DOES INDUSTRY SELF-REGULATION REDUCE ACCIDENTS?

RESPONSIBLE CARE IN THE CHEMICAL SECTOR

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Does Self-Regulation Reduce Industrial Accidents?

Responsible Care in the Chemical Industry

Abstract

This is the first study to evaluate the impact of self-regulation on industrial accidents. We examine Responsible Care in the US chemical manufacturing sector using our author-constructed database of 1,867 firms that own 2,963 plants between 1988 and 2001. Firms' self-selection into RC is instrumented using pollution-related regulatory pressure on firms that influences their probability of joining RC, but not plant-level accidents. The average treatment effect on the treated indicates that RC reduces the likelihood of accidents by 2.99 accidents per 100 plants in a given year. This 69.3% reduction in the likelihood of accidents, accounting for the plants that participate in RC, translates to back-of-the-envelope avoided losses of $0.8 billion to $3.8 billion per year. RC also reduces the likelihood of more narrowly-defined accidents, i.e., process safety accidents and accidents related to violations of RC codes, by 5.75 accidents per 100 plants in a given year or by 85.9%.

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1. Self-regulation and industrial accidents

Major accidents in the chemical industry – Seveso's dioxin release, Bhopal's methyl-isocyanate release and the explosion at AZF Toulouse – highlight the costs from industrial accidents (Kleindorfer and Kunreuther, 1987; Dechy et al., 2004; NCBP, 2011; Capelle-Blanchard and Laguna, 2010). Industrial self-regulation, in which trade associations require members to adhere to codes of conduct, has become one prominent policy response to these accidents. In reaction to Bhopal, the American Chemistry Council (ACC) launched Responsible Care (RC) in the US chemical manufacturing sector (Rees, 1997). Most recently, the National Commission on the BP Oil Spill (NCBP, 2011), ***citing the success of RC***, recommended that the oil and gas drilling sector adopt self-regulation. In turn, the industry association is considering establishing a self-regulation program that includes the features of RC (Dlouhy, 2011).

We examine the impact of Responsible Care, operating within its regulatory context,[1] on work-related accidents involving at least one fatality or three inpatient hospitalizations among workers in the US chemical manufacturing sector. We analyze our author-constructed database which consists of 2,963 plants owned by 1,867 firms between 1988 and 2001. Our study, the first to examine the impact of industry self-regulation on industrial accidents,[2] is of policy interest.

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[1] The chemical manufacturing sector faces regulations and costs of insuring against accidents (Kleindorfer and Kunreuther, 1987). See section 2.1. The chemical manufacturing sector is the Standard Industrial Classification major group 28, i.e., SIC-28. This sector is composed of industries at the SIC-4 digit level (SIC-4) which are listed in the Online Appendix II: Table A1.

[2] The seminal papers examining accidents in the Risk Management Plan database do not examine self-regulation (Kleindorfer et al., 2003). Davis and Wolfram's (2011) analysis of the impact of

First, firms are likely to under-invest in accident prevention because they are able to externalize some of the costs from accidents (Gray and Jones, 1991; Cohen et al., 2011). Accidents in the US chemical industry are estimated to cause losses of $3 billion to $5 billion annually (Collins et al., 2000). Second, despite the justifications for self-regulation programs, i.e., firms, not regulators, have the information, technology and resources for risk management (National Academy of Engineering, 2010; GAO, 2011), empirical studies to date conclude that RC *did not* reduce participants' pollution (King and Lenox, 2000; Gamper-Rabindran and Finger, 2010). Our study assesses RC on the yardstick of accidents. Plausibly, RC, created in response to the Bhopal accident, focused mainly on the implementation of codes related to production safety, instead of pollution reduction, because poor management of production processes caused that accident (Kleindorfer and Kunreuther, 1987). Moreover, the accident outcome, due to mandatory reporting to the Occupational Safety and Health Agency (OSHA) and follow-up investigations, is more reliably measured than the self-reported Toxic Release Inventory (TRI) pollution examined previously (King and Lenox, 2000; Gamper-Rabindran and Finger, 2010).

A key methodological challenge in analyzing the impact of self-regulation programs or voluntary programs is that firms self-select into these programs based on factors that are unobserved by the researcher, but that are likely to be correlated with the program outcomes (Levinson, 2004). Furthermore, the direction of bias from not addressing self-selection is often not known a priori.[3] The first solution to the self-selection problem, i.e., randomizing the

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deregulation on efficiency in nuclear power plants reports some evidence that deregulation improved one measure of plant safety.

[3] In his study of the voluntary program for early compliance under the Acid Rain Program, Montero (1999) finds that plants that are able to reduce their emissions prior to the compliance

programs to participants and non-participants, is inappropriate because a firm's *choice to participate* is an essential feature of these programs. The second solution, i.e., instrumenting for firm's selection, faces the obstacle that valid instruments are available only in limited cases.[4] The criticism of identifying assumptions in several studies underscores the difficulty in proposing valid instruments.[5] Several recent studies (Pizer, Morgenstern and Shih, forthcoming; Kim and Lyon, 2011) have relied on Propensity Score Matching methods (PSM). The authors'

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date and thus, receive excess allowances based on their historical emissions are more likely to opt into the program. In contrast, in their study of RC whose membership codes include pollution reduction, Lenox and Nash (2003) find that more polluting firms are more likely to join RC. Not addressing self-selection would overstate the impact of the program in reducing pollution if these dirtier plants face lower marginal costs in reducing pollution, as a result of declining marginal costs of abatement. The bias would be in the opposite direction if these plants face higher marginal costs of reducing pollution as a result of their reliance on pollution-intensive technologies.

[4] Studies of the voluntary 33-50 program are able to use an instrument based on the Environmental Protection Agency's (EPA) invitation of firms to join the program in several waves that are orthogonal to the program's outcome (Khanna and Damon, 1999; Gamper-Rabindran, 2006; Vidovic and Khanna, 2007).

[5] For example, Brouhle, Griffiths and Wolverton's (2009) study is a valuable contribution but their assumption that several variables do not affect plants' emissions is prone to criticism. In the authors' model, state regulations, prior violations and penalties, and a subset of community pressure variables do not affect plants' emissions, contrary to the evidence in Sigman (1999), Gray and Shimshack (2011) and Hamilton (1995, 1999), respectively.

justification for applying PSM is the absence of valid instruments, but one concern is the authors have not ruled out the potential scenario that firms' selection into the program is based on *unobserved* factors related to outcomes.[6] The PSM estimates are biased when unobserved factors influence both participation and outcomes (Heckman, Ichimura, and Todd, 1997).

To instrument for a plant's parent firm's participation in RC, our study exploits the firm's exposure to impending strict regulations on hazardous air pollutants (HAPs), which are a subset of its TRI pollutants. Impending regulations on HAPs affect the firm's contemporaneous decision to join RC, but do not directly affect plant-level accidents. These anticipated Maximum Available Control Technology (MACT) regulations reduce the additional costs for regulation-affected plants to join RC. Firms that would have to reduce their HAPs in the future anyway may face lower costs to adhere to RC's pollution prevention membership code, and thus, be more likely to participate. The impending MACT regulations are not likely to affect accidents (section 3.3). First, technologies to reduce HAPs released into the environment, e.g., improved incineration or chemical absorption of HAPs (Van Asten and Martinson, 2005), are distinct from

[6] In the 1605b program, which provides project-level reporting options, it is plausible that firms which are already planning a sequestering project are more likely to self-select into the program. These firms are also less likely to undertake actions to reduce the two outcomes analyzed: (i) energy usage examined in Pizer, Morgenstern and Shih (forthcoming); and (ii) carbon dioxide emissions intensity examined in Lyon and Kim (2011). As firms' planned sequestration project is not observed by researchers, matching such firms (which have a planned sequestration project) with other firms that are similar in their observables (but which do not have a planned sequestration project) can bias the studies towards finding that the program did not reduce energy usage or emissions intensity.

actions to reduce plant-level accidents, e.g., preventing pressure buildup, loss of control over reactive processes or exposure of flammable chemicals to heat sources (Hofman, Jacobs and Landy, 1995). Second, EPA's design and implementation of MACT regulations did not consider potential impacts on worker exposure or accidents (Armenti et al., 2003; Armenti, 2004; Robson and Toscano, 2007). Third, even if MACT regulations had reduced HAPs, these reductions are not likely to result in fewer accidents. Many accidents stem from fires, explosions, or acute worker exposure to toxic chemicals, but few HAPs are flammable or acutely toxic. The reduction of HAPs that are carcinogenic or chronically toxic are not likely to reduce deaths or hospitalizations because of the long latency periods between chronic exposure and symptoms of illness (Robson and Toscano, 2007).

We find that RC reduces the likelihood of all accidents at RC participating plants by 2.99 accidents per 100 plants for a given year. This figure is the estimated treatment effect on the treated. Based on estimates of losses from accidents at chemical, petrochemical or OSHA-regulated plants, and the 1,037 average number of plants that participate in RC, this 69.3% reduction in the likelihood of accidents translates to back-of-the-envelope avoided losses of $0.8 billion to $3.8 billion annually (see section 4.4). Narrowing our analysis to process safety[7] accidents and those accidents involving violations of OSHA standards related to RC codes, we find that RC reduces the likelihood of these accidents by 5.75 accidents per 100 plants in a given year, or by 85.9%.

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[7] Process safety denotes the application of management and engineering principles to prevent fires, explosions, and accidental chemical releases at chemical plants (ACC, 1990). It is often not possible to stop a process that is going out of control by simply "pulling the plug" and stopping the production line (Hofman, Jacobs and Landy, 1995).

Our results yield two policy implications. First, RC provides *additional impetus* for plants to improve their safety standards, beyond the incentives they face from government regulations and their potential liability from accidents. RC features can improve senior management's attention to safety and their ability to correct errors, the two key factors in improving plant safety (section 2.2). These features include requiring CEOs of firms to sign off on reports to the ACC, to attend regional meetings where they are subject to peer pressure to improve their firms' safety record, and in requiring plants to conduct safety audits. Top management's commitment to safety can translate into improvements down the production chain, given workers' self-interest in improved safety.

The second policy implication is that the underlying regulatory framework sets the incentives that determine whether self-regulation programs attain their stated goals. Thus, self-regulation programs are best treated as complements to regulation. Our results, that RC reduced accidents, stand in contrast to the results from previous studies, that RC or other voluntary programs did not reduce TRI pollution significantly (King and Lenox, 2000; Morgenstern and Pizer, 2007; Gamper-Rabindran and Finger, 2010). Despite RC's stated goals to reduce both accidents and pollution, RC plants, on average, reduce their accidents but not their TRI pollution. This is because the regulatory framework yields greater net benefits from reducing the likelihood of accidents, e.g., reduced insurance and expected liability costs, than from reducing their TRI pollutants, some of which are unregulated (section 5).

2. Responsible Care and industrial accidents

2.1 Self-regulation

Self-regulation programs operate within a framework of regulations and liability. Chemical plants are subject to the 1992 OSHA Process Safety Management (PSM) rules, which set requirements for management processes when using highly hazardous chemicals, and the 1996 Environmental Protection Agency (EPA) Risk Management Program (RMP), which require plants with specific chemicals to undertake accident prevention programs. Plants are also subject to worker compensation laws, which hold employers liable for work-related deaths and injuries (Kleindorfer et al., 2003).

