DOES INDUSTRY SELF-REGULATION REDUCE POLLUTION? RESPONSIBLE CARE IN THE CHEMICAL INDUSTRY

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Abstract

Self-regulation programs, in which industry associations set membership codes beyond government regulations, are prevalent despite scarce evidence on their effectiveness. We examine Responsible Care (RC) in the US chemical manufacturing sub-sector, whose membership codes include pollution prevention, using our author-constructed panel database of 3,278 plants owned by 1,759 firms between 1988 and 2001. We apply two sets of instrumental variables to address a plant's parent firm's self-selection into the program, using: (i) the characteristics of other plants belonging to the same firm in our multi-plant sample; and (ii) firm participation in the industry association before the establishment of RC and industry-level RC participation in our full sample. We find that on average, plants owned by RC participating firms raise their toxicity-weighted pollution by 15.9% relative to statistically-equivalent plants owned by non-RC participating firms. This estimated increase is large relative to the yearly 4% reduction in pollution among all plants in our sample between 1988 and 2001. Moreover, RC raises plant-level pollution intensity by 15.1%. These results caution against reliance on self-regulation programs modeled on the pre-2002 RC program that did not require third party certification and in those sectors that lack independent third party certification.

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1. Industry Self-Regulation: Responsible Care

Self-regulation programs, in which industry associations set codes of conduct for their members against the backdrop of government regulations, are prominent even in the high risk chemical and nuclear sectors (NCBP, 2011). One major justification for relying on industry self-regulation to manage environmental risks is that firms have more information, expertise and resources than government regulators (National Academy of Engineering, 2010; GAO, 2011). The most prominent of these programs is Responsible Care in the chemical sector. The American Chemistry Council (ACC), that sector's trade association, mandates its members to join the self-regulation program and adhere to its codes including pollution prevention. The ACC describes management strategies and provides technical assistance to members in order to implement these codes (ACC, 1990).

We test the impact of Responsible Care (RC) in the US chemical manufacturing sub-sector[1] on plant-level *pollution* (defined as toxicity-weighted air pollution).[2] Our assessment is timely because high risk sectors are emulating RC, despite limited empirical evidence on its effectiveness. Most recently, the National Commission on the BP Oil Spill, noting that RC *has improved* environmental management in the chemical sub-sector, recommended that the oil and gas drilling sector create a self-regulation program (NCBP, 2011). In turn, that sector's industry association is considering the adoption of a self-regulation program that incorporates features from RC (Dlouhy, 2011). Yet, the only empirical study on RC (King and Lenox, 2000) reports that RC participants reduce their pollution at slower rates than non-participants. However, a key

[1] The Standard Industrial Classification (SIC) preceded the current North American Industry Classification System. We study the SIC-28 chemical manufacturing major-group. The SIC-28 major group contains industries at the SIC 4-digit level (SIC-4). Our plants are from SIC 2851 - Paints, Varnishes, Lacquers, and Enamels (18%), SIC 2821 - Plastics Materials and Synthetic Resins (11%), SIC 2869 - Industrial Organic Chemicals, not elsewhere classified (11%), and other SIC-4 industries.
[2] Most pollution reported to the Toxic Release Inventory is emitted into air (Potoski and Prakash, 2005).

drawback in that innovative study is that it does not address firms' self-selection into the program, which is likely based on factors that are unobserved by researchers but correlated with the program outcome (Hartman, 1988; Levinson, 2004). The direction of bias when firms' self-selection into RC is not addressed is not known a priori (section 2.3). Therefore, King and Lenox (2000) may be biased against or towards finding that RC reduces pollution.

Our study applies instrumental variables to address firms' self-selection into RC. For a plant belonging to a multi-plant firm, we instrument for the RC participation status of a plant's parent firm using characteristics of *other plants* belonging to the same firm. Factors such as strong regulatory pressure on these other plants reduce a firm's overall costs of joining RC (the firm would have to reduce pollution in any case, and it might as well join RC and share the benefits). However, these regulatory factors at *other plants* are less likely to directly affect pollution at a given plant (section 3.5). As imperfect instruments in the full sample, (truly exogenous instruments for single-plant firms are difficult to identify), we use the share of rival plants in the given industry participating in RC and the parent firm's participation in the ACC before the creation of RC.

