TESTING THE EFFECTS OF SELF-REGULATION ON INDUSTRIAL ACCIDENTS

Stephen R. Finger

and

Shanti Gamper-Rabindran

6/15/2012

Revised and Resubmitted to the *Journal of Regulatory Economics*

Authors are listed alphabetically. Stephen R. Finger, Assistant Professor, Moore School of Business, University of South Carolina, 1705 College Street, Columbia, SC 29208 (stephen.finger@moore.sc.edu) and Shanti Gamper-Rabindran, Assistant Professor, Graduate School of Public and International Affairs, University of Pittsburgh, 3205 Posvar Hall, 230 S. Bouquet St., Pittsburgh PA 15217 (shanti1@pitt.edu). Corresponding author: Gamper-Rabindran. We thank participants at the Industry Studies Association, European Association of Environmental and Resource Economists and Association of Public Policy and Management for helpful suggestions. We gratefully acknowledge funding from the National Science Foundation (BCS 0351058 and SES 1127223), University of Pittsburgh's Center for Industry Studies, Central Research Development Fund, University Center for Social and Urban Research, and the European Union Center of Excellence. Errors are our own.

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Abstract

Our study, the first to test the impact of self-regulation on industrial accidents, examines Responsible Care (RC) in the US chemical manufacturing sector. RC requires members to adhere to codes of conduct on production safety and pollution prevention. Using our author-constructed database of 1,867 firms that own 2,963 plants between 1988 and 2001, we instrument for firms' self-selection into RC using pollution-related regulatory pressure on firms that influences their probability of joining RC, but not plant-level accidents. We find that participation in RC reduces the likelihood of accidents by 2.99 accidents per 100 plants in a given year, or by 69.3%. Participation in RC also reduces the likelihood of 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%. Alternatively, estimates using Propensity Score Matching (PSM) methods indicate that participation in RC reduces the likelihood of accidents by 0.66 accidents per 100 plants in a given year. The reduction in the likelihood of accidents, due to participation in RC, contributes to economically significant averted losses, with savings, even based on the smaller PSM estimates, totaling $180 million per year.

(193 words)

Keywords: Corporate Social Responsibility, Industry Self-Regulation, Industrial Accidents, Environmental and Health Safety, Chemical Industry

JEL codes: Q53 Q58 L51 L65 D21

1. Self-regulation and industrial accidents

Major accidents in the chemical industry – Seveso's dioxin release, Bhopal's methyl-isocyanate release and AZF Toulouse's explosion – highlight the costs from industrial accidents (Kleindorfer and Kunreuther, 1987; Dechy et al., 2004; NCBP, 2011; Capelle-Blanchard and Laguna, 2010). Self-regulation programs, in which trade associations mandate members to adopt codes of conduct, have 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, and this program now operates in fifty countries (Börkey, Glachant and Lévêque, 2000). RC requires members to adhere to codes of conduct on production safety and pollution reduction (Börkey, Glachant and Lévêque, 2000). 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 features of RC (Dlouhy, 2011).

Given policymakers' interest in emulating RC as one strategy to reduce accidents, our study provides the first evaluation of the impact of self-regulation programs on accidents.[1] Specifically, we test the impact of participation in RC on work-related accidents involving at least one fatality or three inpatient hospitalizations among workers in the US chemical manufacturing sector. The Occupational Safety and Health Administration (OSHA) mandates the reporting of these accidents, providing a fairly complete record of accidents. A subset of these accidents are process safety (PS) related accidents, in which the production process goes out of

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[1] Cohen et al. (2011) explore alternative policies to improve environmental performance in the oil and gas drilling industry.

control, leading to fires, explosions, or chemical releases (Hofman et al., 1995). We construct a unique database of 2,963 plants owned by 1,867 firms between 1988 and 2001.

The challenge in estimating the effect of participation in RC on accidents is to separate this effect from confounders, such as plants' parent firms selecting into the program (Levinson, 2004), and differences across participating and non-participating plants. While the ideal analysis would compare participating plants with non-participating plants that are similar in all aspects other than their participation status, our analysis applies several complementary estimation strategies to provide as best a comparison as possible. First, our plant-level analysis employs an instrumental variable (IV) strategy to address plants' parent firm's selection in the program. We argue that the instrument, the percentage of a firm's emissions that are subject to hazardous air pollutant standards, affects a plant's parent firm's likelihood of joining the RC program, but does not directly affect the plant-level accident likelihood (section 3.3). Second, we restrict our comparison to various subsets of plants: plants belonging to firms that have similar resources to address safety, i.e. (i) with above median plant-level employees and (ii) above median number of plants, (iii) plants within industries with moderate RC participation rates, and (iv) plants within industries with similar safety challenges., i.e. industries within the middle two quartiles of injury rates prior to the RC program implementation.

Our primary specification, the bivariate probit model, accounts for the binary nature of our outcome and participation variables and applies the instrument to address the endogeneity of the participation variable. We pool observations across plant-years and estimate standard errors clustered at the firm-level. We find that participation in RC reduces the likelihood of all accidents by 2.99 accidents per 100 plants for a given year, a reduction of 69.3%. Narrowing our analysis to process safety accidents and those accidents involving violations of OSHA standards related to RC codes (RC/PS accidents), we find that participation in RC reduces the likelihood of these accidents by 5.75 accidents per 100 plants in a given year, or by 85.9%, with this estimate statistically significant at the 1% level. Because accidents are infrequent events in our dataset, we expect the effect of participation in RC, if any, to be estimated imprecisely.[2] Therefore we treat the results on all accidents, which are significant at the 10% level, as evidence that participation in RC has reduced the likelihood of accidents. Results from specifications restricted to various subsets of plants yield qualitatively similar results to those in our main sample. RC participation leads to reductions in the likelihood of RC/PS accidents of 2.62, 1.59 and 3.00 accidents per 100 plants among plants belonging to firms with above median number of plant-level employees and above median number of plants, and plants operating in industries with moderate RC participation rates, respectively. Results from the subset of plants within industries with similar safety challenges also find a negative coefficient on RC participation, though the estimated effect is statistically insignificant. Although the estimates from the subsets of plants appear smaller, they are not statistically different from the estimates from our full sample.

We find complementary results with alternative specifications. First, we estimate a probit fixed effect model, which is identified on a small sample, because few plants experience changes in their parent firms' RC status and because accidents occur infrequently in our data. This model indicates that participation in RC reduces all accidents and RC/PS accidents by 4.49 and 3.34 accidents per 100 plants in a given year, respectively. Second, Propensity Score Matching (PSM) estimates, whose consistency does not rely on exclusion restrictions, indicate that participation in

[2] Coslett (1981) demonstrates the difficulty in generating precise coefficient estimates from samples with low probability events by comparing the efficiency of estimators based on random samples (as in our data) relative to choice based samples (equal observations of Y=1 and Y=0) of the same size for different underlying event probabilities. He finds the relative efficiency of the random sample is one tenth as high when the probability of the event is 1% versus 25%.

RC reduces the likelihood of all accidents and RC/PS accidents by 0.66 and 0.70 accidents per 100 plants in a given year, respectively. Even the smallest PSM estimates suggest that the participation in the RC program has averted accident-related losses that are economically significant, i.e., $180 million per year in 1990 dollars.

Our results are compatible with findings in previous studies that safety programs can provide additional impetus for top management to improve safety (Scholz and Gray, 1990) (section 2). The RC program requires (i) Chief Executive Officers (CEOs) to sign off on reports to the ACC and to attend regional meetings where they face peer pressure to improve their firms' safety record (NCBP, 2011), and (ii) plants to conduct safety audits (Börkey, Glachant and Lévêque, 2000; Prakash, 2000) that guard against complacency and erosion of safety protection that may occur during periods of no accidents (Deepwater Horizon Study Group (DHSG), 2011).

Our present study stands in contrast to our earlier study (Gamper-Rabindran and Finger, forthcoming) which finds that participants in RC raise their pollution relative to non-participants and King and Lenox's (2000) study which finds that participants in RC reduce their pollution at slower rates than non-participants. Other related studies find that participation in voluntary programs did not reduce pollution (Morgenstern and Pizer, 2007). These contrasting effects of RC participation provide evidence against the view that an unobserved factor, such as a desire to appear "socially responsible", is driving our results. That factor would have to be positively correlated with the likelihood of a firm participating in RC and a plant's willingness to improve safety, but negatively correlated with a plant's willingness to reduce pollution.

These results that RC participation reduces accidents but not pollution reveal that plants are selective in adhering to codes of conduct that are likely to yield net benefits, and that the regulatory and insurance framework plays an important role in influencing the effectiveness of the voluntary or self-regulation program. Plants are likely to receive greater net benefits from reducing their probability of accidents than from reducing their TRI pollution.[3] Implementation of RC's management practices, which require less costly organizational changes (Deily and Gray, 2007), can reduce the likelihood of accidents, which in turn, generates substantial savings by averting accident-related liability (Er, Kunreuther, Rosenthal, 1998). In contrast, achieving RC's pollution reduction goals requires significant capital investment in pollution abatement processes, but plants' reduction of TRI pollutants, several of which are unregulated, do not necessarily yield profits.

2 Industry self-regulation and Responsible Care

Voluntary and self-regulation programs are increasingly used worldwide as a complement to traditional regulations. These programs aim to encourage industries to internalize costs from industrial production, such as pollution and industrial accidents (Morgenstern and Pizer, 2007). Theoretical studies have explored why these programs may or may not achieve their stated goals (Maxwell et al., 2000; Lyon and Maxwell, 2004; Heyes, 2005; Glachant, 2007; Dawson and Segerson, 2008). To date, most empirical studies find that participation in voluntary or self-regulation programs have not reduced pollution (Morgenstern and Pizer, 2007). Studies on the Environmental Protection Agency's (EPA) voluntary Industrial Toxics program find, at best, mixed evidence on pollution reduction (Khanna and Damon, 1999; Gamper-Rabindran, 2006; Vidovic and Khanna, 2007). Previous studies report that participation in the RC program did not reduce plants' pollution (King and Lenox, 2000; Gamper-Rabindran and Finger, forthcoming).

[3] Steps to improve plant safety do not necessarily reduce emissions of TRI chemicals to the environment; many of the TRI chemicals are not flammable, reactive or corrosive (Spellman, 1997).

Our study focuses on the effect of participation in the RC program on industrial accidents. The RC program requires participants to adopt several codes of conduct including the Environmental Health and Safety code, the Process Safety code (ACC, 1990) and the Pollution Prevention code. The ACC describes management practices to implement these codes (ACC, 1990; Rees, 1997; Prakash, 2000). However, like many self-regulation programs, the RC program during our study period did not require third party verification of plants' self-reports on their pollution and safety performance. Moreover, participating firms that fail to adhere to RC's codes are not sanctioned (Rees, 1997).