In response to the Bhopal and Three Mile Island accidents, the chemical and nuclear sectors launched self-regulation programs, i.e., RC and the Institute of Nuclear Power Operations, respectively (Rees, 1994; Rees, 1997). By restricting their membership to those firms that commit to adhere to codes of conduct, the self-regulation program can potentially distinguish purportedly lower risk firms (members) from purportedly higher risk firms (non-members). The self-regulation program, however, faces a collective action problem among members. While all members would benefit if the self-regulation program successfully achieves its stated goals of risk reduction, each member has an incentive to free ride, i.e., join the program but not comply with the codes. The trade association's inability to impose sanctions constrains its ability to limit free-riding (Lyon and Maxwell, 2004; Prakash and Potoski, 2007; Barnett and King, 2008).

Whether self-regulation programs successfully reduce risk is debated. On the one hand, industries have a strong motivation to succeed in self-regulation. These programs can potentially forestall the state's imposition of stricter and more costly regulations (Maxwell et al., 2000). Dawson and Segerson's (2008) theoretical study notes that as long as a subset of firms comply with their commitments, even if other firms free-ride, the self-regulation program can achieve its goals. The compliers are those firms which would face significant costs from more stringent regulation should the self-regulation program fail. On the other hand, Glachant's (2007) theoretical study suggests that in some cases, firms enter self-regulation programs without any intention to comply with their commitments, and then lobby for the weakening of the final legislation. Firms are able to not comply with their commitments because their non-compliance is not immediately observable.

2.2 Responsible Care and potential improvements to participants' safety culture

The two major factors that influence plants' safety are: (1) the senior management's commitment to safety (Pidgeon and O'Leary 2000, Krause, 2004); and (2) the ability of the management and the organization to learn from errors (Reason, 1997, cited in CSB-Texas City, 2007). Further details on the role of top management in plant safety are in the Online Appendix I. Regulations, such as the PSM and RMP rules, and liability in the case of accidents, provide incentives for top management to ensure a basic level of plant safety. RC imposes additional requirements that would bring the plants' safety records to the attention of top management and encourage improvements of their plants' safety.

Chief Executive Officers (CEOs) must sign off on annual reports submitted to the ACC on their firms' environmental health and safety performance (Yosie, 2003). In the absence of the RC requirements, plants must still report their accidents to OSHA, but there is no mechanism to ensure that senior management is made aware of their plants' safety records. CEOs also face peer pressure, which can potentially influence their adherence to RC membership codes. According to the NCBP (2011), "[RC's] success has turned less on the availability of such formal sanctions and more on informal disciplinary mechanisms such as peer pressure and institutional norms of compliance: 'Executives from leading firms pressure their non-compliant counterparts at industry meetings to adopt and adhere to the industrial codes.'" RC's codes include the Environmental Health and Safety (EHS), Process Safety (PS) and Community Awareness and

Emergency Response (CAER) codes (ACC, 1990).[8] These codes promote risk management in the production process, e.g., improving management of pressure or heat-related processes, improving management of flammable, reactive or corrosive chemicals, and minimizing workers' exposure to chemicals (Spellman, 1997).

RC participants must perform self-audits on their safety performance, which can uncover shortcomings in their safety systems. For example, RC requires self-audits of the Process Safety Code. "The code requires companies to have management practices in place to ensure, among other items—periodic assessment and documentation of process hazards, complete documentation on the hazards of materials, and sufficient layers of protection to prevent a single failure from leading to a catastrophic event" (CSB-First Chemical Corp, 2003). These RC features can serve the function of "attention correction," a term used by Scholz and Gray (1990) to describe the effect of bringing safety shortcomings to the attention of management. Top management's attention to safety can then translate into improvements down the production chain, given workers' self-interest in improved safety.

Ultimately, whether the RC program has reduced the likelihood of accidents is an empirical question. While RC features can *potentially* improve safety, the pre-2002 RC program may not provide sufficient incentives for plants to truly implement safety improvements. In particular, pre-2002, the ACC did not have a mechanism to verify plants' safety reports or to verify that plants corrected safety hazards uncovered during self-audits.[9] While the RC program

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[8] Details of RC's codes and management practices are described in ACC (1990).

[9] There are cases in which RC participating plants are made aware of defects in their process hazard analysis, but failed to correct those defects. For example, from OSHA's inspection and citation, Bayer CropScience learned that their process hazard analysis was defective, but the

did introduce third party certification in 2002, our study of the pre-2002 RC program, without third party verification, is of policy interest, because other programs share this characteristic and several industrial sectors lack independent third party certifiers (O'Rourke, 2003; Rosenthal and Kunreuther, 2010).[10]

3. Research questions and data

We test if RC, operating within its regulatory framework, reduced OSHA-reportable accidents. RC and the underlying regulatory and insurance institutions are interactive in their effects. Therefore, we provide an estimate of the impact of RC, given the underlying institutional framework, versus non-participation in the same framework. This estimate remains informative for self-regulation programs operating in comparable institutional settings.

Our sample of 23,780 plant-years in the chemical manufacturing sector (SIC-28) between 1988 and 2001 consists of 2,963 plants owned by 1,867 firms. This sample consists of SIC-28 plants which we have successfully linked across three databases and fulfill three conditions: they (i) report their pollution to the TRI, (ii) report their number of employees to Dun & Bradstreet (D&B) and (iii) are inspected at least once by OSHA between 1984 and 2009. Our TRI-D&B sample contains SIC-28 plants linked across these two databases. Our OSHA sample is derived from inspection reports for SIC-28 plants in the OSHA Integrated Management Information

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plant failed to fully implement corrective actions. Because their process hazard analysis remained defective, safety hazards were not identified and corrected, and those hazards contributed to a subsequent accident at the plant (CSB-Bayer CropScience, 2011).

[10] In 2002, with the launch of RC14001, the ACC required third-party verification of plants' conformance to the RC14001 technical standards (Moffet et al., 2004).

System (IMIS) database. [11] These reports are then matched by plant names, addresses, and SIC-4 code to generate plants' inspection histories. Using Fellegi and Sunter's (1969) matching techniques, we link the TRI-D&B sample with the OSHA sample using plants' names, addresses, geocoded locations and SIC-4 code.[12] Data on accidents is from the IMIS Fatality and Catastrophe Investigation Summaries data (OSHA form 170), also known as the Accident Investigation Summaries (AIS) database. Data on inspections, violations detected during inspections, and related penalties are from the IMIS Inspection database. Data on hazardous air pollutants are from the TRI. Pollutants are restricted to those chemicals reportable since 1987 to the TRI. Tract-level neighborhood demographics are from the Decennial Census, and SIC-4 industry variables are from the Bureau of Economic Analysis. We create annual plant-firm linkages using Mergent Online and Corporate Affiliations Database.

3.1 Accidents

OSHA mandates employers to contact OSHA within eight hours if a work-related accident occurs, i.e., at least one fatality occurs or at least three workers require inpatient hospitalization[13] (CPL 02-00-113 (2.113)). With minor exceptions, reporting to the AIS is

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[11] Plant-level details are recorded in the IMIS database only if they have been inspected at least once. Weil (1996) uses a similar restriction in his analysis of OSHA plants.

[12] The matching is implemented using FEBRL software (Christen, 2008). The algorithm provides an indication of the quality of the match between plants from the two separate databases. For matches that are border-line in quality, we undertake further library research to determine if there is a true match.

[13] This definition excludes offsite motor vehicle accidents, heart attacks that are not work-related, and homicides at the workplace. Prior to 1994 employers had 48 hours to report and the

consistent over time and covers the 29 states where the Federal agency implements OSHA programs, and the rest of the states that are authorized to implement OSHA programs. The AIS spans the years 1984 to 2005. On notification of accidents, OSHA investigates those accidents that are potentially related to violations of OSHA standards and OSHA inspectors issue citations on the confirmed violations (Mendeloff and Kagey, 1990). The AIS data has been found to be reliable; 85% of the fatalities that should be reported to OSHA are in fact being reported and inspections were at least planned for all the fatalities that should unambiguously be inspected (Safety Sciences, 1977, cited in Mendeloff and Kagey, 1990). We do not use the RMP accident database because its first reported accident is in 1994, i.e., 5 years after the start of the RC program (Kleindorfer et al., 2007).

We use three different definitions for accidents, all outcome variables are binary. Our first and broadest definition of accidents is the occurrence of an OSHA-reportable accident as recorded in the AIS for a plant-year. Our second narrower definition, RC or Process Safety (RC/PS) accidents, includes: (i) accidents related to violations of RC-related codes or (ii) process safety accidents, or both. For each accident, we code whether the investigation has cited at least one violation of OSHA standards related to RC codes. One may surmise that these accidents occur, in part due to these violations, because accident investigations focus on the causes of accidents and cite violations uncovered during the inspections.[14] For each accident, we also code whether it is a process safety accident, i.e., accidents that stem from chemical leaks, high

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threshold for reporting had been 5 inpatient hospitalization instead of 3 **(**29 CFR 1904.8. 1993 edition and 1994 edition)**.**

[14] This is an imperfect measure of accidents related to the violations of RC codes because all violations observed during inspections, including those unrelated to the accident, must be cited.

pressure, fires, or explosions, according to OSHA accident investigation summaries.[15] Process-safety accidents are difficult to contain and may turn catastrophic (Hofmann, Jacobs, Landy, 1995). Because attention to routine injuries can deflect attention away from underlying process safety issues (NCBP, 2011; Baker report, 2007, Elliott et al. 2008), we exclude "routine" injuries, unrelated to RC codes, that affect only a few workers in a given accident, such as injuries from falling objects or limbs being caught in machinery. Our third definition, restricted to accidents involving fatalities, captures the most severe incidents.

In our sample of 23,780 plant-years, we observe 304 accidents, and about two thirds of these are RC/PS accidents and about one third are fatal.[16] It is rare for a plant to experience more than one accident in a given year,[17] therefore, treating the accident outcome as a binary variable is appropriate. It is also rare for a plant to experience a large number of accidents in the entire sample period. Of the 304 accidents, 65.8% occur at plants with only one accident and 88.8%

[15] We code as process safety accidents, those accidents: (i) that involve chemical reactions, flammable liquids, over or under-pressure, gas, vapor, mist, fumes or smoke, or (ii) in which fatalities or injuries are related to chemical burns, heat burn, scalding or poisoning. We also include fatalities and injuries related to electrical shock because poor electrical design can contribute to larger scale accidents.

[16] The number of accidents, RC/PS accidents and fatal accidents are 126, 94 and 45 in RC plants; and 178, 118 and 65 in non-RC plants.

[17] Out of the 304 cases of all accidents, only 11 plants had two accidents and one plant had three accidents in the same year. Out of the 212 cases of RC/PS accidents, only five plants had two accidents and one plant had three accidents in the same year. Of the 110 fatal accidents, only one plant had two accidents in the same year.

occur at plants with two or fewer accidents between 1988 and 2001. Of the 212 RC-related accidents, 76.4% occur at plants with one accident and 93.4% occur at plants that have two or fewer accidents in the study period. Of the 110 fatal accidents, 90.1% occur at plants with only one accident during the study period.