We implement a system Generalized Method of Moments (GMM) estimator to our author constructed panel database of the US chemical manufacturing sector, with 3,278 plants owned by 1,759 firms between 1988 and 2001. We examine RC's impact on plant-level pollution because RC's stated goal is to reduce pollution, and total pollution reduction is relevant for environmental protection. We find robust evidence that, controlling for self-selection, RC *fails* to reduce plant-level pollution. Our preferred estimates, from our multi-plant sample, indicate that plants owned by RC participating firms raise their pollution by 15.9% relative to statistically-equivalent plants owned by non-RC participating firms. These estimates are large compared to the yearly 4% reduction in pollution among all plants in our sample between 1988 and 2001,[3] i.e., participation in RC eliminates at least 3 years of this trend. Allowing for the possibility of heterogeneous program effects, we do not find any subsets of plants that reduce their pollution. Our results are robust to the use of different subsets of instruments and the alternative measurement of pollution in pounds. We find comparable results that RC raises pollution by 16.1% in our full sample (though we note the limitations in the instruments used in the full sample). Finally, our estimation using Propensity Score Matching (PSM), a method whose consistency does not rely on exclusion restrictions, yields estimates that range from one third to the full magnitude of the GMM estimates (6.8% to 16.8%). However, the PSM estimates are not statistically significant.[4] As a further check, we examine if RC reduces pollution intensity, defined as the ratio of plants' toxicity-weighted air pollution to their number of employees.[5] Lower pollution intensity would imply a more favorable trade-off between production and pollution (Cole et al., 2005).[6] Instead, we find that RC *raises* pollution intensity by 15.1% in the multi-plant sample.[7]

Our study, consistent with Glachant's (2007) theory that firms may enter self-regulation programs without any intention of meeting their program commitments, has important policy implications. RC has been adopted by chemical associations in 53 countries as of 2008 (ICCA, 2008). Moreover, the pre-2002 RC program shares the two key characteristics of major industry self-regulation programs, i.e., its absence of third party verification and enforceable penalties for non-performance. Programs modeled on RC, such as the petroleum industry's self-regulation

[3] The annual decline is 5.8% for RC participants and 4.2% for non-participants between 1988 and 2001.
[4] The strengths and weaknesses of the GMM and PSM methods are discussed in section 5.21.
[5] For evidence that the number of employees can serve as a proxy for the preferred denominator of output, see Online Appendix III. Plant-level output data is not publicly available.
[6] All things equal, with lowered pollution intensity, the same amount of production would result in less pollution (Cole et al., 2005).

program (Hoffman, 2000) or programs in which certifiers are not truly independent (O'Rourke, 2003; Rosenthal and Kunreuther, 2010), may not improve environmental performance. Our results provide timely guidance to regulators and the oil and gas drilling industry, which are drawing on lessons from RC. Independent third party certification is, in practice, limited in the oil and gas sector (Bea, pers. comm.; Pettit, 2010).[8] Therefore, our result on the ineffectiveness of the pre-2002 RC program, which does not require third party certification, cautions against reliance on self-regulation as the primary policy tool for improving environmental performance.[9] Section 2 reviews the literature on industry self-regulation and outlines the institutional features of the RC program. Section 3 describes our estimation strategy. Section 4 describes our data. Section 5 presents our results, with conclusions and policy implications in Section 6.

2. Industry Self-Regulation and Pollution Reduction

2.1 Can industry self-regulation reduce pollution?

Self-regulation programs limit their membership to firms that commit to their codes of conduct. Whether these programs, which have limited ability to monitor and sanction their members, can ensure their members truly undertake risk reduction is under debate (Kleindorfer and Orts, 1998; Lyon and Maxwell, 2004; Barnett and King, 2008). The industry faces strong incentives to create a credible self-regulation program that reduces pollution if the program could forestall the state's imposition of stricter and more costly regulation (Maxwell et al., 2000). Importantly, Dawson and Segerson's (2008) theoretical study shows that even if other firms were

[7] The estimate is 12.6% in the full sample, in which our instruments are imperfect.
[8] Certifiers, which rely exclusively on clientele from that sector, face economic pressure to provide positive assessments (Bea, pers. comm; Pettit, 2010). Robert Bea, email message to Shanti Gamper-Rabindran on 07/06/2011. Bea is with the Deepwater Horizon Study Group (distinct from NCBP), Center for Catastrophic Risk Management, University of California, Berkeley, Professor Emeritus in Engineering,
[9] Cohen et al. (2011) explore alternative policies to improve environmental performance in the oil and gas drilling sector.

to free-ride, a critical number of firms will reduce their pollution in order to maintain the overall credibility of the self-regulation program.[10]