Regulations and liability in the case of accidents provide incentives for top management to ensure a basic level of plant safety (Baram, 1986; Kleindorfer et al., 2003). Our review of the literature on self-regulation, industrial accidents, and features of the RC program, suggest that participation in the RC program can provide *additional* impetus for plants to improve safety.[4] First, in section 2.1, we describe how self-regulation can improve safety performance relative to the traditional approach of prescriptive command and control regulations (Barkenbus, 1983; NCBP, 2011). We also describe features of the RC program that bring safety issues to the attention of top management. Second, in section 2.2, we describe the industry's collective incentives and plants' individual incentives to improve safety performance. We then explore why these incentives are likely to be stronger for reducing accidents than for reducing pollution.

2.1 Features of Responsible Care that can contribute to safety improvements

Industrial self-regulation, as a complement to traditional regulation, can potentially improve safety performance in technologically complex industries, such as the chemical and nuclear industries (NCBP, 2011). The RC program sets the performance goal of improving

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[4] We draw from these accident reports in the chemical, petrochemical and oil drilling industries because "the organization failures are similar, even if the technical details differ significantly" in these accidents (Hopkins 2000, cited in the Baker Report, 2007).

safety, but plants have the flexibility to choose safety technologies and management systems. Government regulators operate in the background, enforcing regulations (NCBP, 2011), providing oversight, and maintaining an implicit threat to tighten legal regulations should self-regulation fail (Bomsel et al., 1996). The RC program has several strengths over traditional prescriptive regulations. It taps into the industry's superior expertise, resources, and information, which government regulators often lack (National Academy of Engineering, 2010; NCBP, 2011). Furthermore, it allows plants to tailor safety procedures to their unique circumstances and to discover new safety procedures (Barkenbus, 1983).

In these technologically complex industries, accidents occur infrequently, but with potentially severe consequences. The absence of accidents can lead to a culture of complacency at the plants (NCBP, 2011) and a gradual erosion of protection (DHSG, 2011). Managers incorrectly decide that as accidents have not occurred, protective measures can be reduced or removed (DHSG, 2011). The RC program helps guard against this tendency. It requires plants to conduct self-audits, which prompt continuous assessment of plant safety, and encourages the sharing of safety information among members, which promotes the adoption of enhanced safety practices (NCBP, 2011). In contrast to self-regulation, the traditional approach of prescriptive command and control regulations may be less effective at improving safety performance. Plants often treat prescriptive regulations as check-lists to complete and prioritize conformity with rules rather than striving to achieve true improvements in safety. By merely reacting to rules set by the regulators, plants fail to innovate or implement new safety technologies (Barkenbus, 1983).

Safety experts argue that the commitment of Chief Executive Officers (CEOs), Boards of Directors and top managers to safety and their correction of safety shortcomings are fundamental to averting accidents (Reason, 1997; Pidgeon and O'Leary 2000; Krause, 2004). CEOs face peer pressure to meet RC's 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.'"

Features of the RC program serve the function of "attention correction," bringing safety shortcomings to the attention of management and encouraging their correction as CEOs must sign off on annual reports submitted to the ACC on their firms' environmental health and safety performance (Yosie, 2003). Senior managers set the organization's approach to the trade-off between production and process safety, in their choice of financing levels for safety systems and personnel (Baker Report, 2007). They make decisions on the overall safety infrastructure; establishing "objectives and directives; and [putting in place] safety management systems" (Baker Report, 2007). They determine if there is an atmosphere of trust, where personnel are encouraged to come forward to report errors and near misses, and the organization promptly takes corrective action, protecting workers who report and punishing reckless behavior (Reason, 1997, cited in CSB, 2007). This atmosphere is important role to plants' safety, as the lack of a reporting culture and fear of reprisals for reporting unsafe situations were cited as contributing factors to the BP Texas City explosion and the Deepwater Horizon oil spill (CSB, 2007 and NCBP, 2011).

2.2 Plants' incentives to adhere to Responsible Care's safety codes

While features of the RC program can *potentially* improve safety, the self-regulation program will achieve its stated goals only if they are aligned with the industry's and the plants' incentives (Barkenbus, 1983). Indeed, the chemical industry as a whole faces strong incentives to ensure the success of the RC program in improving safety. A series of major accidents worldwide – methyl-isocyanate release in Bhopal, dioxin release in Seveso and pesticide discharge into the Rhine – tarnished the reputation of the entire industry, not only the offending firm (Rees, 1997). The industry recognizes that another major accident at any plant, given the public's fear and distrust, would threaten the entire industry's license to operate (Rees, 1997). Moreover, the success of self-regulation in improving safety can forestall the state's imposition of stricter and more costly regulation (Maxwell et al., 2000). We argue that the industry faces stronger incentives to achieve the RC program's goal of reducing accidents than of reducing routine TRI pollution. Industrial accidents, which may result in worker injuries or deaths, or large chemical releases that threaten public health, are more worrying to the public than is the routine release of pollution into the environment (Slovic et al., 1982).[5] Such accidents are more likely to stir negative publicity that prompts regulators to tighten regulations. For example, following the Bhopal accident, Congress held hearings about the safety of US chemical plants, (Blacconiere & Patten, 1994) and enacted additional regulations aimed at preventing chemical accidents, including EPA's Risk Management Program and OSHA's Process Safety Management standard (Belke and Dietrich, 2005).

Individual chemical plants also face strong incentives to adhere to RC's code on safety, because it is likely to yield net benefits. On the benefit side, plants' implementation of RC's recommended management practices can translate to a lower likelihood of accidents, and in turn, reduced potential liability and insurance costs (Er, Kunreuther, Rosenthal, 1998). On the cost side, several effective actions to improve safety, such as organizational changes and improving the atmosphere for workers to report safety problems, do not require significant investments

[5] These accidents can evoke an element of dread. The public perceive these accidents as indicating a loss of control, signaling the potential for affecting a large number of people, and the potential for further mishaps (Slovic et al., 1982).

(Scholz and Gray, 1990). For example, RC's Process Safety Code requires "companies to have management practices in place to ensure 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, 2003).We argue that plants are more likely to derive net benefits from reducing the likelihood of accidents through effective management practices than from reducing pollution. Plants' reduction of TRI pollutants, several of which are unregulated, does not necessarily yield profits. [6] 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).[7] 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."

3. Research question and estimation models

We test if RC, which operates within a regulatory framework, reduces the likelihood of OSHA-reportable accidents.[8] We compare plants owned by RC participating firms and plants owned by non-RC participating firms, controlling for differences across these two sets of plants

[6] Konar and Cohen's (2001) seminal study notes that the negative correlation between firms' financial performance and total TRI emissions may stem from firms with stronger financial performance undertaking better environmental management. In contrast to TRI emissions, major pollution releases that result in greater Superfund liability can adversely affect firms' capital costs (Garber and Hammitt, 1998).

[7] 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.

[8] The RC program, regulations, and liability for accidents are interactive in their effects. Our estimate of the effect RC remains informative for self-regulation programs operating in comparable institutional settings.

to the extent possible. The terms RC plants and non-RC plants denote plants owned by RC participating firms and plants owned by non-participating firms, respectively.

3.1 Accidents

OSHA's Accident Investigation Summaries (AIS) database records OSHA-reportable accidents for the fifty states. Reporting to the AIS is mandatory and consistent over time. Employers must 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[9] (CPL 02-00-113 (2.113)). Moreover, the AIS data is reliable; 85% of the fatalities that should be reported to OSHA are reported (Mendeloff and Kagey, 1990).[10]

We use three different definitions for accidents. Our first and broadest definition of accidents is the occurrence of an OSHA-reportable accident in 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. We also code whether it is a process safety accident, i.e., accidents that stem from chemical leaks, high pressure, fires, or explosions. Attention to "routine" injuries can deflect attention away from underlying process safety issues (NCBP, 2011; Baker Report, 2007). Therefore, we exclude injuries, which are unrelated to RC codes that affect only a few workers, such as falls or limbs caught in machinery. Our third definition, accidents involving fatalities, captures the most severe incidents.

[9] 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 threshold for reporting had been 5 inpatient hospitalizations instead of 3 (29 CFR 1904.8. 1993 edition and 1994 edition)**.** Time dummies in our model account for this change in definition.

[10] We do not use the Risk Management Plan (RMP) accident database because its first reported accident is in 1994, i.e., five years after the start of the RC program (Kleindorfer et al., 2003).

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 involve fatalities.[11] We treat the accident outcome as a binary variable because it is rare for a plant to experience more than one accident in a given year.[12] It is also rare for a plant to experience a large number of accidents in the entire sample period. Of the 304 accidents, 66% occur at plants with only one accident and 89% occur at plants with two or fewer accidents between 1988 and 2001. Of the 212 RC-related accidents, 76% occur at plants with one accident and 93% occur at plants that have two or fewer accidents in the study period. Of the 110 fatal accidents, 90% occur at plants with only one accident during the study period.

3.2 Estimation model

We estimate the effect of a binary treatment, RC participation, on a binary outcome, the occurrence of an accident. Our estimation model is determined by two latent index models:

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

Plant's accident outcome $$Y_{it} = 1\,[R_{it}\,\beta_1 + X_{it}\,\beta_2 > v_{it}\,] \quad \text{Equation 2}$$

$$\mathrm{C}\,(v_{it}\,,\,\varepsilon_{it}) = \rho$$

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 participates in RC; *X* are covariates, and v_{it} and ε_{it} are the error terms. The instrumental variable, *Z,* captures the plant's parent firm's exposure to impending regulations, as measured by the firm's share of air emissions that are HAPs (section 3.3). These two equations

[11] 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.

[12] For all accidents, only 11 plants had two accidents and one plant had three accidents in the same year. For RC/PS accidents, only five plants had two accidents and one plant had three accidents in the same year. For fatal accidents, only one plant had two accidents in the same year.

map into two interrelated data generating processes: (i) the likelihood the plant is owned by a firm that participates in RC as a function of covariates and the error term, ε_{it}, (Equation 1) and; (ii) the likelihood of the occurrence of an accident at a plant as a function of the observed covariates and an unobserved shock, v_{it}, (Equation 2). The parameter, ρ, captures the correlation between v_{it} and ε_{it}. Participation in RC is endogenous with accidents if there is correlation between the unobserved factors, v_{it} and ε_{it}. This correlation can arise, for example, if plants that devote more resources to accident prevention, conditional on their observed characteristics, are also more (or less) likely to be owned by a firm that is a member of RC.[13] Unobserved latent variables that cause firms to want to improve their images by both joining RC and by improving safety could also lead to correlation in the error terms. The self-selection into the program, if unaddressed, can lead to biased estimates of the impact of participation in RC.

We employ a bivariate probit model, which aims to address two estimation issues: (i) the endogeneity of participation; and (ii) the binary nature of both the outcome and participation variables. We use maximum likelihood to estimate this model (Heckman, 1978 and Maddala, 1983), which jointly estimates the two equations: (i) the treatment equation, i.e., participation in RC and; (ii) the outcome equation, i.e., the likelihood of an accident. This model is widely used in the labor literature to evaluate programs in which participation is endogenous and the outcome and participation variables are binary (Evans and Schwab, 1995; Altonji, Elder and Taber, 2005; and Booker, et al. 2011).

