched control plants. However, matching does not accommodate the dynamic pattern of switching back and forth between participation and not certified/renewed statuses over the long panel of participants included in this current study. The treatment variable takes on a value of one upon adoption or recertification and stays at one for one more year since the renewal cycle is valid for two years. The model augments the panel data estimation with a treatment dummy D_{it} that varies over time and τ_{it} is the period specific average treatment effect on the treated. The dependent variable is (log) toxic pollutants reported annually by the sample of major polluters.

⁵ Results not presented in Table 4.

$$\ln(aggtox)_{it} = \tau_{it}D_{it} + \alpha_i + BR_{it'} + \Sigma R_{-it'} + \Phi X_{it} + \zeta_t year_t + \epsilon_{it} \quad (4)$$

In this section, I estimate *Counterfactual Estimators* for panel data as described in Liu et al. (2024). The authors highlight several advantages in terms of empirically modelling data that is characterized by switching back and forth between participating in the Clean Industry program. This method involves using information from non-participating plants and predicting counterfactuals for the treated plants by estimating models. This method provides the diagnostic tool of “dynamic treatment effects” which are the coefficients of a series of interactions between the participating plant and time dummies capturing the years lapsed or preceding the year of treatment. In other words, one can illustrate a plot of the average treatment effect on the treated for different years relative to the year when the plant gets a Clean Industry certificate at least once during the period studied. The authors also report a placebo test that involves removing the observations for up to two years preceding the intervention and then testing the difference between the observed outcomes and the outcomes predicted from the pool of observations of non-participating for the held-out periods.

Fig. 1 shows that three years post treatment yields the largest decline in toxic pollution discharged into water by 0.89.⁶ In percentage terms, this means a decline in toxic releases by 59 percent. Fig. 2 shows that this specification passes the placebo test in terms of no significant differences in the average outcomes compared with the predicted ones for up to two years preceding the treatment. Fig. 3, Fig. 4 and Fig. 5 estimate the Counterfactual Estimators by focusing on the Automotive, Chemicals, and Metals processing sectors. Almost half of the toxic release reports are from these three types of manufacturing facilities. Similar to the panel data results, within industry average treatment effect on the treated (ATTs) are not statistically significant. I find that automotive plants (ATT=-1.55) experience the largest decline in toxic pollution three years after participation in the Clean Industry program by 78 percent (Fig. 3). However, the downward trend is not maintained in the fourth year. Fig. 4 shows that chemical plants reduce their toxic releases by 42 percent (ATT=0.55) after Clean Industry participation. Fig. 5 shows that metals processing plants do not reduce their toxic discharges following Clean Industry participation.

⁶ Results not presented in the paper are similar upon accounting for pollution reporting bias.