However, skeptics argue that self-regulation programs can serve as 'greenwash,' i.e., firms join these programs to signal green, but fail to reduce their adverse environmental impacts (Lyon and Maxwell, 2011). In other words, firms purport to meet their program commitments without addressing the underlying environmental concerns (Calcott, 2010). Glachant (2007), noting that his theory applies to self-regulation programs such as RC, argues that firms may or may not reduce their pollution in response to their participation in self-regulation programs. Under specific circumstances, "firms may enter strategically into [self-regulation programs] without any willingness to comply, simply to postpone legislative intervention" (Glachant, 2007). In his model, firms' non-compliance with their commitments to the self-regulation program is not observed immediately by the regulator and thus, firms are able to lobby congress to influence the stringency of the final legislation. Despite the possibility that firms may fail to comply with their commitments, the regulator agrees to the self-regulation program. The regulator postpones presenting its legislative proposal to congress until after it has had the opportunity to observe these firms' performance. The regulator chooses this course of action because a self-regulation program in which firms choose to comply with their commitments would achieve greater pollution reduction than the final legislation weakened by lobbying efforts.

2.2 Responsible Care: institutional structure

[10] Participants also benefit from their positive reputation in their interactions with consumers and investors (Maxwell and Decker, 2006). Participation may reduce inspections by regulatory agencies (Maxwell and Decker, 2006; Innes and Sam, 2008) and discourage boycotts by environmental groups or pre-empt their lobbying for stricter regulations (Baron, 2001; Maxwell et al., 2000).

In response to the Bhopal accident, the ACC executive committee reported to its members that the public deeply distrusted the chemical sector and that the industry needed "to improve its performance -- not just its image -- in a way the public can see and appreciate" (Rees, 1997). Subsequently, in September 1988, the ACC adopted the RC program and mandated its members' participation in the program (Rees, 1997). In the next five years, ACC's technical experts developed six Codes of Management Practices for the industry (Rees, 1997).

Several features of the RC program can potentially lead to pollution reduction. First, RC requires firms to commit to the Code of Pollution Prevention.[11] The ACC exercises some oversight on firms by requiring their submission of annual reports on their progress towards code implementation (King and Lenox, 2000). Firms report their TRI pollution releases and their potential environmental and health impacts (Prakash, 2000). Second, RC encourages the sharing of pollution abatement information among members. The ACC has created a database that identifies firms that are willing to share their expertise in implementing the RC codes, and encourages regional networking among firms to enable them to undertake joint activities (Prakash, 2000). Third, some analysts argue that RC creates peer pressure among participants that leads to pollution reduction. "[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'"[12](NCBP, 2011).

[11] "This code is designed to achieve ongoing reductions in the amount of all contaminants and pollutants released to the air, water, and land from member company facilities" (ACC, 1990). Among management practices to achieve this code are the creation of a quantitative inventory of plant's releases to the air, water, and land; plans to reduce pollution; and the consideration of pollution prevention goals in the design of production processes (ACC, 1990).

[12] Email to NCBP from Richard Sears, former geophysicist at Shell, and currently visiting scientist at MIT (NCBP, 2011).

Our study tests the effectiveness of self-regulation programs without third-party verification. We examine the early period of RC, from its formation to the year 2001, when the ACC did not require third-party verification.[13] RC, without third party verification, is of interest, because other programs share this characteristic and several industrial sectors lack independent third party certifiers (O'Rourke, 2003; Rosenthal and Kunreuther, 2010).

2.3 Responsible Care: evidence of its impacts and limitations

The fundamental empirical question is – has RC reduced, left unaffected or raised plant-level pollution? Limitations in King and Lenox's (2000) estimation strategy can affect their conclusions. Their first specification using fixed effects is biased towards finding that RC does not lead to statistically significant effect on pollution because the identification of the fixed effect model relies on the few firms that switch their RC status. Moreover, the production ratio variable that serves as a proxy for plant size in their study can contribute to attenuation bias. That variable is at best, noisy and at worst, uninformative.[14]

Their second specification, which uses Generalized Least Squares (GLS), does not address self-selection. A subsequent study finds that dirtier firms self-select into RC (Lenox and Nash, 2003). A priori, the direction of bias from not addressing self-selection is unknown. In the case that dirtier firms are more reliant on more polluting production technology and their switch to cleaner production technology entails greater costs, the failure to address selection would lead to a bias against finding that RC reduces pollution. The bias would be in the opposite direction if dirtier firms face lower costs of pollution reduction due to declining marginal costs of abatement.

[13] Our author-constructed database spans the years 1988 to 2001 only.

[14] Our analysis of the data and our conversation with researchers and EPA region 1 personnel suggest that the variable does not, in practice, capture plants' annual changes in production. Moreover, the API (2005) survey notes that its members do not have well-established methods for estimating this variable. E.g., a plant that faced a 20% reduction in output may report a production ratio value of 0.8, 8 or 80. King and

Because theory is ambiguous both on the impact of the RC program (section 2.1), and on the direction of bias if self-selection were not accounted for, it is useful to conduct a reassessment of the RC program that addresses self-selection.