The bivariate probit model separately identifies the causal effect of the RC program from the effects of correlated unobservables, by estimating the correlation parameter, ρ, assuming that

[13] Alternatively, the firm may first observe the level of safety at its plants, and then, make its decision on participating in RC. The key estimation issue is that the estimator must address self-selection into RC based on factors unobserved by the researcher.

the errors follow a bivariate normal distribution. The endogenous participation variable can be directly included in the outcome equation in calculating the likelihood function, as long as the correlation parameter is identified. To ensure empirical identification, we include an instrumental variable, *Z*, in the model. Monfardini and Radice (2008) show the advantage of using the instrumental variable, even though ρ is formally identified through non-linearities in the functional form (Wilde, 2000). Specifically, Monfardini and Radice (2008) find the instrumental variable ensures that inferences based on the estimated coefficients remains valid even if the distribution of the errors is misspecified. Results from the bivariate probit models (Table 2) show that ρ ranges from 0.154 to 0.522, and is statistically significant at the 1% level in the model for the RC/PS accidents. These results on ρ, which confirm the correlation between unobservables in the participation and accident equations, underscore the importance of addressing self-selection in our empirical strategy.

We apply the bivariate probit model, instead of the linear IV, because the mean likelihood of accidents in our sample is low, amounting to only 1.28%. The linear IV should not be used when the average probability of the dependent variable is near 0 or 1 (Bhattacharya, Goldman, and McCaffrey, 2006). While the bivariate probit requires that both error terms are distributed bivariate normal for estimates to be unbiased (Angrist, 1999), the bivariate probit remains our preferred specification because it is less biased than the linear IV, even when the errors are non-normal (Bhattacharya, Goldman, and McCaffrey, 2006).

Pooling observations in the bivariate probit

We pool our observations across plant-years. We estimate standard errors clustered at the firm-level to account for the likely correlation across error terms within the same firm. As an alternative, we estimate bootstrap standard errors with 100 replications (Chiburis, Das and

Lokshin, 2011). We choose to pool the observations in our main specification instead of estimating a bivariate probit with plant fixed effects for two reasons. First, the plant fixed effects model is identified for a only a small sample of our data (446 observations) because few plants change their RC status and accidents occur infrequently (section 5.4). Second, we prefer to estimate the pooled model that may bias our results towards zero, instead of the fixed effects model that may bias our results away from zero. Greene's (2004) Monte Carlo experiments find that when plant-level unobservables are correlated with covariates, the coefficients from the pooled probit model are biased towards zero; while those from the probit with fixed effects are biased away from zero. If the direction of bias in the bivariate model is consistent with that of the probit model, our study would understate the effect of RC in reducing the likelihood of accidents.[14]

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 share of a firm's air emissions into the environment that are hazardous air pollutants (HAP). The instrument, the firm's "HAP/air ratio" is defined as the ratio of (i) the sum of its plants' HAP emissions, to (ii) the sum of its plants' air emissions. This variable captures the percent of a plant's emissions that are subject to stricter impending regulations, but does not measure total emissions that may also affect safety. We argue that this instrument meets the two requirements for validity, i.e., it affects the likelihood of a plant belonging to an RC participating firm, and it does not directly affect the likelihood of an accident at the plant, conditional on other included characteristics.

The first requirement for a valid instrument

[14] To our knowledge, tests analogous to those in Greene (2004) have not been conducted for the bivariate probit model.

We argue that the firm's HAP/air ratio influences its contemporaneous decision to participate in RC. During our study period, the chemical manufacturing sector faced impending strict regulations on their emissions of HAPs with expected implementation dates in the late 1990s. These regulations require plants to install the technology that achieves the maximum pollution control among plants in its production category (Van Asten and Martinson, 2005). Firms whose plants have large shares of HAPs would have to reduce these emissions, 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.

This first requirement for a valid instrument can be directly tested. While the raw means indicate that the HAP/air ratio is similar for the two sets of plants (Table 2), the significant difference in this ratio between RC and non-RC plants becomes evident once we control for other confounding variables. As seen in our bivariate probit model with full set of control variables, a plant's parent firm's HAP/air ratio is positively associated with the parent firm's participation in RC. The estimated coefficients on the instrumental variable range between 0.326 and 0.341 (Table 3, columns 1, 3 and 5), while the corresponding marginal effects range between 5.17% and 5.40% (Table 3, columns 2, 4 and 5). The estimated coefficients are statistically significant at the 1% level, whether we estimate standard errors clustered at the firm-level or bootstrap standard errors with 100 replications. Comparison of the raw means masks the difference in the HAP/air ratio for RC and non-RC plants, because factors strongly related to participation in RC are not controlled for, such as a plant's number of employees and a firm's number of plants. One standard deviation increase in these variables corresponds to an increased likelihood of RC participation by 35.5% and 17.6%, respectively. Looking within the subsets of plants owned by firms with (i) with above median plant-level number of employees and (ii) with above median number of plants, the HAP/air ratio is larger for RC plants and non-RC plants, and this difference is statistically significant (Table 5). Similarly, we find larger HAP/air ratio for RC plants than non-RC in the subsets of plants in industries with moderate RC participation rates and moderate pre-RC injury rates (Table 5). Finally, we conduct a Likelihood Ratio (LR) test, which compares the fit of univariate probit models with and without the excluded variable. The LR test, whose p-value is less than 0.001, rejects the null that the plant's parent firm's HAP/air ratio has no effect on the likelihood that the firm is an RC participant. Diagnostic tests for weak instruments are not available for the probit model (Nichols, 2011).[15]

The second requirement for a valid instrument

The instrumental variable, HAP/air ratio, is not likely to affect accidents, conditional on the included measures of plants' emissions, for three reasons. First, control technologies implemented to reduce HAPs are distinct from actions undertaken to improve plant safety.[16] To reduce HAPs, plants install thermal or catalytic oxidizers or chemical absorbers that burn off or absorb a greater fraction of HAPs prior to the release of the air stream into the environment (Van Asten and Martinson, 2005).[17] In contrast, steps undertaken to improve safety include identifying and preventing excessive built-up of pressure in chemical processes, the loss of control of heat-related or reactive processes, or exposure of flammable liquids to ignition sources (Spellman, 1997).

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[15] The raw means of the HAP/air ratio, which fails to control for other differences across plants, show an apparent similarity between these ratios for RC and non-RC plants (Table 1). However, regressing the HAP/air ratio on RC participation and other covariates, we find that the ratio is 4% higher for the RC plants than non-RC plants and the difference is statistically significant at the 1% level.

[16] Jeffrey Siirola, formerly with Eastman Chemical Company, Distinguished Service Professor, Carnegie Mellon University, pers. comm. with Shanti Gamper-Rabindran, 26 October 2011.

[17] 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).

Second, during our study period, regulations aimed at reducing emissions to the environment do not account for workers' exposure, as noted by Adam Finkel, former Director of Health Standards Programs at OSHA.[18] As of 2004, "there was no formal consideration of the overlap between environmental and occupational exposures (outside versus inside the plant)" (Armenti, 2004), due to the separate regulations on environmental protection and occupational safety, and the lack of coordination between OSHA and the Environmental Protection Agency (EPA) (Armenti et al., 2003).

Third, even if impending 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.[19] Out of 190 HAPs, only six are flammable and 26 are acutely toxic. HAPs that are carcinogenic or chronically toxic do not affect short-run deaths or hospitalizations due to their long latency periods (Gray and Jones, 1991). In our accident database, most cases of deaths or hospitalizations due to chemical exposure occur as a result of chemical spills that caused chemical burns. Finally, there is little evidence of a systematic link—whether none, positive, or negative—between pollution reduction strategies in production processes and occupational hazards (Sivin, 2002). Our conversations with the industry and the EPA did not yield evidence that plants change their processes to reduce both HAPs and accidents in response to these HAP regulations.

We specify the instrument as a firm's HAP/air ratio to better capture its exposure to the impending regulations. The alternative specification of the instrument as a firm's total HAPs is prone to the criticism that total HAPs are more correlated with our included pollution-intensity

[18] Dr. Adam Finkel in phone conversation with Shanti Gamper-Rabindran, 15 January 2011.
[19] The top chemicals associated with RMP accidents are ammonia (non-HAP), chlorine (HAP) and flammable mixtures (Kleindorfer et al., 2003).

variables, and therefore, less correlated with the regulations, conditional on the included pollution-intensity variables (see section 3.4). We use pounds, as opposed to toxicity weighted measures, to aggregate HAP emissions because the regulations focus on reducing the amount of HAPs, not the health-risks from HAPs.

3.4 Covariates

Our accident regressions control for OSHA inspections and penalties, along with other covariates. 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. OSHA targets some of their inspections to plants, firms, and industries that have lower safety levels (Tai, 2000; Gray and Mendeloff, 2005). At the same time, inspections and penalties can affect a plant's safety level (Scholz and Gray, 1990; Gray and Scholz, 1993). Inspections and penalties at the same plant and firm account for specific deterrence, while those at the SIC-4 industry and the state level account for general deterrence (Gray and Mendeloff, 2005). The term SIC-4 industries denote industries at the 4-digit Standard Industrial Classification, which operate in the chemical manufacturing sector (SIC 28). Inspections and penalties in the previous year and those accumulated in the prior two to five years are included. The dollar penalty accrued in the past 5 years provides a measure of the firm's safety record. A dummy is included for plants located in the 29 states where the Federal agency implements the OSHA program (Gray and Mendeloff, 2005). We control for a plant's union status and the share of a firm's plants that are unionized. Unions may improve plant safety or conversely, workers in plants with greater inherent risks may be more likely to unionize (Sandy and Elliott, 1996). Again, our study simply needs to control for the association between unions and accidents.

We control imperfectly for the inherent safety levels of the SIC-4 industry and plants in three ways.[20] First, SIC-4 dummies control for industry-specific production technologies, while time dummies control for changes in those technologies (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 and the pollution intensity of the SIC-4 industry relative to the entire chemical manufacturing sector. The plant's pollution intensity is the ratio of its toxicity weighted air pollution to its number of employees. Third, plant size is captured with the log of plant-level number of employees; while firm size is captured by the log of a firm's average number of employees at its plants, the log of the number of plants owned by a firm, and a dummy for a single-plant firm.[21] Finally, the socioeconomic characteristics of a plant's neighborhood capture the community pressure on plants to reduce their risks to surrounding communities (Hamilton, 1995; Elliott et al., 2004). Neighborhood characteristics include the shares of whites, poor people, and non-high school graduates at the tract-level.

4. Data

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 been successfully linked across three databases and fulfill three conditions: they (i) report their pollution to the Toxic Release Inventory (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 consists of SIC-28 plants that have been inspected at least once

[20] The RMP data on hazardous chemicals stored on site is not available before 1999.