3.2 Estimation model

Our estimation model for the impact of RC on accidents is:

Plant hazard level (accident outcome) $Y_{it} = 1\ [R_{it}\, \beta_1 + X_{it}\, \beta_2 > v_{it}\ ]$ Equation 1

Participation in RC $R_{it} = 1\ [Z_{it}\, \alpha_1 + X_{it}\, \alpha_2 > \varepsilon_{it}\ ]$ Equation 2

$$\varepsilon_{it}\ ,\ v_{it} \sim \mathrm{N}\ (0, \Sigma)$$

where observations are for plant i in year t, the dependent variable, Y is a dummy variable for the occurrence of at least one accident during a plant-year, R is a dummy indicating the plant's parent firm's participation in RC, X are covariates, and v_{it} and ε_{it} are the error terms. Z, the instrumental variable, captures the plant's parent firm's exposure to impending MACT regulations, as measured by the firm's share of pollution released into the environment that are HAPs (section 3.3).

We employ a bivariate probit model (Heckman, 1978) in which the outcome (the occurrence of an accident) and the treatment (RC participation) are each determined by latent linear index models with jointly normal error terms. This specification maps directly to two interrelated decision-making processes: (i) the decision to join RC by the plant's parent firm, as a function of covariates and the error term, ε_{it}, with that firm joining RC if its net benefits of joining exceed a threshold, and; (ii) the occurrence of accidents at a plant as a function of the observed covariates and an unobserved hazard shock, v_{it}, with accidents occurring if the combined hazard level and shock at the plant exceed a threshold. The terms v_{it} and ε_{it} may be correlated as *unobserved* factors, known by the firm, and may both affect the firm's decision to join RC and be related to the hazard level at the plant.[18] The bivariate probit corrects for firm's self-selection into RC based on unobserved factors and is correctly specified for a model with an endogenous dummy variable, i.e., the RC participation dummy. As described in section 4.2, we find significant correlation between the errors in the RC participation equation and the errors in the accident equation; therefore, our final estimation model must address self-selection.

The bivariate probit is our preferred specification, given the nature of our accident data. The mean likelihood of accidents in our sample period is low, amounting to only 1.28%. The linear IV does not impose that the predicted probabilities implied by the model range between 0 and 1. This problem is especially severe when the mean of the main outcome is close to either 0 or 1; therefore, the linear IV should not be used when the average probability of the dependent variable is not near 0 or 1 (Bhattacharya, Goldman, and McCaffrey, 2006). Indeed, we find that one third of the predicted probabilities from the linear IV estimated for our accidents data lie outside the [0,1] range.

The bivariate probit requires that both error terms are distributed bivariate normal for estimates to be unbiased (Angrist, 1999). Its identification relies on both the instrument and the functional form (Altonji, Elder and Taber, 2005). The bivariate probit remains our preferred specification because it may be less biased than the linear IV, even when the errors are non-normal (Bhattacharya, Goldman, and McCaffrey, 2006). In simulations with non-normal errors

[18] Alternatively, the firm may first observe the level of hazard at its plants, and then, make its decision on participating in RC. The key estimation issue is that the bivariate probit can address the firm's self-selection into RC based on factors unobserved by the researcher.

the bivariate probit leads to a smaller level of bias over various parameter configurations compared to Linear Probability Model (LPM), often with the smaller variance as well. The authors report that, "[the bivariate probit] nearly always, though not always, performs better than the LPM estimator."[19] We report bootstrap standard errors with 100 replications for the bivariate probit, as recommended by Chiburis, Das and Lokhsin (2011). This strategy addresses the concern that misspecification in the bivariate probit may lead to the underestimation of the standard errors.

3.3 Instrumental variable to address firms' self-selection into RC

As an instrumental variable for a plant's parent firm's participation in RC, we use the firm's share of pollution *released into the environment* that are hazardous air pollutants (HAPs). The instrument, the firm's HAP/TRI ratio, is defined as the ratio of HAPs emissions (as reported to the TRI) to total TRI air emissions for all plants owned by the firm. We argue that the firm's HAP/TRI ratio influences its contemporaneous decision to participate in RC, but does not directly affect plant-level accidents, conditional on their other included characteristics, such as plants' TRI emissions-intensity relative to their SIC-4 and the average TRI emissions-intensity in their SIC-4 relative to the chemical industry as a whole.

During our study period, plants in the chemical manufacturing sector face strict regulations on their emissions of HAPs with expected implementation dates in the late 1990s.

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[19] Simulations by Chiburis, Das and Lokshin (2011), reported in their Figure 5, indicate that for low probabilities such as 0.1, the bias is less for the bivariate probit than the linear IV. In related work, Horrace and Oaxaca (2003) conclude that even with a linear data generating process, the probit leads to lower mean squared errors than OLS, and the difference is largest when conditional probabilities are extreme.

The Clean Air Act requires the EPA to set MACT standards on plants that emit HAPs. MACT standards require existing and new chemical plants to install the technology that has been adopted by plants in the same production category that have achieved the best pollution control and the lowest pollution emissions (Solomon and Han, 2007). Firms whose plants have large shares of HAPs would have to reduce these plants' emissions in the future in response to the impending MACT standards, and would have to do so even in the absence of the RC program. Thus, these firms face little additional costs to meet RC's pollution prevention code, and are more likely, on average, to decide to join RC anyway to benefit from RC's positive publicity.

The instrumental variable, HAP/TRI ratio, is not likely to affect accidents, conditional on the included measures of TRI emissions-intensity. First, control technologies implemented to reduce HAPs emissions into the environment are distinct from actions undertaken to improve plant safety. MACT regulations set stricter emissions limit for HAPs emitted from process vents, storage tanks, wastewater streams, and equipment leaks.[20] Plants install control devices, such as thermal or catalytic oxidizers, which burn off a greater fraction of HAPs in air streams at high temperatures, or chemical absorbers, which absorb a greater fraction of HAPs prior to the release of the air streams into the environment (Van Asten and Martinson, 2005). In contrast, steps undertaken to improve safety include identifying and preventing excessive built-up of

[20] For example, the Miscellaneous Organic National Emission Standards for Hazardous Air Pollutants raised the requirement to controlling 95% of the HAP emissions from storage tanks (Van Asten and Martinson, 2005).

pressure in chemical processes, the loss of control of heat-related or reactive processes, or exposure of flammable liquids to ignition sources (Spellman, 1997).[21]

Second, during our study period, regulations aimed at reducing emissions to the environment do not account for workers' exposure to hazards.[22] Adam Finkel, Director of Health Standards Programs at OSHA between 1998 and 2003, notes that efforts to reduce stack emissions often do not account for worker exposure.[23] As of 2004, "there was no formal consideration of the overlap between environmental and occupational exposures (outside versus inside the plant) and the potential of pollution prevention strategies for addressing both" (Armenti, 2004). This disconnection stems from the distinct regulatory framework separating the EPA and OSHA and the agencies' lack of coordination (Armenti et al., 2003).[24] Gillen (2000),

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[21]We also discussed the distinction between actions for reducing MACTs and actions for reducing plant accidents with Jeffrey Siirola, formerly with Eastman Chemical Company, Distinguished Service Professor, Carnegie Mellon University, pers. comm. with Shanti Gamper-Rabindran. 26 October 2011.

[22] OSHA's and EPA's interagency committees coordinate their interactions in other areas, such as their activities under EPA's RMP and OSHA's Process Safety Management.

[23] Dr. Adam Finkel in phone conversation with Shanti Gamper-Rabindran, 15 January 2011.

[24] Regulations curbing industry's emissions of HAPs to the environment, due to the failure to consider effects on worker safety, can even worsen workers' exposure. In one example, to improve air quality standards, the California Air Resources Board decided in 1997 to phase out chlorinated solvents used in the auto repair industry; unfortunately, that policy inadvertently contributed to the overexposure of workers to the substitute chemical hexane which caused peripheral neuropathy (Wilson et al, 2007).

from the EPA Office of Pollution Prevention and Toxics, reports that as of 2000, "pollution prevention strategies have not typically included the additional step of coordinating on worker health issues."

Third, even if impending MACT regulations led plants to reduce their HAPs, that reduction would not translate to significant reductions in accidents. Many accidents stem from fires, explosions, or acute worker exposure to toxic chemicals, but only a small proportion of HAPs are flammable or acutely toxic. Out of 190[25] HAPs, six are flammable and 26 are acutely toxic. Also, the reduction of HAPs that are carcinogenic or chronically toxic is not likely to reduce deaths or hospitalizations in the short-term because of the long latency period between the chronic exposure to chemicals and the onset of major symptoms (Robson and Toscano, 2007). In our accidents database, most cases of deaths or hospitalizations due to chemical exposure occur as a result of chemical spills that resulted in chemical burns. Finally, there is little evidence of a link - whether none, positive, or negative - between pollution reduction strategies in production processes and occupational hazards (Sivin, 2002). Indeed, a case study documents that the alteration to the production method in order to eliminate the release of pollutants into the environment inadvertently led to an increase in workers' exposure (Sivin, 2002). Additional case studies, presented at an OSHA-EPA conference, indicate that plants complied with emissions limitations from point sources by increasing the fraction of a toxic pollutant that remains in the workplace (Robson and Toscano, 2007).

We have also investigated the possibility that the MACT requirements may have led to plants changing their processes to reduce both HAPs and accidents. Our conversations with the

[25] The top chemicals associated with RMP accidents are ammonia (non-HAP), chlorine (HAP) and flammable mixtures (Kleindorfer et al., 2003).

industry and the EPA have not yielded evidence for this scenario. Finally, our excluded variable would not be invalidated if *after our study period*, MACT regulations affect occupational hazards, whether positively or negatively. Interestingly, significant coordination between policies on emissions to the environment and workers' exposure does not occur even three years after the end of our study period (Armenti, 2004).

We specify the instrument as a firm's HAP/TRI ratio to better capture its exposure to impending MACT regulations. The alternative specification of the instrument as a firm's total HAPs is prone to the criticism that total HAPs may be more highly correlated to our included TRI emissions-intensity variables, and therefore, less highly correlated with MACT regulations, conditional on the included TRI emissions-intensity variables. Our main analysis uses total pounds to aggregate HAPs and TRI because the MACT regulations focus on reducing the pounds of HAPs released into the environment.[26]

3.4 Covariates

Our accident regressions control for regulatory variables, i.e., OSHA inspections and penalties. For our study to be valid, we need to control for the association between inspections/penalties and accidents, but we do not need to isolate the causal effect of inspections/penalties on accidents. A positive association between inspections/penalties and accidents could arise from OSHA's targeting of inspections to plants, firms, and SIC-4 industries

[26] As an alternative specification for the instrument, we weight HAP and TRI values by their toxicity-weights as reported in the Risk Screening Environmental Indicators (RSEI) model (EPA, 2010). Results are in the Online Appendix IV: Table A3.

that have lower safety levels and therefore a higher likelihood of accidents[27] (Tai, 2000). Conversely, a negative association between accidents and inspections/penalties could stem from the potential for inspections and penalties to raise plants' safety levels (Scholz and Gray, 1990; Gray and Scholz, 1993) and thus reduce their likelihood of accidents. We control for inspections and penalties in the previous year and those accumulated in the prior two to five years because enforcement requires time to produce their full effect (Scholz and Gray, 1990). We include inspections and penalties at the firm's plants, the SIC-4 industry and the state to account for the general deterrence effect of inspections (Gray and Mendeloff, 2005). A dummy is included for plants located in the 29 states where the Federal agency implements the OSHA program (Gray and Mendeloff, 2005).