3. Estimation Method

3.1 Method

We estimate the impact of RC by comparing plants owned by RC participating firms with ***statistically equivalent plants*** owned by non-RC firms, i.e., both the average treatment effect and the effect conditional on plant and firm attributes. We achieve this comparison by instrumenting for the RC participation status of the plants' parent firms. The RC membership decision is made at the firm-level and is the same for all of a firm's plants, while pollution performance is specific to each plant. This distinction allows us to motivate and construct variables that are correlated with the likelihood of a plant belonging to a parent firm that is an RC member, but that do not directly affect a plant's pollution.

3.2 Model

The plant-level pollution equation is:

$$y_{ijt} = \sum_{s=1}^{T} \beta_{ys} y_{ij(t-s)} + x_{1ijt}\beta_1 + x_{2it}\beta_2 + p_{ijt}\delta_1 + p_{ijt}\,(x_{3ijt} - \bar{x}_3)\delta_2 + \mu_{ijt}$$

(Plant-level pollution: Equation 1)

The pollution (y_{ijt}) of plant *j* owned by firm *i* at time *t* is affected by its characteristics (x_{1ijt}), characteristics of parent firm *i* (x_{2it}), the participation status of the plant's parent firm (p_{ijt}), a subset of plant characteristics which affect the impact of RC (x_{3ijt}), and an unobserved component (μ_{ijt}). Pollution is also affected by persistent factors such as plant technology, which are unobserved by the researcher. Therefore, our estimation model includes lags of pollution, y_{ijt-}

Lenox (2000) use the production ratio variable for various years and the 1996 plant-level employee from

$_1$, y_{ijt-2}, … to capture the confounding nature of these unobserved variables that change slowly over time (Blundell and Bond, 2000). The second and third terms ($x_{1ijt}\beta_{1,} x_{2it}\beta_2$) account for the effect of plant and firm covariates, respectively, on pollution regardless of RC status. The fourth term ($p_{ijt}\ \delta_1$) captures the effect of RC on the average plant, while the fifth term ($p_{ijt}\ (x_{3ijt} - \bar{x}_3\ )\delta_2$) captures the impact of RC that varies by plant characteristics. We de-mean the x_3 variables in the third term in order to consistently estimate the effect of RC on an average plant with the δ_1 coefficient. The unobserved component is made up of plant, industry, and year components, as well as an idiosyncratic shock, $\mu_{ijt} = \upsilon_j + \eta_{SICj} + \zeta_t + \varepsilon_{ijt}$. We restrict the shocks (ε_{ijt}) to be mean zero, and independent across firms, but allow them to be correlated within the same plant. In addition, we place no restrictions on the variance of the errors.

In our analysis, we estimate Equation 1, addressing two estimation issues: (1) the participation status of plant *j*'s parent firm (p_{ijt}) is endogenous; and (2) the use of the lags of pollution as explanatory variables (y_{ijt-1}, y_{ijt-2},…) introduces "dynamic panel bias" (Nickel, 1981).

Estimation issue #1: instrumenting for plant's parent firms RC participation status

In estimating the plant-level pollution equation (Equation 1), we use two strategies to instrument for the participation status of plant *j*'s parent firm. Our first strategy directly instruments for the participation status of plant *j*'s parent firm (p_{ijt}) using excluded variables. We use two sets of excluded variables. In the full sample, we use instruments that can be defined for single plant firms (see section 3.5). In the sample of plants belonging to multi-plant firms, we use the exogenous characteristics of *other* plants belonging to the same firm as additional instruments. Our construction of these instruments, hereafter the BLP-type instruments, follows the approach in Berry, Levinsohn and Pakes, (1995) and Nevo (2000).

Dun & Bradstreet to generate plant-level employees for other years in their study.

Our direct instrumentation strategy does not involve estimating the likelihood of a plant's parent firm belonging to RC. Nevertheless, the equation is useful in motivating our construction of the BLP-type instruments. The likelihood equation is:

$$p_{ijt} \;=\; 1[x_{1ijt}\theta_1 + \sum_{(s=-j\in i)} x_{1ist}\theta_1 + x_{2it}\theta_2 + z_{1it}\theta_3 + \frac{1}{n}\sum_{(l\in k\neq i)} p_{lt}\theta_4 + + \xi_{ijt} \geq 0]$$

(Plant *j*'s parent firm's participation status: Equation 2)

The dependent variable (p_{ijt}) is the participation status of plant *j*'s parent firm. The likelihood that a plant belongs to an RC firm is affected by the characteristics of plant *j* (x_{1ijt}), the BLP-type instruments that capture characteristics of other plants belonging to firm *i* ($\sum_{(s=-j\in i)} x_{1ist}$), firm-level factors that also affect pollution (x_{2it}), firm-level characteristics unrelated to pollution (z_{1it}), the participation status of rival plants in the same SIC-4 industry[15] ($\frac{1}{n}\sum_{(l\in k\neq i)} p_{lt}$) and an idiosyncratic shock (ξ_{ijt}).