[21] We choose not to link to financial variables because our study will face significant reductions in sample size, making inference impossible. Kleindorfer et al.'s (2004) linkage of the RMP to the financial variables reduced their sample size by 87%.

between 1984 and 2009.[22] The inspection reports from OSHA's Integrated Management Information System (IMIS) database are matched by plant names, addresses, and SIC-4 code to generate plants' inspection histories. Next we link the "TRI-D&B" sample with the OSHA sample based on plants' names, addresses, geocoded locations and SIC-4 code.[23] Data on accidents is from the AIS, also known as the IMIS Fatality and Catastrophe Investigation Summaries database (OSHA form 170). Data on inspections, violations detected during inspections, and penalties are from the IMIS Inspection database. Data on hazardous air pollutants and total air pollutants are from the TRI database. Pollutants are restricted to those chemicals reportable since 1987 to the TRI program. Tract-level neighborhood demographics are from the 1990 Decennial Census. We create annual plant-firm linkages using Mergent Online and Corporate Affiliations Database.

5. Results

5.1 Summary statistics

Table 1 shows that accidents, RC participation rates and injury rates vary widely across the twenty most observed industries in our sample. The likelihood of accidents is about 2.0 to 2.2 accidents per 100 plant-years for "Pesticides and Agriculture Chemicals", "Industrial Inorganic Chemicals" and "Soap and Other Detergents". In contrast, the likelihood is only 0.2 to 0.6 accidents per 100 plant years for "Surface Active Agents", "Paints, Varnishes, Lacquers and Enamels" and "Adhesives and Sealants." Similarly, participation rates vary across industries, ranging as high as 59.4% to 76.4% in "Plastic Materials and Synthetic Resins" and "Alkalines and Chlorine" and as low as 0.5% and 2.1% in "Fertilizers" and "Specialty Cleaning

[22] Weil (1996) uses a similar restriction in his analysis of OSHA plants. IMIS records plants' characteristics based on the last inspection.

[23] We use the Fellegi and Sunter's (1969) matching techniques, implemented using FEBRL software (Christen, 2008). For matches that are border-line in quality, we undertake further library research to determine if there is a true match.

Preparations.” As a measure of safety challenges across industries in the pre-RC period, we examine injury rates from the Bureau of Labor Statistics, defined as fatal or non-fatal injuries, excluding illnesses, which involve medical treatment (beyond first aid), loss of consciousness, restriction of work or motion, or transfer to another job. The injury rates range as high as 9.82 to 10.85 injuries per 100 full time workers in “Paints, Varnishes, Lacquers and Enamels” and “Fertilizers” and as low as 4.32 to 4.64 injuries per 100 full time workers in “Industrial Gases” and “Industrial Inorganic Chemicals”. To control for the variation across industries, our regression models include industry fixed effects. To further restrict our comparison to similar plants, we examine two subsets of plants: (i) plants in industries with RC participation rates between 25% to 75% and (ii) plants in industries within the middle two quartiles of injury rates in the pre-RC period.

As seen in Table 2, 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. The probability of participation in RC, based on the predicted probabilities averaged over all plants in the sample, is 33.4%. Comparison of Table 2, columns 2 and 3 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 greater pollution intensity than other plants in their SIC-4 industry. These factors are associated with greater likelihood of all accidents or RC/PS accidents (Online Appendix Table 5). RC plants’ larger number of employees and RC firms' larger number of plants, which can affect resources available to address safety issues, underscore the importance of controlling for these two factors in our main regression analysis. We further restrict our comparison to plants owned by firms with (i) above median plant-level number of employees and (ii) with above median number of plants.

Next we compare the regulatory variables for RC and non-RC plants. Both set of 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, penalties for most RC plants are slightly larger than non-RC plants. A small subset of RC plants at the highest percentiles of penalties receives much larger penalties than the corresponding non-RC plants. This subset of plants drives the observation that the average penalty for RC plants is much greater than that for non-RC plants.[24]

Finally, it is useful to compare our sample to the population of plants in the OSHA database. Our database represents the larger plants in SIC-28.[25] 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 (forthcoming). Comparison of our sample of linked plants (Table 2, column 1) and SIC-28 OSHA plants that are not linked to our data (Table 2, 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

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[24] 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.

[25] Plants in our sample meet the threshold for reporting to the TRI program and to the IMIS database (11 employees or more). The D&B database tends to include plants with larger numbers of employees.

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 that is less prone to outliers, is fairly similar in the two samples.

5.2 Results: accidents

Coefficients from the bivariate probit models (Table 3) are used to calculate RC's treatment effects on the likelihood of accidents (Table 4). The bivariate probit model estimates the participation equation and the accident equation simultaneously, and the covariates for these two equations are listed in the Online Appendix Tables A1 and A2, respectively. Results from the bivariate probit models provide evidence that participation in RC reduces the likelihood of all accidents and RC/PS accidents. The coefficient on the RC participation dummy is -0.542 for all accidents and -0.916 for RC/PS accidents (Table 3). These coefficients are statistically significant at the 10% level and the 5% level respectively. The coefficient for fatal accidents (-0.305) is not statistically significant. The imprecision of this estimate is likely due to the small number of fatal accidents in the analysis.

The Average Treatment Effects (ATE) on accidents, which are the average of the marginal effect of RC for all plants in the sample, are presented in Table 4 column 3. The ATE estimate provides the anticipated program effect if a program like RC were rolled out in the population of chemical plants that are similar to our sample. Participation in RC reduces the likelihood of all accidents and RC/PS accidents by 1.76 and 2.92 accidents per 100 plants in a given year, respectively (Table 4, column 3). The percentage reductions are substantial, i.e., 71.3% and 87.4%, respectively. Larger effects of RC on RC/PS accidents are compatible with RC's codes of conduct on process safety, environmental and health safety, and the recommended management practices that implement these codes.

The Average Treatment effects on the Treated (ATT) estimates capture the effect of the existing RC program on the plants that had, in fact, participated in the program (Table 4, column 6). Consistent with the ATE estimates, the ATT estimates indicate that participation in RC causes a sizable reduction in all accidents and RC/PS accidents, and that the reductions are larger for the RC/PS accidents. Participation in RC reduces the likelihood of all accidents and RC/PS accidents by 2.99 and 5.75 accidents per 100 plants in a given year, respectively (Table 4, column 6). The percentage reductions for all accidents and RC/PS accidents are substantial (69.3% and 85.9%, respectively). The ATT estimates for RC/PS accidents are statistically significant at the 1% level, while the corresponding coefficients are statistically significant at the 5% level. Statistical significance can differ between the treatment effects (Table 4) and the coefficients (Table 3) because we are estimating non-linear models.

Next, we estimate the bivariate probit models for four subsets of the data. This strategy is one way to address the concern that the linear combinations of control variables in our main analysis may not sufficiently control for systematic differences between RC plants and non-RC plants. Results from these subsets (Table 5) are qualitatively similar to our main analysis. As in our main regression, we find that RC participation leads to larger reductions in RC/PS accidents than in all accidents, and the estimates for RC/PS accidents, which are closely related to the RC program's codes of conduct, are more precise. Restricting our analysis to plants owned by firms with more resources to address safety issues, i.e., (i) firms which own plants with above median number of employees and (ii) firms which own more than the median number of plants, we find that RC participation reduces accidents by 2.62 accidents and 1.59 accidents per 100 plants, respectively (Table 5, column 1 and 2). Restricting our analysis to industries with similar rates of RC participation, ranging from 25% to 75%, we find that RC participation reduces RC/PS accidents by 3.00 accidents per 100 plants (Table 5, column 3). These estimates are statistically significant at the 5%, 10% and 1% level, respectively. While these point estimates in the subsets of the data are smaller than those in our main regression, examination of the standard errors in our main regression indicate that our estimates from the main regression and the various subsets of the data are not statistical different. Our analysis of industries which face similar safety challenges suggest that RC participation reduce accidents by 1.28 accidents per 100 plants, but this estimate is not statistically significant at conventional levels (Table 5, column 4). We also find that participation in RC reduces the likelihood of accidents by 2.57 accidents per 100 plants in the subset of plants operating in industries with moderate RC participation rates (Table 5 column 3). Estimates for the other three subsets of data are negative, but not statistically significant at conventional levels. The smaller sample size in the analysis of subsets of the data is likely to contribute to the imprecision of these estimates.

5.3 Other estimation models

Probit versus Bivariate probit

We compare our results from the bivariate probit models, which address self-selection (Table 6, Panel A), and the probit models, which do not address self-selection (Table 6, Panel B), to examine the direction of the self-selection bias. While the RC coefficients from both models are negative, those from the bivariate probit models are larger in magnitude. This comparison indicates ignoring self-selection leads to underestimation of the impact of participation in RC at reducing the likelihood of accidents. Underestimation may occur because plants whose unobserved characteristics make them more likely to incur accidents, even in the absence of the RC program, are also more likely to belong to RC participating firms.

Bivariate probit with fixed effects

Generally, a plant-level panel dataset provides the opportunity to examine models with plant-level fixed effects that control for unobserved plant characteristics. The fixed effect specification partially controls for self-selection by examining the effect of RC within the same plants, though the timing of the change in RC status may still be endogenous. However, in our dataset, the fixed effects model comes with two major drawbacks. First, because few plants experience changes in their parent firm's RC status and accidents occur infrequently, the fixed effects model in our dataset is identified by a very small sample of plants.[26] Among the 367 plants that experience a change in their parent firm's RC status, only 38 plants (446 observations) experience an accident, with 30 plants (352 observations) experiencing an RC/PS accident, and 17 plants (222 observations) experiencing a fatal accident. Second, as our dependent variable is binary, we estimate non-linear model with plant-level fixed effects, which ignores the incidental parameters problem. Unfortunately, the probit model with plant-level fixed effects is biased away from zero when plant-level unobservables are correlated with covariates (Greene, 2004).

With these limitations in mind, we proceed to estimate the bivariate probit model with plant-level fixed effects (Table 6, Panel C).[27] The estimated coefficients for the RC dummy are negative and statistically significant for all accidents and RC/PS accidents, and about 2-4 times larger than the coefficients in our main models. The larger size of the coefficients in the fixed effect model (Table 6) relative to the pooled model (Table 2) is compatible with the direction of bias for probit fixed effect models, described above (Greene, 2004). Moreover, the use of a

[26] For plants whose RC status does not change, the effect of RC is not separately identified from the plant fixed effects. For plants that never experience an accident, the plant fixed effects perfectly predicts the likelihood of an accident, leading to undefined values for the likelihood function.

[27] As a check, we estimate linear model with plant fixed effects using OLS and 2SLS. The coefficient on the RC participation dummy is negative, though insignificant, for all three accident definitions and for both OLS and 2SLS.

selected sample of plants that experience an accident during our study period is likely to yield these larger coefficients. When we scale the estimated treatment effects, which are generated from the sample of plants that incur an accident during our study period, by the likelihood of a plant being included in the sample, we find results comparable to those in our pooled sample. The ATT estimates indicate RC reduced all accidents and RC/PS accidents by 4.49 and 3.34 accidents per 100 plants, while the ATE estimates indicate that RC reduced all accidents and RC/PS accidents by 3.50 and 2.56 per accidents 100 plants. The probit model with plant fixed effects (Table 6, Panel D) similarly finds negative and statistically significant coefficients for the RC dummy. While these fixed effects estimates are based on small samples, they are compatible with the findings in our main specification that participation in RC reduces the likelihood of accidents.