Higher premiums for worker compensation insurance can influence the firms' safety level; [28] but firm-level insurance data is not publicly available. Larger firms pay insurance premiums that reflect their previous safety record; while smaller plants pay premiums that are the same for all firms in the same industry-occupation category (Ruser, 1985). To proxy for the variation in insurance premiums, we use: (i) the number of average employees in a firm's plants, a dummy for single-plant firms, and the number of plants owned by the firm to capture firm size;

[27] A subset of OSHA's inspections target plants, firms, and industries with poorer safety records; while another subset, i.e., programmed inspections, are undertaken randomly within state-industry cells (Gray and Mendeloff, 2005).

[28] State worker compensation laws make employers liable for all of an injured worker's medical expenses and a portion of lost wages. Except for the largest firms which self-insure, employers are required to purchase insurance to cover their potential liabilities (Ruser, 1985).

(ii) the dollar penalty accrued in the past 5 years to provide a measure of the firm's safety record; and; (iii) SIC-4 industry dummies.

We control for plant size using the log of plant-level number of employees. We also control for a plant's union status[29] and the share of the unionized plants among the plants owned by the parent firm. Again the validity of our study requires our regression to simply control for the association between unions and accidents. A negative association between unions and accidents can arise if unions improve plant safety, e.g., by providing union members with greater information about occupational risks, and a mechanism for voicing their concerns over this risk (Sandy and Elliott, 1996), or by engaging in collective bargaining with management (Bacow, 1980). Conversely, union status and accidents can be positively related if workers in plants with greater inherent hazards are more likely to unionize, or if workers in unionized plants are more likely to be hospitalized for reporting reasons (Sandy and Elliott, 1996). Injured workers in unionized plants may feel protected by the union, and are more able to insist on receiving inpatient hospitalization, thus, triggering the threshold of three in-patient hospitalizations for OSHA reportable accidents.

We control imperfectly for the inherent hazards of the SIC-4 industry and the plants in two ways.[30] First, we include SIC-4 dummy variables and year dummies to control for industry-

[29] The IMIS database provides the information on a plant's union status in the most recent inspection year.

[30] We do not use the RMP data on hazardous chemicals stored on site because (1) that data is not available before 1999, and (2) we suspect minimal overlap between our chemical database and the RMP. Elliott et al. (2008) link only 228 chemical plants out of the 15,219 RMP plants to OSHA's Occupational Injury and Illnesses database.

specific production technologies, which influence both the inherent hazards of the industry and the costs of adopting safety measures (Mendeloff and Gray, 2005). Second, we control for the pollution intensity of the plant relative to other plants operating in the same SIC-4 industry. A plant's pollution intensity is measured as the ratio of its toxicity weighted TRI air pollution to its number of employees.[31] Time dummies account for time variations, including changes in the reporting threshold of five accidents to three accidents in 1994, as well as changes in production technologies over time that influence the inherent hazards of processes and the costs of safety precautions. The socioeconomic characteristics of a plant's neighborhood captures the community pressure on plants to reduce their hazard level (Hamilton, 1995; Elliott et al., 2004), particularly, risks of chemical release, fires, or explosions that can endanger surrounding communities. Neighborhood characteristics include the shares of whites, poor people, and non-high school graduates at the tract-level. Kleindorfer et al.'s (2004) multi-sector study reports that a firm's greater financial resources are associated with fewer RMP accidents. For a given plant, we control imperfectly for its parent firm's resources using the log of a firm's total employees at its plants, a dummy for a single-plant firm, and the log of the number of plants owned by a firm. These measures that are relative to firms' size can, however, influence accidents through the alternative mechanisms described above. We choose not to link to financial variables because our study will face significant reductions in sample size, making inference impossible.[32]

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[31] Gamper-Rabindran and Finger's (2010) analysis of SIC-4 industry level data show that, in measuring pollution intensity, plant-level employees serve as a good proxy for output. For the chemical sector, most of their TRI pollution releases are to air.

[32] Kleindorfer et al. (2004) linked the RMP to the financial variables, which reduced their sample size from 15,219 plants to only 2,025 plants in all sectors.

4. Results

4.1 Summary statistics

In our unbalanced panel data between 1988 and 2001, there are 228 RC-participating firms that own 1,037 plants; and 1,735 non-RC firms that own 2,293 plants. Over time, few plants change their RC status; therefore, our identification relies on the cross-sectional variation in the data. The probability of participation in RC with covariates set at the sample means is 16.1% for all plants. Comparison of Table 1, columns 1 and 2 indicate several similarities and differences across RC and non-RC plants; therefore, we include a full set of control variables in our regression analysis. On average RC plants face greater likelihood of all accidents, RC/PS accidents and fatal accidents (1.59, 1.19 and 0.57 accidents per 100 plants, respectively) than do non-RC plants (1.12, 0.74 and 0.41 accidents per 100 plants, respectively). The greater likelihood of accidents on average for RC plants is partly explained by RC plants' larger average size (measured in number of employees) and their parent firms' larger average size (measured in mean number of employees at firms' plants and the number of plants belonging to firms). These factors are associated with greater likelihood of all accidents or RC/PS accidents (Table 4). RC and non-RC plants have a fairly similar probability of being inspected (12% versus 11%) and the composition of their inspections is fairly similar. However, shares of inspections that lead to violations or penalties are smaller among RC plants than non-RC plants. For inspections that do lead to penalties, RC plants at the highest percentiles of penalties receive much larger penalties than the corresponding non-RC plants. This small subset of RC plants drives the observation in Table 1 that the average penalty for RC plants is much greater than that for non-RC plants. On closer examination, penalties for most RC plants are only slightly larger than non-RC plants, e.g., penalties for RC plants at the 25th, median and 75th percentiles of penalties, are only 30%, 25% and 36% greater than those for corresponding non-RC plants, respectively.

Our database represents the larger plants in SIC-28.[33] We have successfully matched IMIS inspection data to 2,421 of the 3,253 TRI-D&B plants (74.4%), analyzed in Gamper-Rabindran and Finger (2010). Comparison of our sample of linked plants (Table 1, column 1) and SIC-28 OSHA plants that are not linked to our data (Table 1, column 5) indicate that, while we have only matched 25% of the IMIS data to our database, our final database is fairly representative of plants in the chemical sector in their compliance characteristics. The linked sample and the non-linked sample have similar shares of inspections that result in violations, and the counts of violations conditional on non-zero violations. While the mean penalty conditional on non-zero penalty is larger in the linked sample than in the unlinked sample, the median penalty conditional on non-zero penalty, a measure which is less prone to outliers, is fairly similar in the two samples.

4.2 Preliminary regressions

We estimate a probit model of plant's RC participation on firms' HAP/TRI ratio and a full set of covariates. These covariates are the same as those in the accidents regression. Details of the model are in the Online Appendix II: Table A1. We find that a plant's parent firm's HAP/TRI ratio is positively associated with the plant's parent firm's participation in RC. The estimated HAP/TRI coefficient of 0.342 is statistically significant at the 1% level. This result corresponds with our hypothesis that firms with large HAP/TRI ratios anticipate having to

[33] Our plants exceed the reporting threshold for emissions in the TRI. The reporting threshold for number of employees in IMIS is 11 or more employees. The D&B database tends to include plants with larger numbers of employees.

reduce pollution under the MACT regulations; and because they would have to reduce their emissions regardless of RC, they face little additional costs in meeting RC's pollution prevention code, and are thus, more likely to join RC. While no tests can positively determine that an instrument is valid, we check if the instrument is conclusively invalid. The Likelihood Ratio (LR) test, which compares the fit of models with and without the excluded variable, rejects the null that the firm's HAP/TRI ratio has no effect on the probability of a plant being a member of RC. The LR test p-value is less than 0.001. Diagnostic tests for weak instruments are not available for the probit model (Nicholl, 2011).

Next, we estimate three specifications on RC's association with accidents, i.e., the probit, bivariate probit, and linear IV models (Table 2). Using the bivariate probit, we test for the exogeneity of RC in relation to the outcome of accidents. The estimated correlation coefficient, rho, is positive and significant at the 10% level for all accidents, significant at the 5% level for PS/RC accidents, and insignificant for fatal accidents (Table 2, panel B). The positive rho indicates that plants that are more likely to have accidents are also more likely to join RC.

We compare the coefficients on the RC participation dummy from the bivariate probit models, which address self-selection (Table 2, panel B), and from the probit models, which does not address self-selection (Table 2, panel A). This comparison indicates that when self-selection is addressed, we find a greater impact of RC at reducing the likelihood of accidents. While the coefficients from both types of models are negative, those from the bivariate probit models are larger in magnitude. The coefficients for the bivariate probit are statistically significant for both all accidents and RC/PS accidents; while those for the probit are statistically significant for all accidents only. This pattern of plants with greater likelihood of accidents self-selecting into RC is similar to the pattern of more polluting plants self-selecting into RC, detected in Gamper-Rabindran and Finger (2010).

The linear IV (Table 2, panel C), which is inappropriate for reasons outlined in section 3.2, yields coefficients that are smaller in magnitude than the marginal effects from the bivariate probit. Furthermore, the linear IV estimates are not statistically significant. The observation that these two models yield different results in our sample is unsurprising. The bivariate probit and linear IV typically produce similar estimates when the predicted probability is close to 0.5 (Angrist and Pischke, 2009), but our accident data take on more extreme probability values.

4.3 Results: accidents

Results from our preferred specification, the bivariate probit models (Online Appendix III: Table A2), are used to calculate RC's treatment effects on the likelihood of accidents (Table 3) and the marginal effects of other factors that are associated with accidents (Table 4). The coefficient on the RC participation dummy provides the estimated impact of RC on accidents. RC's Average Treatment Effects (ATE) on accidents, which is the average of the marginal effects for all plants in the sample, are presented in Table 3 column 3. The ATE estimates are relevant in considering the anticipated program effect if a program like RC were to be rolled out in the population of chemical plants that are similar to the plants in our sample. As discussed earlier, our sample is likely to represent the larger of the plants in the US chemical manufacturing sector. We find strong evidence that RC reduces all accidents and RC/PS accidents. RC's average treatment effect is to reduce the likelihood of all accidents by 1.76 accidents per 100 plants in a given year (Table 3, column 3) or equivalently, RC reduces the likelihood of all accidents by 71.3%. RC's average treatment effect is calculated from the difference in the estimated likelihood of all accidents if every plant in our sample had participated in RC (0.71 accidents per 100 plants in a given year) and that estimated likelihood if every plant had not participated in RC (2.46 accidents per 100 plants in a given year) (Table 3, column 2 and 1 respectively). The estimated likelihood of accidents is calculated using the estimated coefficients from the bivariate probit model and the plants' true covariates, with the RC participation dummy set to one or zero, respectively.

Using the narrower definition of accidents, we find even stronger average treatment effects of RC on RC/PS accidents. RC's average treatment effect is to reduce the likelihood of RC/PS accidents by 2.92 accidents per 100 plants in a given year (Table 3, column 3) or equivalently, RC reduces the likelihood of RC/PS accidents by 87.4%. Stronger effects of RC on the RC/PS accidents are compatible with RC's codes of conduct on process safety, environmental and health safety, and management practices recommended for implementing these codes. We find that the estimates for fatal accidents are negative, but not statistically significant. The imprecision of the estimates is likely due to the small number of fatal accidents in the analysis.