The participation status of plant *j*'s parent firm is influenced by the characteristics of plants belonging to that firm, which in turn determine the benefits of joining RC and the cost of adhering to RC standards. The term, $\sum_{(s=-j\in i)} x_{1ist}$, captures exogenous characteristics of other plants owned by the same firm *i*, which affect the firm's cost of adhering to RC's standards, but do not directly affect pollution at plant *j*. The participation status for plant *j*'s parent firm can therefore be instrumented using the characteristics of other plants belonging to that parent firm. For example, consider a firm which owns a plant in New Jersey and a plant in Louisiana. In the pollution equation for the Louisiana plant, we instrument for the plant belonging to a firm in RC using the characteristics of the New Jersey plant. If the plant in New Jersey were to face local regulatory pressure to reduce its pollution, it would increase the overall net benefits for the firm

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[15] See section 3.5

to join RC. However, the characteristics of the New Jersey plant do not directly influence the pollution levels in the Louisiana plant.

In estimating the plant-level pollution equation, our second strategy instruments for the participation status of plant *j*'s parent firm (p_{ijt}) using the predicted likelihood that a plant belongs to an RC firm ($\hat{p}_{ijt}$).[16] We estimate the predicted likelihood using Equation 2. While correlated across plants belonging to the same firm, the predicted likelihood can differ across plants belonging to the same firm based on their observed characteristics. In contrast, all plants belonging to the same firm have identical values for the observed participation status plant's parent firm (p_{ijt}) because the RC participation decision is made at the firm-level.

Estimation issue # 2: System GMM to address explanatory variables that are lags of the dependent variable

To address the dynamic panel bias from the inclusion of the lags of pollution, we implement a System GMM estimator (Blundell and Bond, 1998). The system estimator builds a stacked data set with each observation included twice in the analysis. The first set transforms the data following Arellano and Bond (1991), taking orthogonal differences[17] of each variable to eliminate the unobserved plant fixed effect and instrumenting for the lagged differences of the dependent variable using lagged levels. The second set includes the untransformed data in levels, instrumenting for lagged dependent variables using lagged differences. The inclusion of the untransformed set in the system GMM, along with the

[16] The estimated likelihood is a valid instrument for plant *j*'s parent firm's RC status, even if the likelihood function is misspecified (Wooldridge, 2010).

[17] Because we have an unbalanced panel with gaps in observations for some of the plants, we create the orthogonal differences by subtracting the mean of the future values, as suggested by Arellano and Bover (1995). This approach eliminates plant fixed effects from the estimating equations in a similar manner to the first differences procedure, but reduces the number of observations that must be excluded due to missing data (Roodman, 2008).

transformed set, increases the efficiency of the system GMM estimator.[18] The system GMM also allows for the consistent estimation of exogenous time invariant factors, such as industry subsector dummies, or demographic data from the 1990 census. We use a two-step GMM that is efficient under heteroskedasticity and follows Windmeijer (2005) to correct for small sample bias.

The system GMM estimator requires that the error terms are not serially correlated. We test this condition using on the Arellano-Bond AR(2) test of second-order auto-correlation in the differenced error terms.[19] After conducting specification tests, we conclude that including two lags of the dependent variable as explanatory variables is sufficient to capture previous shocks to the unobserved variables and thus, ensure that the error terms are not serially correlated.

3.3 Heterogeneous program effects

In the analysis which allows the effect of RC to vary with firm and plant characteristics, the variable of interest is (p_{ijt} $(x_{3ijt} - \bar{x}_3)$) in Equation 1. We use the predicted likelihood a plant parent firm's RC participation status ($\hat{p}_{ijt}$) interacted with de-meaned covariates to instrument for (p_{ijt} $(x_{3ijt} - \bar{x}_3)$). The predicted likelihood is correlated with (p_{ijt}) and independent of (μ_{ijt}) by construction. Therefore, the predicted likelihood interacted with the de-meaned covariates are valid instruments for (p_{ijt} $(x_{3ijt} - \bar{x}_3)$).