Propensity Score Matching method

We use Propensity Score Matching (PSM), which does not rely on the exclusion restrictions for identification.[28] However, PSM does not address the impact of *unobserved* factors that affect both the likelihood of accidents and firm's self-selection into RC (Heckman, Ichimura and Todd, 1997). Overall, the PSM results support our main results that participation in RC reduces the likelihood of all accidents and PS/RC accidents, though the PSM estimates are about one-tenth to one-half the size of the respective estimates from the bivariate probit models. We apply matching with replacement on a trimmed sample (Smith and Todd, 2005). We match on one nearest neighbor and using oversampling, match on five nearest neighbors. Based on the ATE estimates, participation in RC reduces all accidents and RC/PS accidents by 0.80 accidents and 0.54 accidents per 100 plants in a given year, with these estimates statistically significant at

[28] As the IV and PSM models have their strengths and limitations (Wooldridge, 2010), we present results from both models. The PSM method has been applied to binary outcome variables in studies such as Aakvik (2001) and Caliendo, Hujer, and Thomson (2008).

the 1% level (Table 7. column 1). The 5-nearest neighbor model yields comparable results (Table 7, column 2). Based on the ATT estimates, participation in RC reduces the likelihood of RC/PS accidents by 0.70 accidents per 100 plants in a given year, with the estimate significant at the 5% level (Table 7, column 1). The ATT estimates from 5-nearest neighbor model indicate participation in RC reduces the likelihood of all accidents by 0.66 accidents per 100 plants in a given year, with the estimate significant at the 10% level (Table 7, column 2). The smaller magnitude of the PSM estimates relative to bivariate probit estimates is consistent with our findings in section 5.3, that not addressing self-selection would lead to the understatement of the effects of participation in RC in reducing the likelihood of accidents.

5.4 Economic significance of the reduction in the probability of accidents

We provide a simple back of the envelope estimate of the losses averted from the reduction in the probability of accidents. We use the figure of $26 million for property damage alone from OSHA-related accidents in the chemical and petroleum industries between 1982 and 1988 (Charles River Associate (1989) study cited in Broder and Morell (1991)). First, we use the smaller ATT estimates from the PSM, i.e., participation in RC reduces the likelihood of all accidents by 0.66 accidents per 100 plants in a given year. Second, we use the larger ATT estimates from the bivariate probit, i.e., participation in RC reduces the likelihood of all accidents by 2.99 accidents per 100 plants in a given year. This reduction in the likelihood of accidents, accounting for the 1,037 average plants that participate in RC, translates into savings between $180 million to $800 million per year, based on 1990 values.

5.5 Other results

We briefly consider other factors that are associated with the likelihood of accidents (Online Appendix Table A2). From the environmental justice perspective, our findings that plants located in neighborhoods with lower shares of whites are associated with greater likelihood of 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 0.20 and 0.24 accidents per 100 plants. These are large increases relative to the predicted probability of all accidents and RC/PS accidents (1.47 and 1.43 accidents per 100 plants in a given year, respectively). 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 0.41 and 0.48 accidents per 100 plants in a given year, respectively. The positive association between inspections and accidents suggest that OSHA's targeting of inspections to plants which are expected to have lower safety levels is the dominant effect in our data. Similarly, the positive association between union status and accidents indicates that the greater propensity to unionize at plants with greater inherent risks is the dominant effect in our data.

6. Conclusion

Our study finds that participation in RC reduces the likelihood of accidents at participating plants, suggesting that the features of the RC program do provide additional impetus for plants to improve safety (section 2.2). The ATT estimates, based on the bivariate probit models, indicate that participation in RC reduces the likelihood of all accidents and RC/PS accidents by 2.99 and 5.75 accidents per 100 plants in a given year (Table 4). These estimates, corresponding to 69.3% and 85.9% reductions in the likelihood of accidents, are statistically significant at the 10% and the 1% level, respectively. We expect the effect of participation in RC, if any, to be estimated imprecisely because accidents occur infrequently. Therefore we treat even those results that are significant at the 10% level, as evidence that participation in RC has reduced the likelihood of accidents.

Further analysis of subsets of the data gives us confidence that the observed reduction in accidents is not driven by differences in RC and non-RC plants that are not fully captured by the linear combination of control variables in our main regression. Participation in RC significantly reduced the likelihood of RC/PS accidents in a number of the subset of plants, both restricting the analysis to plants owned by parent firms with similar resources and plants in industries with similar RC participation levels..

Alternative estimation procedures yield supporting evidence as well. First, our bivariate probit model with plant-level fixed effects, which controls for unobserved plant characteristics, but whose main drawback is its small sample size, indicates that RC reduces all accidents and RC/PS accidents by 4.49 and 3.34 accidents per 100 plants in a given year (Table 6). Second, results from the PSM estimation, which does not rely on the validity of our instrument to address self-selection, also find that participation in RC reduced accidents. The ATT estimates indicate that RC reduces all accidents and PS/RC accidents by 0.66 accidents and 0.70 accidents per 100 plants in a given year and these estimates are statistically significant at the 10% and 5% level, respectively (Table 7). Importantly, even the smaller PSM estimates indicate that the RC program has averted accident-related losses that are economically significant, i.e., about $180 million per year in 1990 dollars.

We believe that our analysis sufficiently controls for self-selection bias for three reasons. First, our results in our main specification that relies on the validity of our instrument are similar to the results from alternative estimation strategies that do not require the same assumptions to hold. Second, we find a positive correlation between the instrument and participation in RC, and our study of the industry suggests that the instrument is unlikely to directly affect the likelihood of accidents. Third, taken in conjunction with Gamper-Rabindran and Finger (forthcoming), which find that RC participants raise their TRI pollution relative to non-participants, it is unlikely that our findings are driven by latent variables. These variables would have to be positively correlated with a firm's likelihood of participating in RC and a plant's willingness to improve safety, but negatively correlated with a plant's willingness to reduce pollution.

The contrasting results that RC participation reduces the likelihood of accidents but raises TRI pollution reveals an important policy lesson. The regulatory and insurance framework plays an important role in influencing the effectiveness of the voluntary or self-regulation program, by affecting participants' net benefits. As described in section 2.2, in the case of the RC program, plants are likely to receive greater net benefits from reducing their probability of accidents than from reducing their TRI pollution. 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. On the cost side, increased managerial attention to safety and organizational changes, which do not impose significant costs, can lead to reduced likelihood of accidents (Scholz and Gray, 1990), while capital investments are needed to reduce pollution (Allen and Shonnard, 2001).

The alternative explanation for RC plants reducing their likelihood of accidents, but not their TRI pollution, is that the ACC has emphasized RC's safety codes over its pollution prevention code. We find this explanation less persuasive. The requirement of reporting to the ACC on the progress of achieving RC codes and the peer pressure on CEOs to achieve those codes applies to RC's code on pollution reduction as well. Several studies that examine RC as a policy tool to reduce pollution have detailed RC's requirements to establish the goal of pollution prevention and the response of plants to meet these requirements (Prakash, 2000; King and Lenox, 2000; Börkey, Glachant and Lévêque, 2000; Yosie, 2003).

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 the chemical sector.

References

Aakvik, A. 2001. "Bounding a Matching Estimator: The Case of a Norwegian Training Program." *Oxford Bulletin of Economics and Statistics* 63 (1):115–143.

Allen, D.T. and D.R. Shonnard. 2001. *Green Engineering: Environmentally Conscious Design of Chemical Processes and Products.* Upper Saddle River, New Jersey: Prentice Hall.

Altonji, J.G., T.E. Elder and C.R. Taber. 2005. "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools." *The Journal of Political Economy* 113 (1):151-184.

American Chemistry Council (ACC) [renamed Chemical Manufacturers' Association.] 1990. "Responsible Care: Codes of Management Practices." Archived at the International Labor Organization Corporate Codes of Conduct.

Angrist, J.D. 1999. "Estimation of Limited Dependent Variable Models with Dummy Endogenous Regressors: Simple Strategies for Empirical Practice." *Journal of Business and Economics Statistics* 19 (1): 2-28.

Armenti, K. 2004. "Pollution Prevention and Worker Protection." In U.S. General Services Administration." *Sustainable Development and Society* Washington, DC: GSA Office of Governmental Policy: 41-48.

Armenti, K., R. Moure-Eraso, C. Slatin, and K. Geiser. 2003. "Joint Occupational and Environmental Pollution Prevention Strategies: A Model for Primary Prevention." *New Solutions, A Journal of Environmental and Occupational Health Policy* 13 (3): 241-259.

Baker Report. 2007. The Report of the BP U.S. Refineries Independent Safety Review Panel.

Baram, M. S. 1986. "Public Health and the Law: Chemical Industry Accidents, Liability, and Community Right to Know." *American Journal of Public Health* 76 (5): 568-572.

Barkenbus, J.N. 1983."Is Self-regulation Possible?" *Journal of Policy Analysis and Management* 2(4): 576–588

Belke, J.C. and Dietrich, D.Y. 2005. "The Post-Bhopal and Post-9/11 Transformations in Chemical Emergency Prevention and Response Policy in the United States." *Journal of Loss Prevention in the Process Industries* 18: 375–379

Bhattacharya, J., D. Goldman and D. McCaffrey. 2006. “Estimating Probit Models With Self-selected Treatments.” *Statistics in Medicine* 25(3): 389-413.

Blacconiere, W.G. and Patten, D. M. 1994. “Environmental Disclosures, Regulatory Costs and Changes in Firm Value,” *Journal of Accounting and Economics* 18: 357-377.

Booker, K., T.R. Sass, B. Gill and R. Zimmer. 2011. “The Effects of Charter High Schools on Educational Attainment.” *Journal of Labor Economics* 29 (2): 377-415.

Bomsel, O., P. Börkey, M. Glachant, F. Lévêque. 1996. “Is There Room for Environmental Self-regulation in the Mining Sector?” *Resources Policy* 22 (1–2): 79–86

Börkey, P., M. Glachant and F. Lévêque. 2000. Voluntary Approaches for Environmental Policy in OECD Countries: An Assessment. Center for Industrial Economics. Paris School of Mines and OECD.

Broder, I.E. and J.F. Morrall. 1991. “Incentives for Firms to Provide Safety: Regulatory Authority and Capital Market Reactions.” *Journal of Regulatory Economics* 3(4): 309-322.

Caliendo, M., R. Hujer and S. Thomson. 2008. “The Employment Effects of Job Creation Schemes in Germany: A Microeconometric Evaluation.” In T. Fomby, R.C. Hill, D.L. Millimet, J.A. Smith (Eds.). *Advances in Econometrics, Volume 21: Estimating and Evaluating Treatment Effects in Econometrics* Bingley: Emerald Group Publishing Ltd. pp. 383–428.

Capelle-Blancard, G. and M.-A. Laguna. 2010. “How Does the Stock Market Respond to Chemical Disasters?” *Journal of Environmental Economics and Management* 59 (2): 192-205.