RC's Average Treatment effects on the Treated (ATT), which is the average of the marginal effects for RC participating plants, are reported in Table 3 column 6. The ATT estimates are relevant in understanding the effect of the existing RC program on the plants that had, in fact, participated in the program. Consistent with the ATE estimates, the ATT estimates indicates that RC causes a sizable reduction in all accidents and RC/PS accidents, and the reductions are much larger for the RC/PS accidents. RC's treatment effect on the treated is to reduce the likelihood of all accidents by 2.99 accidents per 100 plants in a given year. This effect is calculated from the difference in the estimated likelihood of all accidents for RC plants (1.32 accidents per 100 plants) and the estimated likelihood of all accidents if those RC plants had not participated in RC (4.31 accidents per 100 plants) (Table 3, columns 4-6). RC's treatment effect on the treated is much larger on RC/PS accidents, i.e., the reduction in accidents is 5.75 accidents per 100 plants in a given year (Table 3, columns 4-6). The percentage reductions for all accidents and RC/PS accidents are substantial (69.3% and 85.9%, respectively).

Our results are robust to the addition of dummies for OSHA's ten administrative regions. Coefficients for the RC participation dummy from these specifications are negative and similar in magnitude to the corresponding coefficients for each accident specification in our main regressions. The coefficients for the RC dummy in all accidents, RC/PS accidents and fatal accidents specifications (-0.450, -0.805, and -0.202, respectively) are statistically significant at the 5% level, 10% level and not statistically significant, respectively.

Our preferred specification is the bivariate probit which can address firms' self-selection into RC based on unobserved factors. In contrast, the Propensity Score Matching method (PSM), used in recent studies (Kim and Lyon, 2011; Pizer, Morgenstern and Shih, forthcoming) cannot address this key problem in estimating the impact of self-regulation programs. We estimate the PSM model for comparison, and the details are in the Online Appendix V: Table A4. Overall, the PSM results are compatible with our main results from the bivariate probit, i.e., that RC reduces all accidents and PS/RC accidents. The PSM estimates are about half the size of the estimates from the bivariate probit. The smaller magnitude of the PSM estimates is consistent with our findings in section 4.2, that not addressing self-selection would lead to the understatement of the effects of RC in reducing accidents.

4.4 Economic significance of the reduction in the probability of accidents

We provide a simple back-of-the-envelope calculation to illustrate the economic significance of the size of the reduction in the probability of accidents. Our upper-bound estimate of the average costs of an OSHA accident is $124 million. This value comes from Broder and Morrall's (1991) study of the decline in stock market value of firm in response to an accident at an OSHA regulated plant, which can potentially capture property damages and liability costs.[34] This $124 million is likely to represent larger losses from accidents because the study examines publicly traded firms, which tend to be larger firms, whose accidents are significant enough to be reported in the Wall Street Journal. Our lower-bound estimate of $26 million for an accident comes from a Charles River Associate (1989) study, cited in Broder and Morell (1991), of property damage incurred in OSHA-related accidents in the chemical and petroleum industries between 1982 and 1988. That study examined accidents that involved property damage reported in regional newspapers. The average treatment effect on the treated estimates indicate that RC reduces the likelihood of all accidents by 2.99 accidents per 100 plants in a given year (Table 3, column 3). This reduction in the likelihood of accidents, accounting for the 1,037 average plants that participate in RC, translates into savings between $0.8 billion to $3.8 billion per year, based on 1990 values.

4.5 Other factors that influence accidents

We calculate the association between a given covariate and the likelihood of accidents, by setting the values of the other covariates at the mean of the sample, and using estimates from the bivariate probit model. From the environmental justice perspective, our finding that plants located in neighborhoods with lower shares of whites are associated with greater likelihood of

[34] These costs may still be an underestimate of the social costs from accidents. Imperfections in the legal process can prevent workers from recovering their full costs (e.g. value of life, loss of income, and pain and suffering). In such cases, the stock market decline would not fully capture the social costs of accidents because part of the costs is shifted onto workers.

accidents is of concern. One standard deviation decline in the share of whites in the plants' neighborhoods is associated with an increase in the likelihood for all accidents and for RC/PS accidents by 0.13 accidents per 100 plants (Table 4). These are large increases relative to the likelihood of all accidents (0.77 accidents per 100 plants in a given year) and RC/PS accidents (0.66 accidents per 100 plants in a given year) for the mean plant.

One standard deviation increase in a plant's pollution intensity relative to its SIC-4 industry is associated with an increase in the likelihood of all accidents and RC/PS accidents by 0.25 accidents and 0.27 accidents per 100 plants in a given year, respectively. This variable, may capture, albeit imperfectly, the hazards inherent in a plant relative to others in its SIC-4 industry. Plant size is associated with greater likelihood of accidents. The log of a one standard deviation increase in plant-level employees and a similar increase in mean employees at the firm's plants is associated with an increase in the likelihood of all accidents by 0.15 and 0.31 accidents per 100 plants in a given year, respectively. Estimates for the two measures of unionization are not statistically significant. This finding may reflect the potentially opposing effects of unionization on plant safety, as discussed in section 3.4.

Larger number of inspections at the plant in the two to five years prior, by one standard deviation, is associated with a higher likelihood of all accidents and RC/PS accidents, i.e., 0.19 accidents per 100 plants in a given year. This positive association arises from the targeting of inspections at plants with poorer safety records (section 3.4). Plants' location in states with federally-run OSHA is associated with lower likelihood of accidents and RC/PS accidents, but higher likelihood of fatal accidents. Nevertheless, the literature does not provide any indication that federally-run programs and state-run programs differ in their effectiveness. Three industries are associated with a lower likelihood of accidents, i.e., Carbon Black, Diagnostic Substances, and Paints, Varnishes, Lacquers and Enamels.

5. Conclusion

We conclude that RC, operating within the regulatory framework in the chemical manufacturing sector, reduces the likelihood of accidents at participating plants. RC's treatment effect on the treated is to reduce the likelihood of accidents by 2.99 accidents per 100 plants in a given year (Table 3). This 69.3% reduction in the likelihood of accidents, accounting for the plants that participate in RC, translates to back-of-the-envelope avoided losses of $0.8 billion to $3.8 billion per year. RC also reduces the likelihood of more narrowly-defined accidents, i.e., process safety accidents and accidents related to violations of RC codes, by 5.75 accidents per 100 plants in a given year or by 85.9% (Table 3).

Our results, that RC reduces the likelihood of accidents, correspond to the features of the RC program that provide additional incentives, beyond regulations and potential liability for accidents, for plants to improve their safety. In particular, RC features can raise management's attention to safety and their ability to correct errors, two key factors for improving safety (Scholz and Gray, 1990; Belke, 1998; CSB-Texas City, 2007; Baker Report, 2007; NCBP, 2011). RC features alert CEOs to the hazard level at their plants, by requiring CEOs to sign off on reports to the ACC on process safety incidents and accidents at their plants (Yosei, 2003), and by requiring self-audits that can potentially uncover shortcomings in the safety systems (CSB-First Chemical Corp, 2003). RC features also subject CEOs to peer pressure to improve their plant safety, by requiring each CEO to attend quarterly meetings with their regional groups and discuss their progress towards RC goals (NCBP, 2011).

RC mandates membership codes on workplace safety and on pollution prevention. Our results that RC reduces the likelihood of accidents stand in contrast to previous studies' results that RC and other voluntary programs cause little or no reduction in TRI pollution (King and Lenox, 2000, Morgenstern and Pizer, 2007; Gamper-Rabindran and Finger, 2010). This dichotomy, that RC plants reduce their likelihood of accidents but fail to reduce their pollution, reveals an important lesson in the operation of self-regulation programs. The underlying regulatory and insurance framework, by affecting the net benefit to plants from reducing their accidents or pollution, influences plants' decisions in attaining their stated goals in self-regulation programs. Specifically, the regulatory framework results in plants reaping greater net benefits when they undertake actions to reduce accidents, than when they undertake actions to reduce TRI pollution.[35] On the benefits side, the implementation of RC codes and management practices can translate into a lower likelihood of accidents, and in turn, reduce potential liability and insurance costs (Er, Kunreuther, Rosenthal, 1998). In contrast, plants' reduction of TRI pollutants, several of which are unregulated, does not necessarily yield profits. Konar and Cohen (2001) note that their finding of a negative correlation between firms' financial performance and their TRI releases may stem from firms with stronger financial performance undertaking better environmental management.[36] On the cost side, RC's management practices can raise

[35] Steps to improve plant safety, such as minimizing risk from pressure or heat-related processes and chemicals that are flammable, reactive or corrosive, do not necessarily reduce emissions of TRI chemicals to the environment; many of the TRI chemicals are not flammable, reactive or corrosive (Spellman, 1997).

[36] In contrast to TRI emissions, major pollution releases that result in greater Superfund liability can adversely affect firms' capital costs (Garber and Hammitt, 1998).

management's attention to safety. Increased management attention to safety and organizational changes can lead to a reduced likelihood of accidents (Scholz and Gray, 1990).[37] In contrast, to meet pollution reduction goals, organizational changes alone do not suffice, instead investments are needed to redesign the production process or to treat end-of-pipe pollution (Allen and Shonnard, 2001). The view that improving safety can be achieved at lower costs than reducing pollution is compatible with Deily and Gray's (2007) observation that, "EPA regulations frequently require large equipment investments," while OSHA regulations are generally less costly but more detailed.

The observation that, on average, RC plants meet RC's codes on plant safety but fail to meet RC's codes on pollution reduction, which corresponds to the underlying regulatory and insurance framework, provides an important policy lesson on self-regulation programs. The strength of the underlying regulatory framework, which affects plants' costs and benefits, are likely to influence whether plants attain their stated goals in self-regulation programs. Therefore, self-regulation programs should be treated as complements, and not substitutes, to regulatory programs.

Our study, the only one to date that evaluates the impact of self-regulation on accidents, focuses on RC because it is widely emulated. To assess the potential role of self-regulation in other sectors, such as oil and gas drilling, one would need to examine the extent to which features of RC are adopted and to compare the regulatory frameworks in that sector relative to

[37] Our point is that there are potentially low cost changes, such as organizational changes, that can bring about marginal improvements in safety. There are, of course, other cases in which improvements in plant safety would require large capital investments.

the chemical manufacturing sector. Future work should assess that self-regulation program, if and when it is implemented.