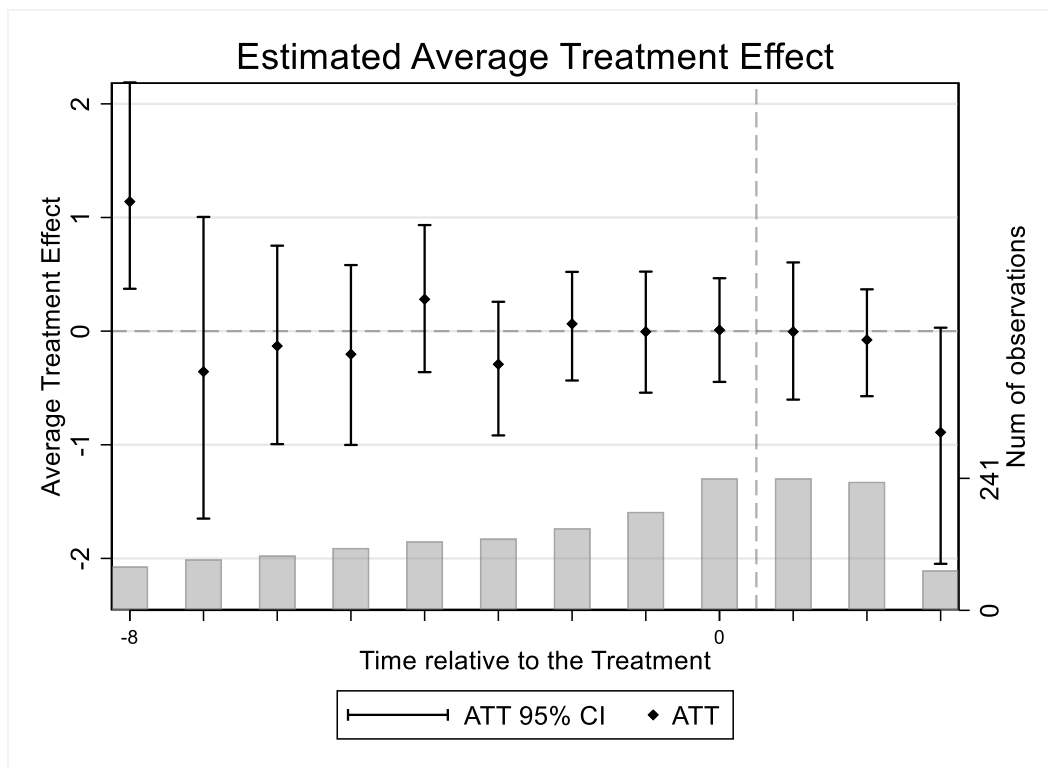


Fig. 1 Average Treatment Effect on the treated for all plants

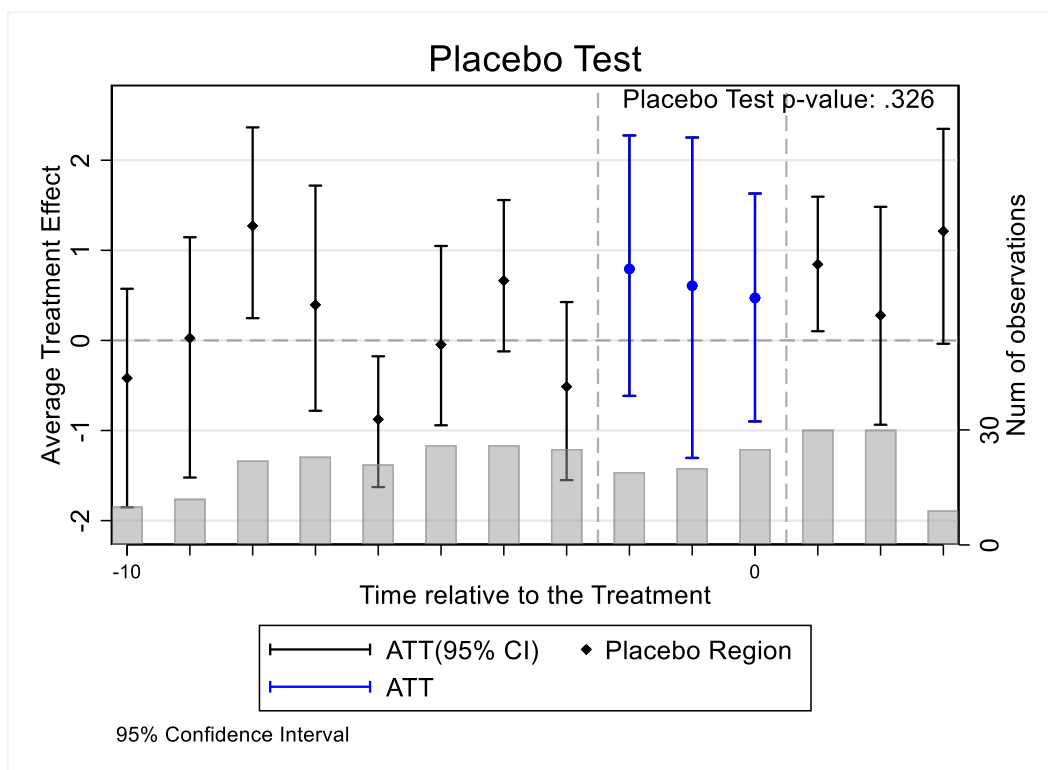


Fig. 2 Placebo Test on the average treatment effect on the treated for all plants