The estimated effect of participation on the pollution of an individual plant is:

$$\left(p_{ijt}\hat{\delta}_1 \quad + p_{ijt}\left(x_{3ijt} - \bar{x}_3\right)\hat{\delta}_2\right).$$

We use the Delta Method (Oehlert, 1992) to calculate the standard errors of these estimates and determine for which plants the program has a significant effect on pollution.

[18] The alternative difference GMM method is less efficient when past levels are weak instruments for the transformed differences.

3.4 Dependent variable

Our dependent variable, pollution, is the log of toxicity-weighted chemical releases into the air. We limit our analysis to chemicals whose TRI reporting requirements are consistent since 1988. We use toxicity-weighted pollution to control for variation in the toxicity of chemicals (EPA, 2009).

3.5 Instrumental variables (IV) for self-selection

We run two analyses. First, for the multi-plant sample, we are able to use BLP-type instruments. Second, for the full sample, we use imperfect instruments that can be defined for single-plant firms. We are confident in the exclusion restrictions for our BLP instruments, and therefore, our preferred estimates are those from the multi-plant sample. Because the instruments in the full sample are imperfect, we treat those results with caution. Nevertheless, our results from these two samples are consistent (section 5.21).

Our intuition for the BLP-type instruments is that for a given plant *j*, these variables measured at *other plants* belonging to the firm influences the parent firm's cost-benefit calculus in joining RC, but these variables measured at *other plants* do not directly affect plant *j*'s pollution. When constructing the firm-level instrumental variables for plant *j*, we exclude that plant to ensure the instrument is exogenous. The first instrument is the firm's ratio of hazardous air pollutants (HAPs) to TRI. The Clean Air Act (CAA) requires the Environmental Protection Agency (EPA) to set strict technological regulations to reduce HAPs (Van Asten and Martinson, 2005). Plants emitting HAPs will have to reduce their pollution, even in the absence of RC. Thus, firms whose plants have high shares of HAPs face less additional costs to comply with RC and are more likely to join RC. The second instrument is the firm's SIC pollution index which

[19] Since $\Delta\ \varepsilon_{ijt}$ is related to $\Delta\varepsilon_{ijt-1}$ through ε_{ijt-1} which appears in both terms, first-order serial correlation of differences is predicted.

captures the firm's operation in more polluting industries.[20] The third instrument is the firm's plants' pollution relative to other plants in the same industry.[21] These two variables, which reflect the firm's production technology, are likely to influence the firm's pollution abatement costs (Arora and Cason, 1995) and thus, its likelihood to join RC.[22] The fourth instrument consists of four variables that measure the neighborhood pressure on plants to reduce their pollution, which in turn, affects their parent firm's likelihood of joining RC. These four variables, measured at the census tracts in which the plants are located, are urban density and the shares of whites, poor and non-high school graduates (Hamilton, 1995; Arora and Cason, 1999). We also include county-level National Ambient Air Quality Standards (NAAQS) non-attainment status.

In using the characteristics of other plants belonging to the same firm as instruments, we assume that there are limited spillovers across plants in pollution reducing technologies, e.g., the implementation of new technology at one plant does not make it significantly less costly to reduce pollution at other plants owned by the same firm. One may argue that whether such spillovers are extensive enough to invalidate our instruments is an empirical matter. Therefore, we check and confirm the empirical validity of these assumptions using over-identification tests (see section 5.22).

For our full sample, we require instruments that can be defined for single-plant firms, but truly exogenous instruments are difficult to identify for single-plant firms. We use two imperfect

[20] We measure how polluting an industry is as the ratio of (a) the average pollution of plants operating in SIC-28xx to (b) the average pollution of all plants operating in SIC-28. In creating this variable for plant *j*, we average the industry pollution for all other plants belonging to the firm that owns plant *j*.

[21] We measure the firm's relative pollution as the average over all of the firm's plants of the following ratio: (a) the average pollution of the firm's plants to (b) the average pollution of other plants operating the same SIC-4 industry.

instruments in our full sample. The first is the share of plants in the given industry that participate in RC.[23] If rival plants in the same industry are members of RC, it may affect the benefits of a firm joining, but is unlikely to directly affect a plant's pollution. A plant may receive positive recognition from consumers or investors if it is one of the few in the industry that is a member of RC, or may be looked upon negatively if it is in the minority of plants that do not participate.