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Table 1. Summary statistics: Means of variables for various subsets of plants for the period 1988 to 2001

	[1]	[2]	[3]	[4]	[5]
	RC & non-RC	RC	Non-RC	Comparison	Non-linked
	plants	plants	plants	RC & Non-RC plants	SIC-28 plants
No. obs. in plant-years	23,780	7,929	15,851		-
No. plants	2,963	1,037	2,293		14,519
No. firms	1,867	228	1,735		-
Frequency of Accidents (# accidents/plant-years)					
- All Accidents	1.28%	1.59%	1.12%	***	-
- RC/PS accidents	0.89%	1.19%	0.74%	***	-
- Fatal accidents	0.46%	0.57%	0.41%	***	-
Firms' HAP/TRI	0.77	0.76	0.77	*	-
Plant's union status	33.3%	44.1%	27.9%	***	15.9%
# plant employees	159	278	100	***	-
# plants owned by a parent firm	8	16	4	***	-
Plant in state with federally-run OSHA	68.9%	71.3%	67.7%	***	61.3%
Plant's neighborhood: % urban	75.1%	69.4%	78.0%	***	-
Plant's neighborhood: % white	77.3%	78.8%	76.6%	*	-
Plant's neighborhood: % < high school	32.2%	32.0%	32.2%		-
Plant's neighborhood: % poverty	15.2%	14.9%	15.3%		-
% obs. with inspections	0.11	0.12	0.11	*	-
No. obs. with inspections	2,699	952	1,747		9,205
% inspections that lead to violations	70.3%	63.9%	73.8%	***	68.7%
% inspections that lead to penalties	60.0%	52.7%	63.9%	***	54.9%
# violations for obs. with non-zero violation	7.49	8.11	7.20	***	6.47
Mean penalty for obs. with non-zero penalty	$28,662	$69,489	$10,313	***	$12,515
Median penalty for obs. with non-zero penalty	$3,200	$3,750	$3,000		$2,000
Log (penalty) for obs.w.non-zero penalty	8.13	8.38	8.01		7.65
No. obs. with non-zero violations	1,897	608	1,289		6,320
No. obs. with non-zero penalty	1,619	502	1,117		4,383

Notes: The differences in the means of RC and non-RC plants are statistically different at the ***1%. **5%, and *10% level. The non-linked OSHA sample in column [5] are SIC-28 plants that have been inspected at least once between 1984 and 2009. The inspection data provides information on plants' union status, location, and SIC-4. However, these plants are not linked to our main sample and are excluded from our main analysis.

Table 2: Comparison of the estimated impact of RC on accidents from the bivariate probit, probit and linear IV models

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
	All accidents			RC/PS accidents			Fatal accidents		
	n=304			n=212			n=110		
	Rho	Probit Coeff	Average Marginal Effects	Rho	Probit Coeff	Average Marginal Effects	Rho	Probit Coeff	Average Marginal Effects
Panel A: Probit									
RC participation dummy		-0.097*	-0.003*		-0.060	-0.001		-0.067	-0.001
		(0.059)	(0.002)		(0.088)	(0.001)		(0.094)	(0.001)
Panel B: Bivariate Probit									
RC participation dummy	0.287*	-0.542*	-0.018*	0.522**	-0.916*	-0.029*	0.154	-0.305	-0.004
		(0.287)	(0.011)		(0.517)	(0.017)		(0.392)	(0.006)
Panel C: Linear IV									
RC participation dummy			-0.003			-0.001			-0.001
			(0.005)			(0.004)			(0.003)

Notes: No. obs.=23,780. RC/PS accidents denotes (i) accidents related to violations of OSHA standards that are related to RC codes of conduct or (ii) process safety accidents, or both. All specifications include covariates as in the main regressions (see Table 3). We compare the average marginal effects from the bivariate probit with coefficients from the linear IV. The average marginal effects of the bivariate probit is calculated by averaging the marginal effects for all plants in our sample. In turn, the marginal effect at a given plant is calculated from the difference in (1) the predicted accident at the plant (measured with the estimated coefficients and the plant's covariates) with the RC dummy set to one, and (2) the predicted accident measured analagously with the RC dummy set to zero. Bootstrap standard errors with 100 replications are reported for the bivariate probit and probit regressions. Statistically significant at the ***1%, **5% and *10% level, respectively.

Table 3: Treatment effects of RC on the likelihood of accidents

	[1]	[2]	[3]		[4]	[5]	[6]
	Average Treatment Effect (ATE)				Average Treatment on the Treated (ATT)		
		All plants				RC plants	
		n=23,780				n=7,929	
All accidents	RC=0	RC=1	RC effect		RC=0	RC=1	RC effect
	2.46%	0.71%	-1.76%*		4.31%	1.32%	-2.99%*
RC/PS accidents	3.35%	0.42%	-2.92%*		6.70%	0.95%	-5.75%*
Fatal accidents	0.69%	0.30%	-0.39%		1.10%	0.50%	-0.60%

Notes: The RC treatment effects are calculated using estimated coefficients from the main bivariate probit regressions in Table 3. The ATE is the average of the marginal effects calculated over all plants in the sample. The ATT is the average of the the marginal effects calculated over RC participating plants in the sample. The RC=0 column estimates the probability of accidents using the estimated coefficients and the plants' true covariates, and the RC participation dummy set to zero. The RC=1 column estimates the probability of accidents in a similar way, but with the RC participation dummy set to one. The RC treatment effect is the difference between these two probabilities. E.g., the ATE estimate indicates that RC reduced all accidents by 1.76 accidents per 100 plants in a given year. Statistically significant at the ***1%, **5% and *10% level.

Table 4. Marginal effects of factors associated with the likelihood of accidents calculated from the bivariate probit coefficients

	[1]	[2]	[3]	[4]	[5]	[6]
	All Accidents		RC/PS accidents		Fatal accidents	
	Prob Acc.=0.765%		Prob Acc.=0.655%		Prob Acc. = 0.256%	
	dPr(Acc)	ΔPr(Acc>0)	dPr(Acc)	ΔPr(Acc>0)	dPr(Acc)	ΔPr(Acc>0)
	dX	$\mid \Delta\sigma_x)$	dX	$\mid \Delta\sigma_x)$	dX	$\mid \Delta\sigma_x)$
†RC participation dummy	-0.974%*		-1.379%*		-0.215%	
Plant's pollution intensity relative to that of its SIC-4	0.711%***	0.252%***	0.762%***	0.270%***	0.163%	0.058%
Pollution intensity of the plant's SIC-4 industry	0.661%	0.203%	0.678%	0.208%	0.413%	0.127%
Plant's neighborhood: % white	-0.455%**	-0.127%**	-0.476%**	-0.133%**	-0.176%	-0.049%
Plant's neighborhood: % urban	0.127%	0.049%	0.132%	0.051%	-0.012%	-0.005%
Plant's neighborhood: % poor	-0.777%	-0.114%	-0.522%	-0.077%	-0.173%	-0.025%
Plant's neighborhood: % < high school education	0.589%	0.098%	0.332%	0.055%	0.223%	0.037%
†Dummy for unionized plant	0.212%		0.013%		0.030%	
% firm's plants that are unionized	-0.194%	-0.069%	0.033%	0.012%	-0.104%	-0.037%
Log (# plant employees)	0.113%**	0.146%**	0.088%	0.114%	0.057%	0.074%
Log (mean # employees at firm's plants)	0.271%***	0.311%***	0.283%***	0.325%***	0.048%	0.055%
Log (# firm's plants)	0.188%	0.236%	0.285%	0.359%	-0.018%	-0.023%
†Dummy for single-plant firm	-0.031%		-0.133%		-0.057%	
†Dummy for plant in states with federally-run OSHA	-0.947%***		-0.512%***		0.156%*	
Log (plant's $ cumulative penalties in years t-2 to t-5)	-0.024%	-0.078%	-0.021%	-0.071%	-0.005%	-0.017%
Log (plant's $ penalties in year t-1)	0.050%	0.102%	0.050%	0.104%	-0.021%	-0.043%
Cumulative inspections at plant in years t-2 to t-5	0.256%***	0.193%***	0.253%***	0.191%***	0.074%*	0.056%*
†Dummy for ≥ 1 inspection at the plant in year t-1	-0.149%		-0.149%		0.165%	
% of firm's plants inspected in year t-1	-0.031%	-0.007%	0.020%	0.005%	-0.250%	-0.058%
Log (mean $ penalties at firm's plants in year t-1)	0.004%	0.014%	-0.023%	-0.084%	0.022%*	0.078%*
†Dummy for no inspections at firm's plants in t-1	-0.032%		-0.090%		0.038%	
% of plants inspected in the state in year t-1	4.103%**	0.124%**	2.333%	0.071%	-0.351%	-0.011%
Log (mean $ penalties in the state in year t-1)	0.027%	0.047%	0.033%	0.057%	0.028%*	0.049%*
% of plants in the SIC-4 inspected in year t-1	-0.814%	-0.015%	-4.140%	-0.077%	-0.777%	-0.014%
Log (mean $ penalties in the SIC-4 in year t-1)	0.052%	0.057%	0.077%	0.084%	0.015%	0.017%
†SIC 2835 - Diagnostic Substances	-0.451%		-0.121%		-0.267%***	
†SIC 2851 - Paints, Varnishes, Lacquers, Enamels	-0.761%***		-0.628%**		-0.248%**	
†SIC 2895 - Carbon Black	-0.830%***		-0.705%***		-0.280%***	
†Year = 1989	0.205%		0.505%		0.295%*	
†Year = 1994	-0.392%*		-0.321%		-0.130%	
†Year = 1998	-0.390%*		-0.283%			

Notes: Obs.=23,780. Results of the bivariate probit regressions are in Table 3. "Prob Acc." denotes the predicted probability of accidents for the mean plant in the sample, i.e. the values of covariates are set at their means. † denotes a binary variable and the marginal effect on the likelihood of accidents is estimated for the switch of the dummy from 0 to 1. For continuous variables, the marginal effect is estimated for one standard deviation increase in those variables (columns, 2, 4 and 6). Statistically significant year and SIC-4 dummies are reported. Statistically significant at the ***1%. **5% and *10% level.

Online Appendix I: The role of top management in plant safety

Scholz and Gray (1990), based on field interviews and statistical research, report that managerial attention to risk is an important component of a firm's decision-making process on safety issues. Drawing on Cyert and March's (1963) behavioral theory of the firm, they note that: (1) firms react to feedback rather than engage in long-run planning; (2) firms solve particular problems, rather than general optimization, and; (3) firms learn, i.e., they "adapt goals and attention rules as the environment changes" (Scholz and Gray, 1990). Similarly, accident investigation reports note that the underlying cause of many accidents is the plants' "poor safety culture," where safety culture is defined as: (1) the senior management's commitment to safety (Pidgeon and O'Leary 2000, Krause, 2004); and (2) the ability of the management and the organization to learn from errors (Reason, 1997, cited in CSB-Texas City, 2007).

Senior managers play a key role in plant safety, first, they establish "objectives and directives; they recommend safety management systems and site-level mechanisms such as incident investigation, safety committees, safety action tracking systems, hazard analysis, behavior observation and feedback" (NCBP, 2011). Second, in choosing the financing levels for process safety systems, senior managers set the potential trade-off between production and process safety (CCPS, 1992 cited in Baker Report, 2007). Moreover, "management not acting on early warnings signs of problems" is noted as one root cause of chemical accidents investigated by the EPA and OSHA (Belke, 1998). "An effective safety culture avoids incidents by being informed," i.e., by encouraging first, reporting, and second, learning (Reason, 1997, cited in CSB-Texas City, 2007). In turn, the "reporting errors and near-misses requires an atmosphere of trust, where personnel are encouraged to come forward and organizations promptly respond in a meaningful way" (Reason, 1997, cited in CSB-Texas City, 2007). Further details on the role of top management in plant safety, summarized from the accident investigation reports, are in Finger and Gamper-Rabindran (2011).