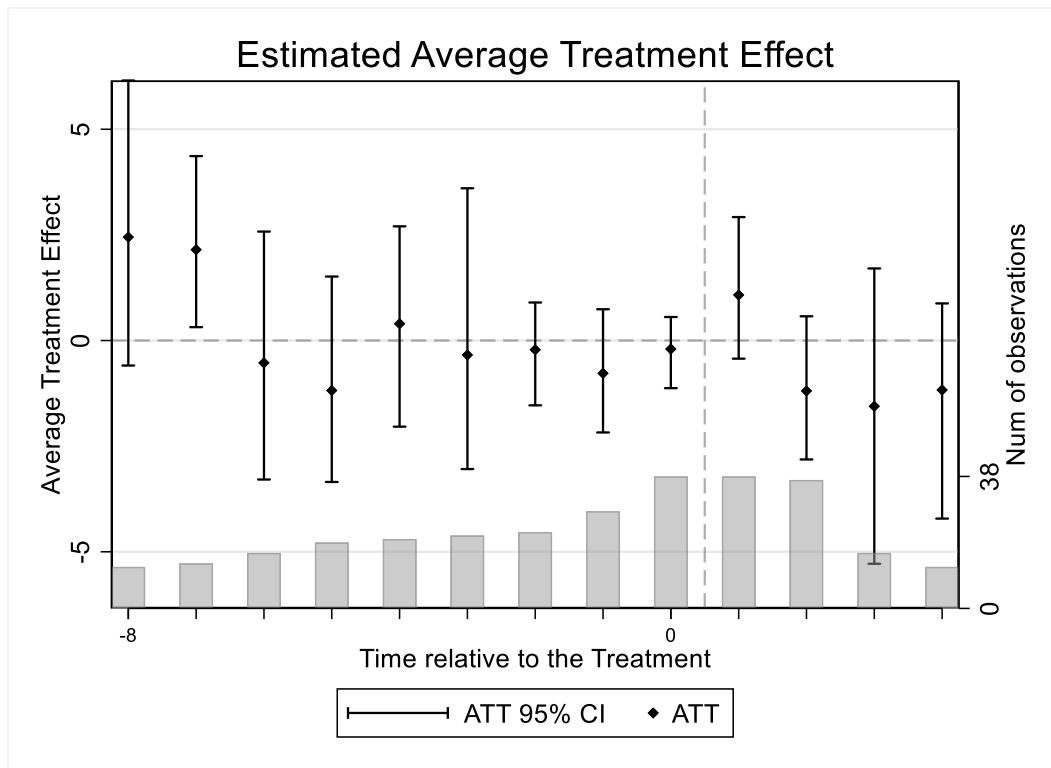


Fig. 3 Average Treatment Effect on the treated for automotive plants

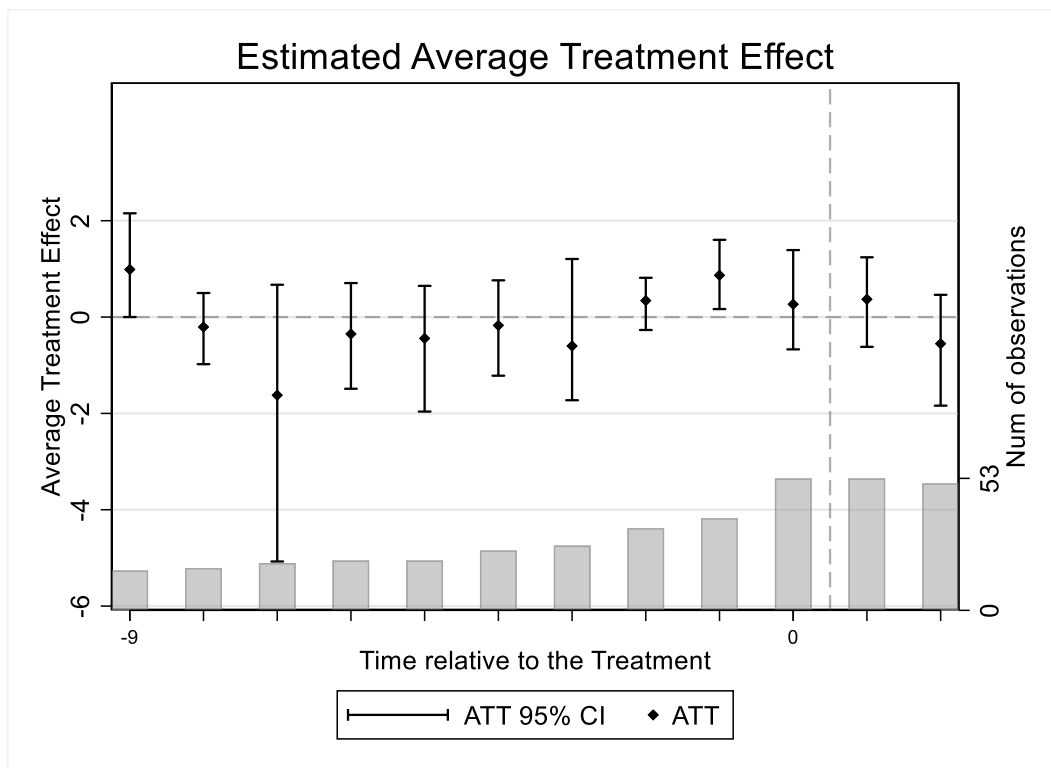


Fig. 4 Average Treatment Effect on the treated for chemical plants

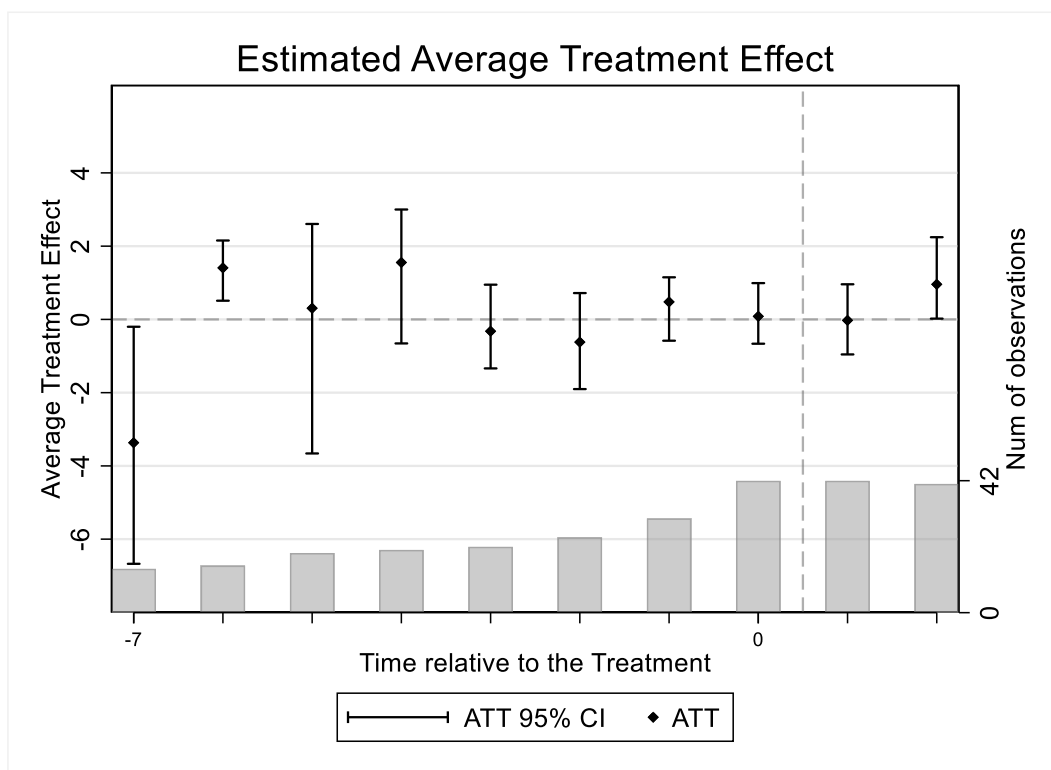


Fig. 5 Average Treatment Effect on the treated for metals processing plants

These results are robust to an alternative and more flexible estimation technique of the matrix completion method. Fig. 6 shows that the average treatment effect on the treated declines in the third year by 56 percent ($ATT=-0.818$) post participation in the Clean Industry program. This specification also passes the placebo test (Fig. 7). By type of manufacturing facility, automotive plants reduce their toxic discharges by 80 percent ($ATT=-1.59$) three years after Clean Industry participation (Fig. 8). Again, the downward trend is not maintained in the fourth year. Chemical plants exhibit decline post treatment by 30 percent ($ATT=-0.35$) (Fig. 9). Metals processing plants do not exhibit any declining trend in their average treatment effects over time (Fig. 10).