The second instrument in the full sample is the firm's participation in the ACC before the creation of RC. Prior to the creation of RC in October 1989, it is likely that firms that were already ACC members received a positive net benefit from membership in the trade association, such as benefits from the association's public relations and lobbying efforts (Givel, 2007). After RC was implemented and made a condition of membership in the ACC, the ACC did not change its trade association mission, but simply added additional obligations and benefits for its members. Therefore, holding all else equal, firms which were members prior to RC were more likely to receive a positive net benefit from the trade association and self-regulation benefits of RC compared to firms that had not yet joined ACC. While we are confident in the exclusion requirement for our BLP-type instruments, it is difficult to argue that these instruments that can be defined for single-plant firms are completely exogenous.[24]

3.6 Control variables

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[22] Plants with dirtier technologies may find it more expensive to abate pollution if they are reliant on these technologies or alternatively, they may find it cheaper to abate pollution due to declining marginal abatement costs (Arora and Cason, 1995).

[23] There is significant variation in this variable across industries, with a mean and standard deviation of 26.9% and 16.4%, respectively.

[24] These instruments are imperfect. One could argue that some SIC-4 industries may have had technological options that allow for less costly pollution reduction. One could also argue that larger firms have more to benefit from joining the ACC. But these firms also have more at stake in ensuring that RC succeeds and thus, are more likely to reduce pollution at their plants. Our inclusion of control variables to

We control for factors that are likely to influence participation in voluntary programs (DeCanio and Watkins, 1998) and plants' pollution. Firm size is measured using the log of the lagged firm's employees across plants and the number of plants owned by the firm. Larger firms may have greater financial resources to invest in pollution abatement. They may also face greater demand, and therefore, have more to gain from signaling green to their consumers (Arora and Cason, 1995). A dummy variable for single-plant firms captures the differences between single-plant and multi-plant firms. We control for neighborhood pressure on plants using tract-level socioeconomic characteristics (Hamilton, 1995; Arora and Cason, 1999). The plant's HAP/TRI ratio captures its exposure to regulations targeting HAPs. A plant's participation in a highly polluting industry is captured by the plant's SIC-4 Industry Pollution index.[25] The plant's lag relative pollution captures its pollution relative to other plants in its SIC-4 industry. Industry-level variables at the SIC-4 level are included, i.e., producer price index, shipment quantity index, the Herfindahl-Hirschman index and SIC-4 dummies.[26] Year dummies control for changes in federal regulations and available technologies.

4 Data

4.1 Data sources

Our data consists of chemical manufacturing plants (SIC-28) that are both required to report their pollution to the TRI and that report their number of employees to Dun & Bradstreet (D&B). While itsself-reported nature is a limitation, the TRI data is one of the few

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control for SIC-4 pollution and firm size (section 3.6) reduces, but does not eliminate, these two concerns respectively.

[25] This variable is defined as the ratio of (a) the average pollution in the plant's SIC-28xx to (b) the average pollution in the entire SIC-28.

[26] The quantity and price indices are normalized to 100 within the specific SIC-4 industry in 2000. The Herfindahl-Hirschman index is calculated using the value of shipments of the largest 50 firms in the SIC-4 industry, as reported in the quinquennial Census of Manufacturers. Data for interceding years is linearly interpolated.

comprehensive sources of pollution data that has been widely used (Konar and Cohen, 2001; Hamilton, 2005; Greenstone, 2003; Gamper-Rabindran, 2006). The chemical-specific toxicity-weights are from the Risk Screening Environmental Indicators model (EPA, 2009). Plant-level counts of EPA inspections are from the EPA's Air Facilities System (AFS). Annual county-level non-attainment status for the criteria air pollutants under the CAA are from the EPA (EPA, 2007). The SIC-4 Herfindahl–Hirshman Index is from the Census Bureau, while the quantity of shipment and the producer price indices are from the Bureau of Economic Analysis. Our sample is likely to include the larger plants within the US chemical sector, as larger plants tend to report to D&B. Furthermore, plants are required to report to the TRI only if their pollution exceeds a specific threshold (EPA, 2009).[27] We link a firm to all its plants operating in the chemical manufacturing sub-sector (SIC-28) that report to the TRI. Therefore, for a firm which operates in both chemical and non-chemical manufacturing sectors, the firm's pollution and number of employees is only from its plants operating in SIC-28. We create annual plant-firm linkages using Mergent Online and Corporate Affiliations Database.