Online Appendix II: Probit of RC participation on HAP/TRI ratio

Table A1 shows that the instrument, the firm's HAP/TRI ratio, is correlated with the firm's participation in RC. The estimated HAP/TRI coefficient of 0.342 is statistically significant at the 1% level.

As seen in Table A1, several factors are associated positively with participation in RC, including plants' operation in more pollution-intensive industries, plants' greater pollution intensity than their SIC-4 average, and ownership by larger firms, measured by the number of plants or the average number of employees. Mean penalties at plants belonging to the same firm and at plants located in the same state are positively correlated with participation in RC. Measures of community pressure do not show consistent patterns. Two measures of strong community pressure, i.e., larger shares of whites and lower shares of non-high school graduates, are positively associated with RC participation; while surprisingly, another measure of strong community pressure, i.e., smaller shares of poor people, is negatively associated with RC participation. The inspections variables do not show consistent patterns. One measure of inspection pressure, i.e., the share of plants inspected in the state in the previous year, is positively associated with RC participation; while another measure of inspection pressure, i.e., the presence of inspections at a firm's plants in the previous year, is negatively associated with RC.

Table A1: Probit regression of RC participation on firm's HAP/TRI ratio and other covariates			
Firm's HAP/TRI ratio	0.342***	Log (plant's $ cumulative penalties in	-0.007
	(0.052)	years t-2 and t-5)	(0.005)
Plant's pollution intensity relative to	0.437***	Log (plant's $ penalties in year t-1)	-0.004
that of its SIC-4	(0.036)		(0.009)
Plant's pollution intensity of the SIC-4	0.699***	Cumulative inspections at plant	-0.025
in which a plant operates	(0.174)	in years t-2 to t-5	(0.024)
Plant's neighborhood: % white	0.196***	Dummy for at least one inspection at	0.009
	(0.060)	the plant in year t-1	(0.062)
Plant's neighborhood: % urban	-0.061*	% of firm's plants inspected in year t-1	0.090
	(0.034)		(0.083)
Plant's neighborhood: % poor	0.261**	Log(mean $penalties at firm's plants	0.009*
	(0.121)	in year t-1)	(0.005)
Plant's neighborhood: % < high	-0.301***	Dummy for no inspections at firm's plants	0.180***
school education	(0.095)	in year t-1	(0.046)
Dummy for a unionized plant	0.006	% of plants inspected in the state	1.655***
	(0.029)	in year t-1	(0.488)
% firm's plants that are unionized	0.361***	Log (mean $ penalties in the state	0.030***
	(0.042)	in year t-1)	(0.009)
Log (# plant employees)	-0.045***	% of plants in the SIC-4 inspected	0.596
	(0.014)	in year t-1	(0.975)
Log (mean # employees at firm's plants)	0.521***	Log (mean $ penalties in the SIC-4	0.015
	(0.020)	in year t-1)	(0.016)
Log (# firm's plants)	0.860***	Dummy for plants in states with	0.032
	(0.022)	federally-run OSHA	(0.031)
Dummy for single-plant firm	-0.090*		
	(0.049)		
Notes: Bootstrap standard errors with 100 replications are reported.			
Statistically significant at ***1%, **5% and*10%			

Table A1: (continued) Regression of RC participation on firm's HAP/TRI ratio and other covariates			
SIC 2812 - Alkalies and Chlorine	0.644***	SIC 2844 - Perfumes, Cosmetics,	-0.925***
	(0.162)	and Other Toilet Prep	(0.142)
SIC 2813 - Industrial Gases	-0.129	SIC 2851 - Paints, Varnishes,	-1.645***
	(0.107)	Lacquers, and Enamels	(0.063)
SIC 2816 - Inorganic Pigments	-0.307*	SIC 2861 - Gum and Wood Chemicals	-0.350**
	(0.165)		(0.146)
SIC 2819 - Industrial Inorganic Chemicals	-0.080	SIC 2865 - Cyclic Organic Crudes	0.059
n.e.c.	(0.124)	and Organic Dyes	(0.120)
SIC 2821 - Plastics Materials	0.123	SIC 2869 - Industrial Organic Chemicals	0.225**
Synthetic Resins	(0.078)	n.e.c.	(0.095)
SIC 2822 - Synthetic Rubber	-0.494***	SIC 2873 - Nitrogenous Fertilizers	-1.300***
	(0.172)		(0.129)
SIC 2824 - Manmade Organic Fibers	-0.334***	SIC 2874 - Phosphatic Fertilizers	-2.297***
	(0.118)		(0.236)
SIC 2833 - Medicinal Chemicals	-0.606***	SIC 2875 - Fertilizers, Mixing Only	-3.031***
and Botanical Products	(0.119)		(0.491)
SIC 2834 - Pharmaceutical Preparations	-1.152***	SIC 2879 - Pesticides and Agricultural	-0.529***
	(0.098)	Chemicals	(0.077)
SIC 2835 - In Vitro and In Vivo	-1.309***	SIC 2891 - Adhesives and Sealants	-0.433***
Diagnostic Substances	(0.200)		(0.081)
SIC 2841 - Soap and Other Detergents	-0.921***	SIC 2892 - Explosives	-1.755***
	(0.091)		(0.161)
SIC 2842 - Specialty Cleaning	-2.002***	SIC 2893 - Printing Ink	-1.114***
Preparations	(0.136)		(0.078)
SIC 2843 - Surface Active Agents	0.227**	SIC 2895 - Carbon Black	-0.806***
Agents and Assistants	(0.098)		(0.197)
Notes: Bootstrap standard errors with 100 replications are reported. Statistically significant at ***1%, **5% and*10%			
Year dummies are included in the specification			

Online Appendix III: Bivariate probit regressions of RC's impact on accidents

Table A2: Bivariate probit regression on the impact of RC participation on plant-level accidents			
	[1]	[2]	[3]
	All accidents	RC/PS accidents	Fatal accidents
RC participation dummy	-0.542*	-0.916*	-0.305
	(0.287)	(0.517)	(0.392)
Plant's pollution intensity relative to	0.337***	0.415***	0.206*
that of its SIC-4	(0.066)	(0.090)	(0.122)
Pollution intensity of the plant's	0.314	0.369	0.522
SIC-4 industry	(0.315)	(0.329)	(0.413)
Plant's neighborhood: % white	-0.216**	-0.259**	-0.222
	(0.105)	(0.131)	(0.193)
Plant's neighborhood: % urban	0.060	0.072	-0.015
	(0.067)	(0.064)	(0.082)
Plant's neighborhood: % poor	-0.369	-0.284	-0.218
	(0.241)	(0.211)	(0.414)
Plant's neighborhood: % <high	0.280	0.181	0.281
school edution	(0.194)	(0.166)	(0.229)
Dummy for unionized plant	0.096*	0.007	0.038
	(0.056)	(0.076)	(0.088)
% firm's plants that are unionized	-0.092	0.018	-0.131
	(0.083)	(0.115)	(0.118)
Log (# plant employees)	0.054**	0.048	0.072
	(0.025)	(0.030)	(0.055)
Log (mean # employees at firm's	0.129***	0.154**	0.061
plants)	(0.041)	(0.066)	(0.066)
Log (# firm's plants)	0.089	0.155	-0.023
	(0.061)	(0.102)	(0.095)
Dummy for single-plant firm	-0.015	-0.074	-0.074
	(0.079)	(0.110)	(0.112)
Dummy for plants in states with	-0.370***	-0.246***	0.219**
federally-run OSHA	(0.055)	(0.070)	(0.095)
Constant	-3.645***	-4.039***	-4.088***
	(0.498)	(0.492)	(0.749)
Rho	0.287*	0.522**	0.154
	(0.177)	(0.250)	(0.207)
No obs.	23,780	23,780	23,780
No accidents	304	212	110

Notes: Bootstrap standard errors with 100 replications are reported. Statistically significant at the ***1%, **5%, and *10%

Table A2 (con't): Bivariate probit regression on the impact of RC participation on plant-level accidents

	[1]	[2]	[3]
	All accidents	RC/PS accidents	Fatal accidents
Log (plant's $ cumulative penalties	-0.011	-0.012	-0.006
in years t-2 to t-5)	(0.009)	(0.009)	(0.014)
Log (plant's $ penalties in year t-1)	0.024	0.028	-0.026
	(0.019)	(0.020)	(0.025)
Cumulative inspections at the plant	0.122***	0.138***	0.093
in years t-2 to t-5	(0.035)	(0.041)	(0.062)
Dummy for at least one inspection at	-0.076	-0.089	0.172
the plant in year t-1	(0.150)	(0.140)	(0.176)
% of firm's plants inspected in year t-1	-0.015	0.011	-0.316*
	(0.142)	(0.137)	(0.191)
Log (mean $ penalties at firm's plants	0.002	-0.013	0.0274*
in year t-1)	(0.009)	(0.012)	(0.015)
Dummy for no inspections at the firm's	-0.015	-0.048	0.048
plants in year t-1	(0.096)	(0.090)	(0.139)
% of plants inspected in the state	1.947***	1.271*	-0.443
in year t-1	(0.671)	(0.752)	(1.314)
Log (mean $ penalties in the state	0.013	0.018	0.0352*
in year t-1)	(0.019)	(0.019)	(0.019)
% of plants in the SIC-4 inspected	-0.386	-2.254	-0.981
in year t-1	(2.248)	(1.990)	(2.225)
Log (mean $ penalties in the SIC-4	0.025	0.042	0.019
in year t-1)	(0.026)	(0.041)	(0.040)
SIC 2835 - Diagnostic Substances	-0.306	-0.0721	-3.743***
	(2.218)	(2.070)	(0.265)
SIC 2851 - Paints, Varnishes	-0.496***	-0.464**	-0.427**
Lacquers, and Enamels	(0.155)	(0.233)	(0.197)
SIC 2895 - Carbon Black	-4.329***	-3.892***	-4.407***
	(0.396)	(0.403)	(0.520)
Year = 1989	0.088	0.217	0.267*
	(0.136)	(0.187)	(0.213)
Year = 1994	-0.235**	-0.218	-0.209
	(0.119)	(0.166)	(0.249)
Year = 1998	-0.235*	-0.187	-0.0371
	(0.127)	(0.196)	(0.212)

Notes: SIC-4 and year dummies with statistically signifiant coefficients are reported. SIC 2899 chemicals not elsewhere classifed (n.e.c.) and the year 2001 are the omitted categories. Bootstrap standard errors with 100 replications are reported. Statistically significant at ***1%, **5% and *10%.

Online Appendix IV:
RC treatment effects estimated with an alternative specification for the instrument

Table A3 provides results on RC's treatment effect using an alternative specification for the instrument. Specifically, we use the firm's HAP/TRI ratio, in which the HAP and TRI chemicals are aggregated using toxicity weights from the RSEI. Results from this specification are consistent with our main results. For example, RC's treatment effect on the treated from this alternative specification is to reduce all accidents and RC/PS accidents by 4.34 and 7.38 accidents per 100 plants in a given year, respectively (Table A3, column 6). The corresponding figures from our main specification in Table 3 are 2.99 and 5.75 accidents per 100 plants in a given year, respectively. RC's average treatment effect from this alternative specification is to reduce all accidents and RC/PS accidents by 2.41 and 3.66 accidents per 100 plants in a given year, respectively (Table A3, column 3). The corresponding figures from our main specification are 1.76 and 2.92 accidents per 100 plants in a given year, respectively. Both this and the main specifications do not find statistically significant effects of RC on fatal accidents (Table A3, column 3 and 6; Table 3 column 3 and 6).