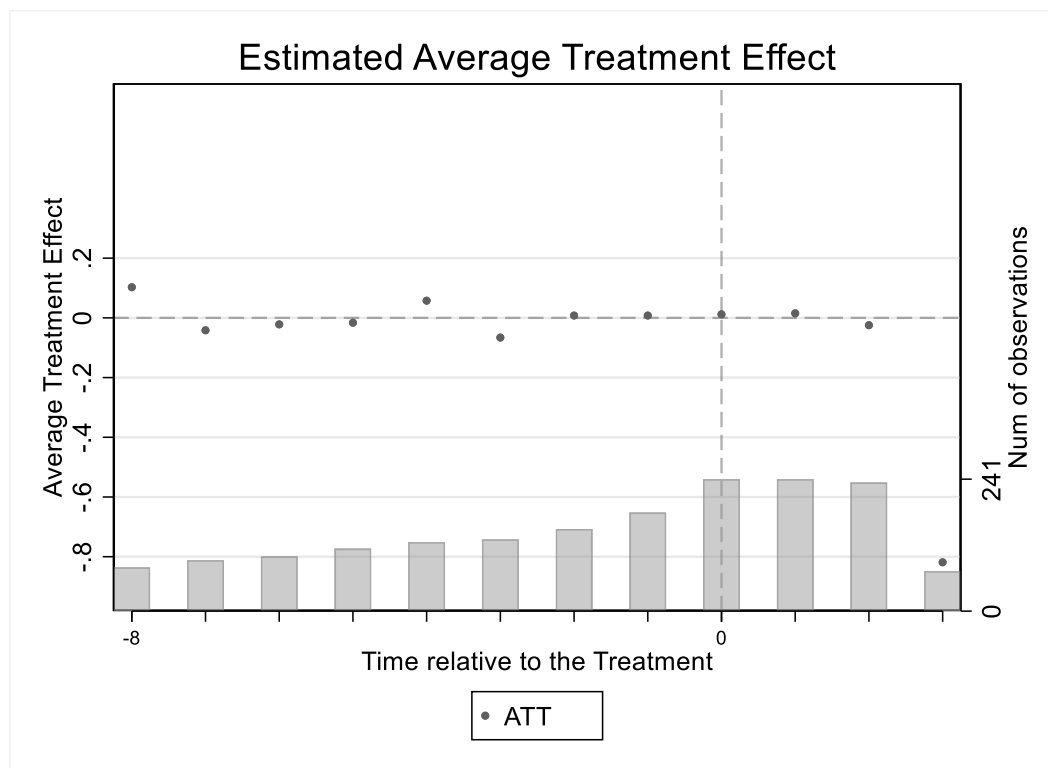


Fig. 6 Matrix Completion Method for all plants

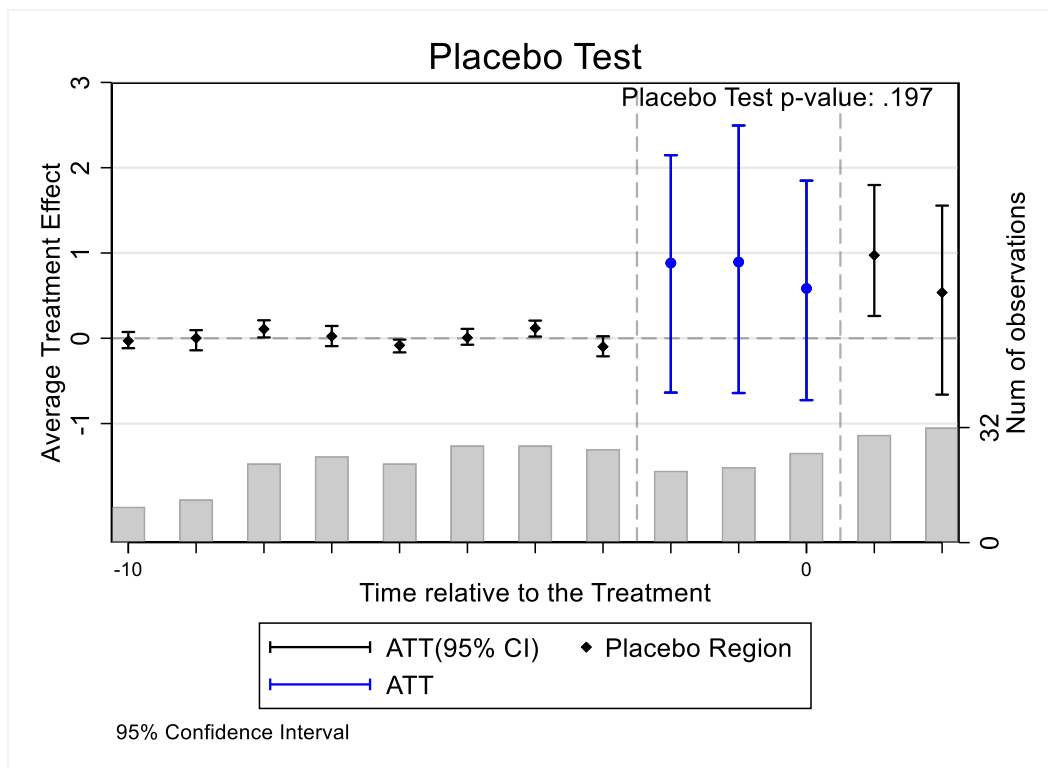


Fig. 7 Placebo Test for the Matrix Completion Method

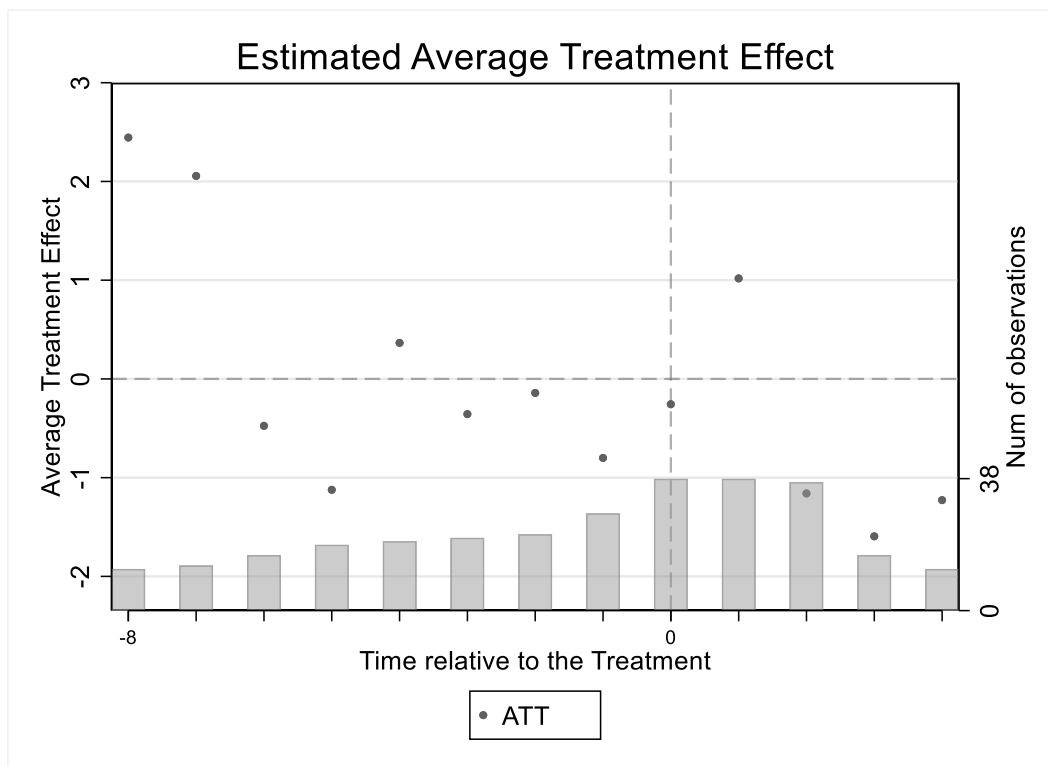


Fig. 8 Matrix Completion Method for automotive plants

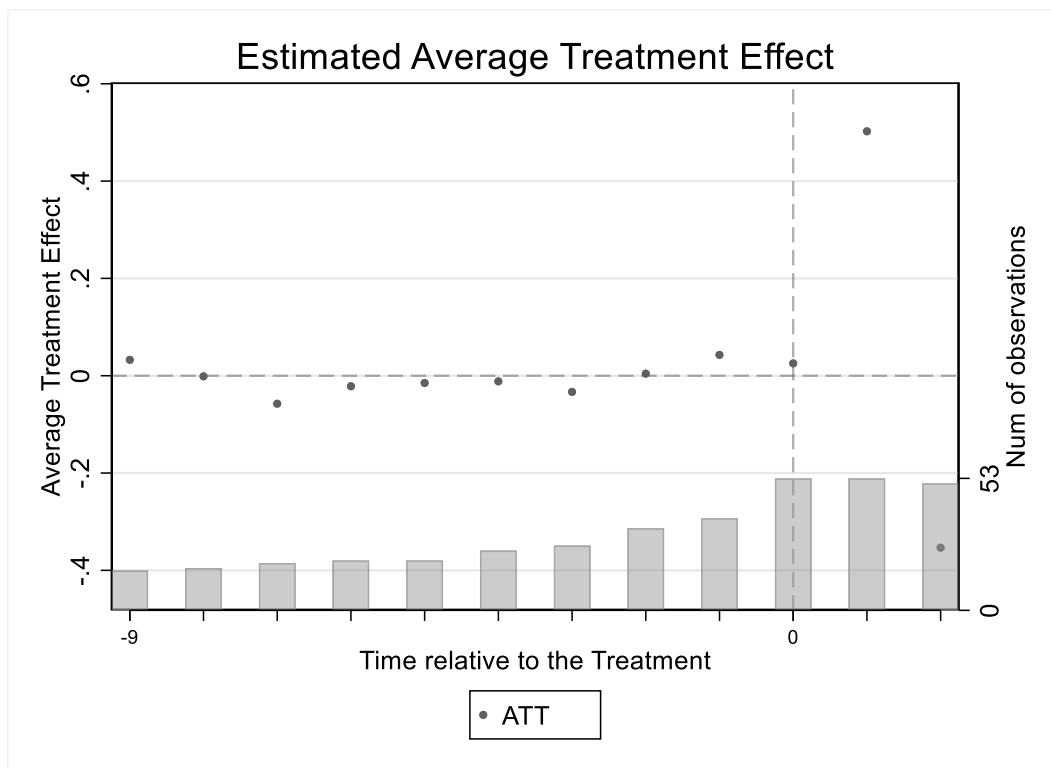


Fig. 9 Matrix Completion Method for chemical plants

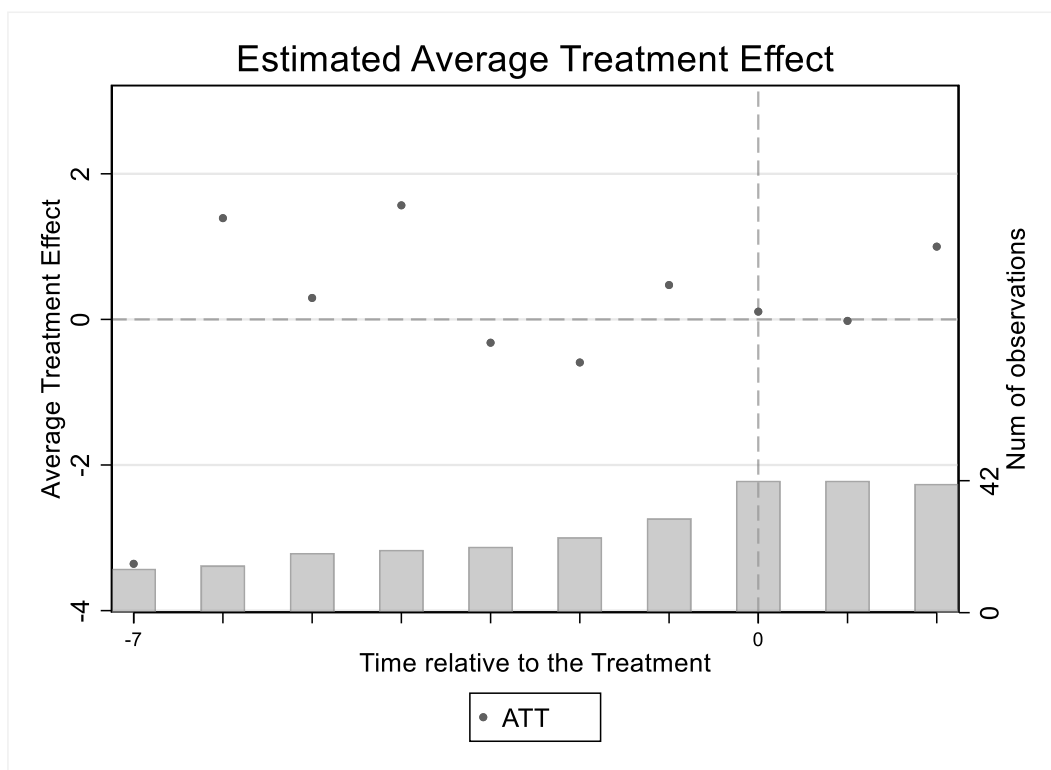


Fig. 10 Matrix Completion Method for metal processing plants

6 Conclusions

This paper finds the first comprehensive evidence that major toxic polluters in Mexico that participate in the Clean Industry program improve their environmental performance. I also find that Clean Industry participants are more likely to report pollution. Using a sample of 3,436 plants that are required to report their toxic releases into water, I establish that Clean Industry