Charles River Associates, Inc. 1989. Industrial Profile and Cost Assessment of a Proposed OSHA. Standard Concerning Process Hazard Managements in the Chemical and Petroleum Industries. Prepared for the Occupational Safety and Health Administration. Boston, Massachusetts.

Chemical Safety Board (CSB-First Chemical Corp). 2003. Investigation Report: Explosion and Fire: First Chemical Corp. Washington DC.

Chemical Safety Board (CSB-Texas City). 2007. Final Investigation Report: Refinery Explosion and Fire. BP American Refinery Explosion, Texas City, Texas.

Chiburis, R.C., J. Das and M. Lokshin. 2011. “A Practical Comparison of the Bivariate Probit and Linear IV Estimators.” *World Bank Policy Research Working Paper 5601.*

Christen, P. 2008. “FEBRL: A Freely Available Record Linkage System with a Graphical User Interface.” *Proceedings of the Second Australasian Workshop on Health Data and Knowledge Management* 80: 17–25.

Cohen, M.A., M. Gottlieb, J. Linn and N. Richardson. 2011. “Deepwater Drilling: Law, Policy, and Economics of Firm Organization and Safety.” *Resources for the Future Discussion Paper 10-65*.

Cosslett, S. 1981. “Efficient Estimation of Discrete-choice Models.” in C. F. Manski and D. McFadden (eds.) *Structural Analysis of Discrete Data with Econometric Applications*. Cambridge, Mass. MIT Press: 51-111.

Dawson, N.L. and K. Segerson. 2008. “Voluntary Agreements with Industries: Participation Incentives with Industry-wide Targets.” *Land Economics* 84 (1): 97-114.

Dechy, N., T. Bourdeaux, N. Ayrault, M.-A. Kordek and J.-C. Le Coze. 2004. “First Lessons of the Toulouse Ammonium Nitrate Disaster, 21st September 2001, AZF Plant, France.” *Journal of Hazardous Materials* 111 (1-3): 131-138.

Deepwater Horizon Study Group. 2011. Final Report on the Investigation of the Macondo Well Blowout. Center for Catastrophic Risk Management. University of California at Berkeley.

Deily, M.E. and W.B. Gray. 2007. “Agency Structure and Firm Culture: OSHA, EPA, and the Steel Industry.” *Journal of Law, Economics, and Organization* 23 (3): 685-709.

Dlouhy, J.A. 2011. “Safety Plans Could Clash: Offshore Drillers Pressured to Form Watchdog.” *Houston Chronicle* January 9, 2011.

Elliott, M.R., Y. Wang, P.R. Kleindorfer and R.A. Lowe. 2004. “Environmental Justice: Community Pressure and Frequency and Severity of U.S. Chemical Industry Accidents.” *Journal of Epidemiology and Community Health* 58 (1): 24-30.

Er, J., H.C. Kunreuther and I. Rosenthal. 1998. “Utilizing Third-party Inspections for Preventing Major Chemical Accidents.” *Risk Analysis* 18 (2): 145-153.

Evans, W. N. and R.M. Schwab. 1995. “Finishing High School and Starting College: Do Catholic Schools Make a Difference?” *Quarterly Journal of Economics* 110 (4): 947-974.

Fellegi, I.P. and A.B. Sunter. 1969. “A Theory for Record Linkage.” *Journal of the American Statistical Association* 64 (328): 1183-1210.

Gamper-Rabindran, S. 2006. “Did the EPA’s Voluntary Industrial Toxics Program Reduce Plants’ Emissions? A GIS Analysis of Distributional Impacts and a By-media Analysis of Substitution.” *Journal of Environmental Economics and Management* 52(1): 391-410.

Gamper-Rabindran, S. and S. Finger. “Does Self-regulation Reduce Pollution? Responsible Care Program in the Chemical Industry.” *Journal of Regulatory Economics,* forthcoming.

Garber, S. and J.K. Hammitt. 1998. “Risk Premiums for Environmental Liability: Does Superfund Increase the Cost of Capital?” *Journal of Environmental Economics and Management* 36 (3): 267-294.

Glachant, M. 2007. “Non-binding Voluntary Agreements.” *Journal of Environmental Economics and Management* 54 (1): 32-48.

Gray, W. B & Jones, C.A. 1991. “Are OSHA Health Inspections Effective? A Longitudinal Study in the Manufacturing Sector.” *Review of Economics and Statistics* 73 (3): 504-508.

Gray, W.B and J.M. Mendeloff. 2005. “The Declining Effects of OSHA Inspections on Manufacturing Injuries: 1979 to 1998.” *Industrial and Labor Relations Review* 58 (4): 571-587.

Gray, W.B. and J.T. Scholz. 1993. “Does Regulatory Enforcement Work? A Panel Analysis of OSHA Enforcement.” *Law and Society Review* 27 (1): 177-213.

Greene, W., 2004. “The Behaviour of the Maximum Likelihood Estimator of Limited Dependent Variable Models in the Presence of Fixed Effects.” *Econometrics Journal* 7: 98–119.

Hamilton, J.T. 1995. "Testing for Environmental Racism: Prejudice, Profits, Political Power?" *Journal of Policy Analysis and Management* 14 (1): 107-132.

Heckman, J.J. 1978. “Dummy Endogenous Variables in Simultaneous Equation System.” *Econometrica* 46 (6): 931-959.

Heckman, J.J., H. Ichimura and P.E. Todd. 1997. “Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme.” *The Review of Economic Studies 64* (221): 605-654.

Heyes, A. 2005. “A Signalling Motive for Self-Regulation in the Shadow of Coercion” *Journal of Economics and Business* 57(3): 238-46.

Hofmann, D.A., R. Jacobs, and F.L. Landy. 1995. “High Reliability Process Industries: Individual, Micro, and Macro Organizational Influences on Safety.” *Journal of Safety Research* 26 (3): 131–149.

Hopkins, A. 2000. *Lessons from Longford: The Esso Gas Plant Explosion*. CCH Australia Limited.

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

King, A.A. and M.J. Lenox. 2000. “Industry Self-regulation Without Sanctions: The Chemical Industry’s Responsible Care Program.” *Academy of Management Journal* 43 (4): 698–716.

Klein, L. R. 1953. *A Textbook of Econometrics*. Evanston, IL: Row, Peterson & Co. p. 258.

Kleindorfer, P.R. and H.C. Kunreuther (Eds.). 1987. *Insuring and Managing Hazardous Risks: From Seveso to Bhopal and Beyond.* New York: Springer-Verlag.

Kleindorfer, P.R., J.C. Belke, M.R. Elliott, K. Lee, R.A. Lowe and H.I. Feldman. 2003. “Accident Epidemiology and the U.S. Chemical Industry: Accident History and Worst-case Data from RMP Info.” *Risk Analysis* 23 (5): 865-881.

Kleindorfer, P.R., M.R. Elliott, Y. Wang and R. Lowe. 2004. “Drivers of Accident Preparedness and Safety: Evidence from the RMP Rule.” *Journal of Hazardous Material* 115 (1-3): 9-16.

Konar, S. and M.A. Cohen, 2001. "Does The Market Value Environmental Performance?" *Review of Economics and Statistics* 83(2): 281-289.

Krause, R.T. 2004. “Influencing the Behavior of Senior Leadership: What Makes a Great Safety Leader?” *Professional Safety* 49(6): 29-33.

Levinson, A. 2004. “Review of New Tools for Environmental Protection: Education, Information, and Voluntary Measures.” *Journal of Economic Literature* 42 (1): 171-231.

Lyon, T.P. and J.W. Maxwell. 2004. *Corporate Environmentalism and Public Policy.* Cambridge, UK: Cambridge University Press.

Maddala, G.S. 1983. *Limited-dependent and Qualitative Variables in Econometrics.* Cambridge University Press.

Maxwell, J.W., T. Lyon and S. Hackett. 2000. “Self-regulation and Social Welfare: The Political Economy of Corporate Environmentalism.” *Journal of Law and Economics* 63 (43): 583-617.

Mendeloff, J.M. and W.B. Gray. 2005. “Inside the Black Box: How Do OSHA Inspections Lead to Reductions in Workplace Injuries?” *Law and Policy* 27 (2): 219-237.

Mendeloff, J.M. and B.T. Kagey. 1990. “Using OSHA Accident Investigations to Study Patterns in Work Fatalities.” *Journal of Occupational Medicine* 32 (11): 1117-1123.

Morgenstern, Richard and William A. Pizer. 2007. *Reality Check: The Nature and Performance of Voluntary Environmental Programs in the United States, Europe, and Japan.* Washington DC: RFF Press.

Monfardini, C. and R. Radice. 2008. “Testing Exogeneity in the Bivariate Probit Model: A Monte Carlo Study.” *Oxford Bulletin of Economics and Statistics* 70 (2): 271–282.

National Academy of Engineering; National Research Council. 2010. *Interim Report on Causes of the Deepwater Horizon Oil Rig Blowout and Ways to Prevent Such Events.* Washington, D.C.: The National Academies Press.

National Commission on the BP Deepwater Horizon Oil Spill and Offshore Drilling (NCBP). 2011. *Deep Water: The Gulf Oil Disaster and the Future of Offshore Drilling*. Part I: Report to the President. Part II Recommendations.

Nichols, A. 2011. “Causal Inference for Binary Regression.” Stata Conference Chicago (version June 14, 2011).

Pidgeon, N. and M. O’Leary. 2000. “Man-made Disasters: Why Technology and Organizations (Sometimes) Fail.” *Safety Science* 34 (1-3): 15-30.

Prakash, A. 2000. “Responsible Care: An Assessment.” *Business & Society* 39 (2): 183-209.

Reason, J. 1997. *Managing the Risks of Organizational Accidents.* Burlington, Vermont: Ashgate Publishing Ltd.

Rees, J.V. 1997. “The Development of Communitarian Regulation in the Chemical Industry.” *Law and Policy* 17 (4): 477-528.

Sandy, R. and R.F. Elliott. 1996. “Unions and Risk: Their Impact on the Level of Compensation for Fatal Risk.” *Economica* 63 (250): 291-309.

Scholz, J.T. and W.B. Gray. 1990. “OSHA Enforcement and Workplace Injuries: A Behavioral Approach to Risk Assessment.” *Journal of Risk and Uncertainty* 3 (3): 283-305.

Sivin, D. 2002. Impact of a Pollution Prevention Program on Occupational Exposures. Philadelphia, PA: American Public Health Association 130th Annual Meeting.

Slovic, P., B. Fischhoff, S. Lichtenstein. 1982. “Why Study Risk Perception?” *Risk Analysis* 2(2): 83–93

Smith, J.A. and P.E. Todd. 2005. “Does Matching Overcome LaLonde’s Critique of Nonexperimental Estimators?” *Journal of Econometrics* 125 (1-2): 305-353.

Spellman, F.R. 1997. *A Guide to Compliance for Process Safety Management/ Risk Management Planning.* Lancaster PA: Technomic Publishing Co.