Table A3: Treatment effects of RC on the likelihood of accidents using an alternative specification for the instrument

	[1]	[2]	[3]	[4]	[5]	[6]
	Average Treatment Effect (ATE)			Average Treatment on the Treated (ATT)		
	All plants			RC participating plants		
	n=23,780			n=7,929		
	RC=0	RC=1	RC effect	RC=0	RC=1	RC effect
All Accidents	3.05%	0.64%	-2.41%*	5.63%	1.29%	-4.34%*
RC/PS-Related Accidents	4.07%	0.41%	-3.66%**	8.33%	0.95%	-7.38%**
Fatal accidents	0.82%	0.27%	-0.55%	1.40%	0.48%	-0.92%

Notes: The instrument, the firm's HAP/TRI, is created by agregating HAP and TRI chemicals using toxicity weights from the Risk Screening Environmental Indicators Model (EPA, 2010)

We examine the relationship between the firm's toxicity weighted HAP/TRI ratio and the firm's participation in RC. In the probit regression of RC participation on firm's toxicity weighted HAP/TRI ratio and other covariates, the coefficient on firm's HAP/TRI ratio is 0.515 and statistically significant at the 5% level. The toxicity weighted HAP/TRI ratio has a mean of 0.78 for RC plants and a mean of 0.79 for non-RC plants, respectively, and these means are statistically different at the 10% level.

Online Appendix V: Propensity Score Matching Method

Our preferred method is the bivariate probit, instrumenting for firms' selection into RC using firms' HAP/TRI ratio. The strength of this approach is its ability to address firms' selection into RC based on unobserved factors. Firms are likely to have private information that jointly affects their decision to join RC and the likelihood of an accident at their plants. We believe the evidence is persuasive on the exclusion requirement. Firms' HAP/TRI ratio affect their contemporaneous decision to join RC, but are not directly related to accidents at their plants. We note that this assumption cannot be empirically tested.

As a comparison to the bivariate probit, we apply the Propensity Score Matching (PSM) method, which does not rely on the exclusion requirements for identification. Overall, the PSM results support our main results from the bivariate probit, i.e., RC reduces the likelihood of all accidents and PS/RC accidents, though the PSM estimates are about half the size of the estimates from the bivariate probit. The PSM ATE estimate for all accidents indicates a reduction of 0.80 accidents per 100 plants in a given year, while the corresponding bivariate probit ATE estimate indicates a reduction of 1.76 accidents per 100 plants in a given year. However, we note that the PSM method suffers from an important drawback, i.e., it assumes that matching on the observables can fully control for the differences between the RC and non-RC participants, and thus, identify the effect of RC. In reality, it is likely that firms self-select into the RC program based on *unobserved* factors.

Method

PSM has been applied to analyses of binary outcomes, e.g., estimating the effects of job training on employment and medical surgeries on mortality (GAO, 1994; Aakvik, 2001; Caliendo, Hujer, and Thomson, 2008). PSM estimates are based on comparing the likelihood of accidents at RC participating plants to the likelihood at non-RC participating plants with similar propensity scores. The ATT measures the difference in (a) the likelihood of accidents for RC plants and (b) the corresponding likelihood for non-RC plants that are matched to the respective RC plants. The ATE measures the difference in (c) the weighted average likelihood of accidents at an RC plant and (d) the weighted average likelihood of accidents at a non-RC plant. In turn, the value (c) is estimated from observed RC plants and RC plants that are matched to observed non-RC plants. The value (d) is estimated from the observed non-RC plants and those matched to observed RC plants.

The ATE and ATT are only identified in regions of common support, i.e., for similar propensity scores, observations of both RC plants and non-RC plants are needed (Heckman, LaLonde, and Smith, 1999). Based on our bivariate probit estimates, the likelihood of an accident at the 25th percentile plant is 0.37 accidents per 100 plants in a given year, while the likelihood at the 75th percentile is 1.94 accidents per 100 plants in a given year. To make a valid comparison, RC plants at a specific range of propensity scores need to be compared with non-RC plants that are similar in their range of propensity scores. In the case where there are sizable numbers of non-RC plants to serve as matches, we would be able draw an inference on the likelihood of accidents for the non-RC plants. In contrast, consider the extreme case in which only a single non-RC plant is available to serve as the match. We would have the impossible task of inferring the likelihood of accidents from the single matched plant, which would have had either no accident or an accident.

Trimming the sample restricts our analysis to regions of common support (Smith and Todd, 2005). We generate propensity scores using a probit model of RC participation on covariates. We trim the sample by dropping observations at the top and bottom quintiles of the propensity scores – the top quintiles are populated largely by RC plants, while the bottom quintiles are populated largely by non-RC plants. Observations in the middle three quintiles have estimated propensity scores between 0.0030 and 0.78. While trimming results in the loss of 40% of our observations, it ensures that our analyses are restricted to regions with sufficient data to enable appropriate matches and therefore, yield reasonable inferences.

We use nearest neighbor matching, in which a treatment case (RC plant) is compared with the control case (non-RC plant) that is the closest match based on the absolute value of the difference in their propensity scores. Matching is done with or without replacement; matching with replacement allows a control case to be used as a match for more than one treated case.

Results

Our preferred specification, matching nearest neighbors (1-NN) with replacement on the trimmed sample, is presented in Table A4, column 1. Overall, the PSM results support our main results from the bivariate probit that RC reduced all accidents and PS/RC accidents. However, the PSM estimates are about half the size of the IV estimates. Based on the ATE estimates, RC reduces all accidents by 0.80 accidents per 100 plants in a given year and RC reduces RC/PS accidents by 0.54 accidents per 100 plants in a given year. The ATT estimates for RC/PS accidents are similar to the ATE estimates, i.e., RC leads to reduction of 0.70 RC/PS accidents per 100 plants in a given year. The ATT estimates for all accidents are not statistically significant. Effects on fatal accidents are not statistically significant for either the ATE or the ATT estimates.

Next, we consider variations in the matching procedure. Our PSM results are robust to the use of oversampling, i.e., using 5 closest matches (5-NN) (column 2). The ATE estimates are similar for all accidents and PS/RC accidents, whether we match nearest neighbors or use oversampling (column 1 and 2, respectively). The ATE estimates for fatal accidents are both negative, but statistically significant only in the oversampling specification. For the ATT estimates, the size of the coefficients for all accidents and PS/RC accidents are comparable in the 1-NN and 5-NN specifications, and their signs are both negative, but the coefficients are significant in only one of the two specifications. The ATE estimates, unsurprisingly, are less sensitive than the ATT estimates to variations in the matching procedure because the effects at the highest and lowest percentiles of the propensity score even out.

Our preferred specification with the trimmed sample is matching with replacement. For comparison, we show the nearest neighbor matching with no replacement in the trimmed sample in column 3. The non-replacement procedure results in estimates that are smaller in magnitude and the estimates are no longer significant. Only the ATT estimates of RC/PS accidents remains statistically significant. The rarity of accidents in our sample is likely to make our analysis sensitive to the replacement method. When matching is done without replacement, a control case is used only once. This means that there are fewer available observations for subsequent matching, leading to less precise matches. However, more unique controls are used as counterfactuals, increasing the efficiency of the estimates. The median difference between propensity scores with replacement in column 1 is 0.00018, while the median difference without replacement in column 2 is 0.289.

Our preferred procedure is to trim the sample. For comparison, we present the results from the nearest neighbor matching with replacement on a sample that is not trimmed. As seen in column 4, the failure to trim leads to ATT estimates that are positive and statistically significant. Examination of our sample indicates that matching a large number of observations to a relatively small number of controls in the top and bottom quintiles of the propensity score are driving these results.[38]

We consider one alternative to trimming as a strategy to improve the quality of matches. Using the 1-NN matching, we specify a caliper and match without replacement. Specifying the caliper, which requires the control case's propensity score to be within a certain distance, helps reduce cases of poor matches. Specifying no replacement avoids the situation in which the few cases of poor matches in the top and bottom quintiles drive the results in the non-trimmed sample. As seen in column 5, the specification with a caliper and no replacement in the non-trimmed sample yields coefficients that are negative but not statistically significant for all accidents and PS/RC accidents for both the ATE and ATT estimates. The coefficients for fatal accidents are not statistically significant.

Conclusion

Overall, the PSM results support our main results from the bivariate probit, i.e., RC reduced all accidents and PS/RC accidents. Both the bivariate probit (Table 3) and the PSM models (Table A4, column 1) yield negative and statistically significant estimates. The PSM estimates are about half the size of the estimates from the bivariate probit. It is not surprising that the PSM model, which makes the conditional independence assumption, yields estimates that are smaller in magnitude than the bivariate probit. The direction of bias when self-selection based on unobservables is not addressed, as revealed in the comparison of the probit and bivariate probit models (section 4.2), is to understate the effect of RC in reducing accidents.

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[38]When we match with replacement in the non-trimmed sample, the 4,748 non-RC observations in the bottom quintile of propensity scores are matched to only 9 distinct RC observations that do not experience any accidents. In contrast, the 4,484 RC observations from the top quintile are matched to only 266 different non-RC observations all of which experience accidents. The effect at the bottom quintile makes the RC program look effective, while that at the top quintile makes the RC program look ineffective. Overall, the effect that RC fails to reduce accidents dominates the final estimates of ATT in the non-trimmed sample.

Table A4: RC treatment effects estimated with Propensity Score Methods

	[1]	[2]	[3]	[4]	[5]
Nearest Neighbors	1	5	1	1	1
Replacement	Y	Y	N	Y	N
Trimmed sample	Y	Y	Y	N	N
Caliper	None	None	None	None	0.01
Panel A: All accidents					
ATE	-0.800%***	-0.840%***	-0.247%	-0.210%*	-0.216%
	(0.210%)	(0.204%)	(0.231%)	(0.125%)	(0.298%)
ATT	-0.611%	-0.660%*	-0.410%*	0.770%***	-0.109%
	(0.465%)	(0.376%)	(0.235%)	(0.266%)	(0.335%)
Panel B: RC/PS accidents					
ATE	-0.540%***	-0.520%***	-0.226%	-0.097%	-0.144%
	(0.139%)	(0.166%)	(0.197%)	(0.120%)	(0.234%)
ATT	-0.700%**	-0.559%	-0.203%	0.560%***	-0.109%
	(0.353%)	(0.392%)	(0.211%)	(0.199%)	(0.240%)
Panel C: Fatal accidents					
ATE	-0.119%	-0.210%*	0.087%	-0.025%	0.072%
	(0.108%)	(0.120%)	(0.108%)	(0.080%)	(0.162%)
ATT	0.320%	0.052%	0.000%	0.420%**	0.182%
	(0.195%)	(0.215%)	(0.148%)	(0.185%)	(0.199%)
Observations	14268	14268	6874	23780	5557
RC=1 obs.	3437	3437	3437	7929	2754
RC=0 obs.	10831	10831	3437	15851	2803

Notes: ATE denotes average treatment effects. ATT denotes average treatment effects on the treated. Bootstrapped standard errors in parentheses. Statistically significant at the ***1%, **5% and *10%. The ATE estimates for all accidents in column 1 indicate a reduction of 0.8 accidents per 100 plants in a given year