participants reduce their annual toxic discharges by 1,204 kgs annually. However, the coefficients fall out of statistical significance upon considering the sub-sample of plants within the automobile, chemical, and metal processing sectors, separately. Smaller sample sizes might be driving these results. Upon considering a staggered adoption framework with entry and exit, I find an average treatment effect on the treated of -0.8 in the third year after graduating from their certification period of two years. This corresponds to a reduction of 56 percent in the third year after being treated. I consider this finding economically significant as it incorporates the true certification and recertification of these plants as they enroll and exit the program with considerable variability. More specifically, only a few polluters remain in the program for almost two decades studied.

I infer that the national voluntary environmental program provides the appropriate incentives to these polluters to reduce their toxic releases relative to levels before certification or renewals. This contrasts with the previous studies that claim self-selection of heavily polluting manufacturing plants into the Clean Industry program to obtain regulatory relief. Contrary to expectations, I find that higher toxic violations in the last three years lower the probability of participation in the program. On the other hand, I find some evidence of higher amounts fined on other plants in the same municipality leading to higher participation.

I present evidence that despite higher pollution levels of participants versus non-participants, these plants reduce their mandatory toxics upon obtaining Clean Industry certificates. I infer positive evidence of the overall efficacy of third-party certification for a large sample of polluters in Mexico. A potential limitation of this study is that I do not investigate the impacts of both ISO14001 certification and Clean Industry participants. However, my estimates might have minimal upward bias if Clean Industry certification is the more stringent environmental management system (as shown by Henriques et al. 2013). To the extent that the ISO certification underwent significant changes in building outcome-based measures such as toxic emissions, my estimates might be synergistically determined with the plant's enrollment in the ISO14001. In the context of developing countries, where corruption and bureaucracy are rampant, these results are more meaningful as it shows that voluntary mechanisms are effective tools of pollution control.

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