Tai, E. 2000. *OSHA Compliance Management: A Guide for Long-term Health Care Facilities*. New York: CRC Press.

Van Asten, M. and C. Martinson. 2005. “MON MACT Impact.” *Products Finishing* 70 (3): 54

Vidovic, M., and N. Khanna. 2007. Can Voluntary Pollution Control Programs Fulfill Their Promises? Further Evidence from EPA’s 33/50 Program. *Journal of Environmental Economics and Management* 53: 180–195.

Weil, D. 1996. “If OSHA is So Bad, Why is Compliance So Good?” *Rand Journal of Economics* 27 (3): 618-640.

Wilde, J. 2000. “Identification of Multiple Equation Probit Models with Endogenous Dummy Regressors.” *Economics Letters* 69: 309-312.

Wooldridge, J. 2010. *Econometric Analysis of Cross Section and Panel Data.* Cambridge: MIT Press

Yosie, T.F. 2003. “Peer Reviewed: Responsible Care at 15 Years.” *Environmental Science & Technology*. 37 (21): 400A-406A.

Table 1: Industry-level rates of participation in RC, likelihood of accidents and mean injury rates.

Industry	[1] No. obs.	[2] Participation rate in RC	[3] Likelihood of accident	[4] Mean injury rate (1985-8)
SIC 2851 - Paints, Varnishes, Lacquers, and Enamels	4,736	9.5%	0.5%	9.82
SIC 2869 - Industrial Organic Chemicals, n.e.c.	2,872	56.0%	1.7%	4.96
SIC 2821 - Plastics Materials and Synthetic Resins	2,631	59.4%	1.3%	6.00
SIC 2819 - Industrial Inorganic Chemicals, n.e.c.	2,045	48.5%	2.2%	4.64
SIC 2899 - Chemicals, n.e.c.	1,767	29.5%	1.1%	7.92
SIC 2891 - Adhesives and Sealants	1,320	25.5%	0.6%	9.36
SIC 2842 - Specialty Cleaning Preparations	973	2.1%	1.1%	8.94
SIC 2841 - Soap and Other Detergents	877	13.2%	2.2%	6.30
SIC 2865 - Cyclic Organic Crudes and Organic Dyes	831	47.5%	1.9%	6.12
SIC 2879 - Pesticides and Agricultural Chemicals, n.e.c.	786	29.8%	2.0%	5.40
SIC 2893 - Printing Ink	755	27.9%	0.7%	8.92
SIC 2834 - Pharmaceutical Preparations	675	20.3%	1.9%	4.86
SIC 2843 - Surface Active Agents and Assistants	455	42.6%	0.2%	8.24
SIC 2873 - Nitrogenous Fertilizers	365	9.0%	1.4%	7.48
SIC 2833 - Medicinal Chemicals and Botanical Products	354	47.5%	1.7%	6.08
SIC 2816 - Inorganic Pigments	352	56.8%	1.1%	6.46
SIC 2812 - Alkalies and Chlorine	305	76.4%	1.6%	6.26
SIC 2844 - Perfumes, Cosmetics, and Other Toilet Preps	293	16.7%	1.7%	7.48
SIC 2875 - Fertilizers, Mixing Only	221	0.5%	1.4%	10.85
SIC 2813 - Industrial Gases	220	50.5%	1.8%	4.32

The table shows the top twenty industries in the number of observations in our sample. The participation rate in RC is calculated as the ratio of the number of RC plant years to the plant years in the sample for a given industry. The likelihood of accidents is the ratio of the number of accidents to the number of plant years for a given industry. The injury rate is the number of cases of fatal or non-fatal injuries, excluding illness, that result in lost or restricted workdays, per 100 full time workers. This data is from the Bureau of Labor Statistics' Occupational Injuries and Illness Incidences Rate Data. The term n.e.c.denotes not elsewhere classified.

Table 2. Summary statistics: Means of variables for various subsets of plants for the period 1988 to 2001

	[1] RC & non-RC plants	[2] RC plants	[3] Non-RC plants	[4] Comparison RC & Non-RC plants	[5] Non-linked 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%	***	-
Plant's parent firm's HAP/air ratio	0.774	0.764	0.778	*	-
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 pollution intensity relative to its SIC-4	1.021	1.077	0.993	***	
Pollution intensity of the plant's SIC-4 industry	1.028	1.156	0.964	***	
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 for RC and non-RC plants are statistically different at the ***1%. **5%, and *10% level. (i) While the raw means indicate that plants' parent firms' HAP/air ratio for RC and non-RC plants are fairly close and statistically different at the 10% level; we note that, after controlling for differences between RC and non-RC plants, these ratios are 4% larger for RC plants than non-RC plants, and this difference between RC and non-RC plants is significant at the 1% level. (ii) Our sample (column 1) consists of the set of plants which have been successfully linked with the OSHA inspection database (i.e., plants inspected at least once between 1984 and 2009). The OSHA database provides information on plants' union status, location and SIC-4. The plants in column 5 are from the OSHA inspection database that are not linked to our sample and are excluded from our analysis. Our sample (column 1) is largely comparable with the non-linked sample of OSHA plants (column 5).

Table 3: Bivariate probit regression of the impact of Responsible Care participation on accidents

	[1]	[2]	[3]	[4]	[5]	[6]
	All accidents		RC/PS accidents		Fatal accidents	
	Coefficient	Marginal effects	Coefficient	Marginal effects	Coefficient	Marginal effects
Equation 1: The outcome variable is the plant's parent firm's participation in RC.						
Plant's parent firm's HAP/air ratio	0.336***	5.32%**	0.326***	5.17%**	0.341***	5.40%**
	(0.125)	(2.58%)	(0.125)	(2.61%)	(0.125)	(2.76%)
Control variables	incl		incl		incl	
Equation 2: The outcome variable is the presence/absence of an accident.						
RC participation dummy	-0.542*	-1.76%*	-0.916**	-2.92%**	-0.305	-0.39%
	(0.326)	(1.07%)	(0.362)	(1.83%)	(0.395)	(0.32%)
ρ which captures the correlation between	0.287		0.522***		0.154	
the error terms in Equations 1 and 2.	(0.246)		(0.179)		(0.223)	
Control variables	incl		incl		incl	
No of accidents	304		212		110	
Observations	23,780		23,780		23,780	

Notes: The table shows results for three separate bivariate probit models, i.e., the models for all accidents (column 1 and 2) RC/PS accidents (column 3 and 4) and fatal accidents (column 5 and 6). RC/PS accidents indicate process safety accidents and those accidents involving violations of OSHA standards related to RC codes. Each bivariate probit model estimates Equation 1 and Equation 2 simultaneously. Our sample includes 1,867 firms that own 2,963 plants between 1988 and 2001. Control variables are listed in the online appendix Table A1 and A2. We report standard errors clustered on firms in parentheses. Asterisks denote statistically significance at the ***1%, ** 5% and * 10% level. As an alternative strategy, we estimate bootstrap standard errors with 100 replications. In the models with bootstrap standard errors, the coefficients on the HAP/air ratio are statistically significant at the 1% level for all three models. The coefficients for the RC participation dummy in the models for all accidents and the RC/PS accidents are statistically significant at the 10% level. That coefficient in the model for fatal accidents is not statistically significant. The statistical significance of the coefficients (columns 1, 3, 5) and marginal effects (column 2, 4, 6) can differ in these non-linear models.

Table 4: Treatment effects of Responsible Care on the likelihood of accidents

	[1]	[2]	[3]		[4]	[5]	[6]
	Average Treatment Effects (ATE)				Average Treatment Effect on the Treated (ATT)		
	RC=1	RC=0	RC Effect		RC=1	RC=0	RC Effect
All accidents	0.71%	2.46%	-1.76%*		1.32%	4.31%	-2.99%*
No accidents=304			(1.07%)				(1.73%)
RC/PS accidents	0.42%	3.35%	-2.92%**		0.95%	6.70%	-5.75%***
No accidents=212			(1.83%)				(2.24%)
Fatal accidents	0.30%	0.69%	-0.39%		0.50%	1.10%	-0.60%
No accidents=110			(0.32%)				(0.51%)

Obs=23,780. (i) The RC treatment effects are calculated using estimated coefficients from the main bivariate probit models in Table 2. The ATE is the average of the marginal effects calculated over all plants in the sample. The ATT is the average of 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. (ii) The interpretation of the estimates are as follows. Eg., the ATE estimate for all accidents in column 3 indicates that RC reduces the likelihood of RC by 1.76 accidents per 100 plants in a given year. (iii) The Delta method (Klein, 1953) is used to calculate standard errors that are clustered at the firm-level. (iv) Because we are estimating non-linear models, the statistical significance can differ between (a) treatment effects, shown in this table and (b) the coefficients, shown in Table 2. For most models, the statistical significance is the same in Table 2 and 3. For the models on RC/PS accidents, we obtain greater statistical signifiance for the ATT and ATE estimates than for the coefficients.

Table 5: The Average Treatment Effect on the Treated (ATT) estimates of RC participation in differents subsets of the data

	[1]	[2]	[3]	[4]
	Subset 1	Subset 2	Subset 3	Subset 4
	Plants belonging to firms with		Plants in industries whose	
	> median no. of employees (>68 employees)	> median no. of plants (>3 plants)	RC participation rates are between 25% and 75%	Pre-RC injury rates are in the middle quartiles
ATT estimates of RC participation on all accidents	-2.21%	-0.97%	-2.57**	-1.31%
	(1.41%)	(0.94%)	(1.20%)	(0.84%)
ATT estimates of RC participation on RC/PS accidents	-2.62%**	-1.59%*	-3.00%***	-1.28%
	(1.56%)	(0.87%)	(0.95%)	(1.37%)
ATT estimates of RC participation on fatal accidents	-0.58%	-0.37%	1.12%	-0.08%
	(0.46%)	(0.35%)	(1.83%)	(0.55%)
<u>Data description</u>				
No. obs: RC Plants	6,221	6,837	6,864	4,465
No. obs: Non-RC Plants	5,678	4,011	8,258	8,270
% obs. with accidents: RC	1.75%	1.67%	1.68%	1.28%
% obs. with accidents: Non-RC	1.81%	1.05%	1.22%	1.33%
<u>The mean plant's parent firm's HAP/air ratio for RC and non-RC plants are statistically different at the 1% level</u>				
RC plants	0.772	0.763	0.761	0.796
Non-RC plants	0.759	0.731	0.745	0.753

We estimate the bivariate probit model for four different subsets of data. Each model is estimated for three outcomes: (i) all accidents, (ii) RC/PS accidents, and (iii) fatal accidents. Standard errors for the coefficient estimates are clustered at the firm-level. The Delta Method is used to calculate standard errors for the ATT estimates. The ATT estimates indicate, for example, that RC participation reduces the likelihood of RC/PS accidents by 2.62 accidents per 100 plants in the first subset of plants (column 1). Statistically significant at the ***1%, **5% and *10%.

Table 6: Bivariate probit and probit regressions of Responsible Care partipation on accidents						
	[1]	[2]	[3]	[4]	[5]	[6]
	All accidents		RC/PS accidents		Fatal accidents	
	ρ	Coefficient on RC participation dummy	ρ	Coefficient on RC participation dummy	ρ	Coefficient on RC participation dummy
Panel A: Bivariate probit model						
	0.287	-0.542*	0.522***	-0.916**	0.154	-0.305
	(0.246)	(0.326)	(0.179)	(0.362)	(0.223)	(0.395)
No. obs.		23,780		23,780		23,780
Panel B: Probit model						
		-0.093		-0.053		-0.066
		(0.067)		(0.069)		(0.088)
No. obs.		23,780		23,780		23,780
Panel C : Bivariate probit model with plant fixed effects						
	-0.569	-2.213***	-0.418	-2.415***	0.762	-0.622
	(0.731)	(0.270)	(0.555)	(0.346)	(0.514)	(0.767)
No. obs.		446		352		222
Panel D: Probit model with fixed effects		-0.513*		-0.766*		1.200
		(0.312)		(0.403)		(1.438)
No. obs.		446		352		222

We estimate four different models corresponding to Panel A, B, C, and D. Each model is estimated for three outcomes: (i) all accidents, (ii) RC/PS accidents, and (iii) fatal accidents. Identification for the fixed effects models in Panel C and D come from plants that have both (i) switched their RC status, and (ii) experienced at least one accident. The parameter ρ captures the correlation between the error terms in the accident equation and the participation equation in the bivariate probit model. Standard errors are clustered at the firm-level. Statistically significant at the ***1%, **5% and *10%.

Table 7: Responsible Care treatment effects estimated with Propensity Score Methods		
	[1]	[2]
Nearest Neighbors	1	5
Replacement	Y	Y
Trimmed sample	Y	Y
Panel A: All accidents		
Average Treatment Effects (ATE)	-0.800%***	-0.840%***
	(0.210%)	(0.204%)
Average Treatment Effects on the Treated (ATT)	-0.611%	-0.660%*
	(0.465%)	(0.376%)
Panel B: RC/PS accidents		
Average Treatment Effects (ATE)	-0.540%***	-0.520%***
	(0.139%)	(0.166%)
Average Treatment Effects on the Treated (ATT)	-0.700%**	-0.559%
	(0.353%)	(0.392%)
Panel C: Fatal accidents		
Average Treatment Effects (ATE)	-0.119%	-0.210%*
	(0.108%)	(0.120%)
Average Treatment Effects on the Treated (ATT)	0.320%	0.052%
	(0.195%)	(0.215%)
Observations	14,268	14,268
RC=1 obs.	3,437	3,437
RC=0 obs.	10,831	10,831

Notes. Bootstrapped standard errors in parentheses. Statistically significant at the ***1%, **5% and *10%. The interpretation of the estimates as are follows. For example, the ATE estimate in column 1 indicates that RC reduces the likelihood of all accidents by 0.8 accidents per 100 plants for a given year.

Online Appendix

Table A1: Bivariate Probit Regression Models: Equation 1 with participation in Responsible Care as the outcome variable

Marginal effects of factors associated with the participation in Responsible Care

	[1]	[2]	[3]	[4]	[5]	[6]
	All accidents		RC/PS accidents		Fatal accidents	
	Prob.RC=0.334		Prob.RC=0.334		Prob.RC=0.334	
	dPr(RC)	Δ Pr(RC>0)	dPr(RC)	Δ Pr(RC>0)	dPr(RC)	Δ Pr(RC>0)
	dX	$\mid \Delta\sigma_x$	dX	$\mid \Delta\sigma_x$	dX	$\mid \Delta\sigma_x$
Plant's parent firm's HAP/air ratio	5.32%**	1.53%**	5.17%**	1.49%**	5.40%**	1.55%**
Plant's pollution intensity relative to its SIC-4	6.92%***	2.45%***	6.93%***	2.45%***	6.93%***	2.46%***
Pollution intensity of the plant's SIC-4 relative to SIC-28	11.0%**	3.37%**	11.0%**	3.39%**	11.0%**	3.38%**
Plant's neighborhood: % white	3.10%	0.86%	3.09%	0.86%	3.10%	0.86%
Plant's neighborhood: % urban	-0.94%	-0.37%	-0.92%	-0.36%	-0.95%	-0.37%
Plant's neighborhood: % poor	4.13%	0.61%	4.00%	0.59%	4.14%	0.61%
Plant's neighborhood: < high school education	-4.76%	-0.80%	-4.79%	-0.80%	-4.76%	-0.80%
†Dummy for unionized plant	0.13%		0.14%		0.10%	
% firm's plants that are unionized	5.65%***	2.01%***	5.62%***	2.00%***	5.71%***	2.03%***
Log (# plant employees)	-0.71%	-0.92%	-0.72%	-0.93%	-0.71%	-0.92%
Log (mean # employees at firm's plants)	8.27%***	9.49%***	8.27%***	9.49%***	8.26%***	9.48%***
Log (# firm's plants)	13.7%***	17.2%***	13.7%***	17.2%***	13.6%***	17.2%***
†Dummy for single-plant firm	-1.37%		-1.31%		-1.42%	
Log (plant's $ cumulative penalties in year t-2 to t-5)	-0.11%	-0.37%	-0.11%	-0.36%	-0.11%	-0.35%
Log (plant's $ penalties in year t-1)	-0.07%	-0.13%	-0.08%	-0.16%	-0.06%	-0.13%
Cumulative inspections in year t-2 to t-5	-0.40%	-0.30%	-0.42%	-0.32%	-0.40%	-0.30%
Dummy for $\geq$ 1 inspections in year t-1	0.16%	0.05%	0.18%	0.06%	0.12%	0.04%
% firm's plants that are unionized	1.48%	0.34%	1.40%	0.32%	1.45%	0.33%
Log (mean $ penalties at firm's plants in year t-1)	0.14%	0.49%	0.15%	0.52%	0.14%	0.49%
†Dummy for no inspections at firm's plants in t-1	2.86%*		2.88%*		2.85%*	
% of plants inspected in state in year t-1	25.9%**	0.78%**	25.9%**	0.78%**	26.2%**	0.79%**
Log (mean $ penalties in state in year t-1)	0.48%**	0.84%**	0.47%**	0.82%**	0.48%**	0.83%**
% plants inspected in SIC-4 in year t-1	8.40%	0.16%	8.45%	0.16%	9.29%	0.17%
Log (mean $ penalties in SIC-4 in year t-1)	0.25%	0.27%	0.24%	0.26%	0.24%	0.26%
†Dummy for plants in states with federally run OSHA	0.48%		0.49%		0.50%	

Obs. =23,780. "Prob. RC" denotes the predicted probability that the plant belongs to a RC participating firm. We estimate the average of the marginal effects calculated over all plants in the sample. † denotes a binary variable and 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 (column 2, 4, 6). The chemical sector (SIC-28) consists of industries at the 4 digit Standard Industrial Classification (SIC-4). SIC-4 industry and time dummies are included in the models. Statistically significant at the ***1%, **5% and *10%.

Table A2: Bivariate Probit Regression Models: Equation 2 with accidents as the outcome variable

Marginal effects of factors associated with accidents

	[1]	[2]	[3]	[4]	[5]	[6]
	All accidents		RC/PS accidents		Fatal accidents	
	Prob.Acc=1.47%		Prob.Acc.=1.43%		Prob.Acc.=0.49%	
	dPr(Acc)	ΔPr(Acc>0)	dPr(Acc)	ΔPr(Acc>0)	dPr(Acc)	ΔPr(Acc>0)
	dX	$\| \Delta\sigma_x$	dX	$\| \Delta\sigma_x$	dX	$\| \Delta\sigma_x$
†Responsible Care participation dummy	-1.76%*		-2.92%**		-0.39%	
Plant's pollution intensity relative to that of its SIC-4	1.15%***	0.41%***	1.35%***	0.48%***	0.27%*	0.10%*
Pollution intensity of the plant's SIC-4 relative to SIC-28	1.07%	0.33%	1.20%	0.37%	0.69%	0.21%
Plant's neighborhood: % white	-0.73%*	-0.20%*	-0.84%**	-0.24%**	-0.30%	-0.08%
Plant's neighborhood: % urban	0.20%	0.08%	0.23%	0.09%	-0.02%	-0.01%
Plant's neighborhood: % poor	-1.25%	-0.18%	-0.92%	-0.14%	-0.29%	-0.04%
Plant's neighborhood: % < high school education	0.95%	0.16%	0.59%	0.10%	0.37%	0.06%
†Dummy for unionized plant	0.33%*		0.02%		0.05%	
% firm's plants that are unionized	-0.31%	-0.11%	0.06%	0.02%	-0.17%	-0.06%
Log (# plant employees)	0.18%**	0.24%**	0.16%*	0.20%*	0.10%	0.13%
Log (mean # employees at firm's plants	0.44%	0.50%	0.50%	0.58%	0.08%	0.09%
Log (# firm's plants)	0.30%	0.38%	0.50%	0.64%	-0.03%	-0.04%
†Dummy for single-plant firm	-0.05%		-0.24%		-0.10%	
†Dummy for plant in states with federally-run OSHA	1.26%***		-0.80%***		0.29%**	
Log (plant's $ cumulative penalities in years t-2 to t-5)	-0.04%	-0.13%	-0.04%	-0.13%	-0.01%	-0.03%
Log (plant's $ penalties in year t-1)	0.08%	0.17%	0.09%	0.18%	-0.04%	-0.07%
Cumulative inspections in years t-2 to t-5	0.41%***	0.31%***	0.45%***	0.03%***	0.12%*	0.09%*
†Dummy for ≥1 inspections in t-1	-0.26%	-0.08%	-0.29%	-0.09%	0.23%	0.07%
% firm's plants inspected in year t-1	-0.05%	-0.01%	0.04%	0.01%	-0.42%	-0.10%
Log (mean $ penalties af firm's plants in year t-1)	0.01%	0.02%	-0.04%	-0.15%	0.04%*	0.131%*
†Dummy for no inspections at firm's plants in t-1	-0.05%		-0.16%		0.06%	
% of plants inspected in the state in year t-1	6.61%**	0.20%**	4.13%	0.13%	-0.59%	-0.02%
Log (mean $ penalties in the state in year t-1)	0.04%	0.08%	0.06%	0.10%	0.05%	0.08%
% of plants inspected in the SIC-4 in year t-1	-1.31%	-0.02%	-7.33%	-0.14%	-1.31%	-0.02%
Log (mean $ penalties in the SIC-4 in year t-1)	0.08%	0.09%	0.14%	0.15%	0.03%	0.03%

Obs. =23,780. "Prob. Acc." denotes the predicted probability of accidents. We estimate the average of the marginal effects calculated over all plants in the sample. † denotes a binary variable and 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, 6). The chemical sector (SIC-28) consists of industries at the 4 digit Standard Industrial Classification (SIC-4) SIC-4 industry and time dummies are included in the models. Statistically significant at the ***1%, **5% and *10%.