4.2 Data description

RC participants have grown slightly from 124 firms (or 718 plants) in 1988 to 137 firms (or 925 plants) in 2001. The probability of being owned by a participant in RC, with covariates set at the sample means, is 21% for all plants and 60% for plants owned by multi-plant firms. Comparison of columns 3 and 4 in Table 1 indicates that RC and non-RC participants differ systematically in their characteristics. For example, on average, plants that belong to RC participating firms are larger, measured in number of employees; and tend to belong to multi-plant firms with a larger number of plants. RC plants operate in more concentrated industries, as

[27] Plants operating in SIC-28 are required to report to the TRI if they: (1) had 10 or more full-time employees or the equivalent; and (3) "manufactured" or "processed" more than 25,000 pounds or

measured by the Herfindahl-Hirshman Index. Therefore, our regression analyses employ control variables to account for these differences across RC and non-RC plants. On average, RC plants are more polluting (measured in toxicity-weighted air pollution) than non-RC plants, but the pollution for both cohorts declines over our sample period. RC plants operate in more polluting industries, as indicated by the SIC-4 Industry Pollution Index (defined in section 3.6). Therefore, our regression analysis employs SIC-4 industry dummies to ensure that our analysis compares RC and non-RC plants within the same industry. Our within industry comparisons indicate that in most industries, RC plants are more polluting than non-RC plants operating in the same industry. The least polluting industry, the diagnostic substances industry, is one of the few exceptions in which RC plants are less polluting than non-RC plants.

5. Regression results

Our sample covers 22,822 observations of plant-years, from 3,278 unique plants and 1,759 different parent firms. Our analysis spans the years 1990-2001, as each year of observations requires two lagged years of data. Our dependent variable is the log of the ratio of toxicity-weighted air pollution at a plant. We report robust standard errors.

5.1 Preliminary regressions

Our choice of system GMM as our preferred model is informed by our review of several preliminary specifications. The OLS model, regressing pollution on RC participation status (RC-status) and other control variables, indicates that RC participation is associated with larger pollution (Table 2, columns 1 and 5). The inclusion of plant fixed effects (FE) reduces the magnitude of this coefficient (Table 2, columns 2 and 6), but the estimated effect is still positive and significant.

“otherwise used” more than 10,000 pounds of any listed chemical during a calendar year.

Importantly, comparisons of models, with and without instrumental variables, underscore the need to control for self-selection in our final estimation model. Instrumenting for RC-status reduces the coefficient estimates, as seen in two comparisons: (i) comparison of the instrumental variables with fixed effects (IV-FE) model with the FE model (Table 2, column 3 and 7 versus columns 2 and 6, respectively); and (ii) comparison of the System GMM model (Table 3) with the model containing lagged dependent variables and FE (Table 2, columns 4 and 8). In this setting, it is the firms that are less likely to reduce their pollution that self-select into the program.[28] As detailed below, our preferred GMM estimates indicate that, after controlling for self-selection, RC's effect in raising pollution is still large and statistically significant, but its effect is less pronounced.

Our system GMM model includes lagged dependent variables to control for persistence in production technology. We can rule out the concern that these lagged variables are driving our GMM results that RC raises pollution. In four out of six specifications that exclude the lagged variables, the RC estimates remain positive and statistically significant (Table 2, columns 1-3, 5-7). The inclusion of these lagged variables, in fact, reduces the RC estimates, as seen in the comparison of the FE estimates and the FE estimates with lagged dependent variables (Table 2, columns 2 and 4 and Table 2, columns 6 and 8).

5.2 System GMM regressions

5.21 Main results

Table 3 shows the results of the system GMM estimation on the effect of RC participation on pollution. In the system GMM estimation: (i) we instrument for RC status, to

[28] The Durbin-Wu-Hausman statistic values, though statistically significant in the OLS specifications, are no longer significant at conventional levels in the specifications with plant fixed effects and lagged dependent variables. Nevertheless, we still instrument for self-selection in our main specifications to minimize potential bias.

control for self-selection, using either the excluded variables or the predicted probability of participation; and (ii) we instrument for the lagged dependent variables with second-order and higher lagged levels for the difference equations and lagged differences for the level equations.

Our preferred specification is the multi-plant sample in which the BLP-type instruments are arguably exogenous. We find that RC raises pollution by 15.9% in the specification in which the excluded variables serve as instruments for RC participation (Table 3, column 1), and by 16.0% in the specification in which the predicted probability of participation serves as the instrument (Table 3, column 2). In the full sample, in which our instruments are imperfect, we also find that RC raises pollution by 16.1% and 20.4% in the two analogous specifications (Table 3, column 3 and 4).

Our results across specifications (Table 3, columns 1-4) show that RC raises pollution; plants owned by firms participating in RC have larger amounts of pollution than statistically equivalent plants owned by non-RC participating firms. Across specifications, the estimated coefficients on the RC status are positive, statistically significant, and fairly similar in size. These estimated increases – ranging from 15.9% to 20.4% – are large relative to the yearly 4% reduction of pollution among all plants in our sample between 1988 and 2001. To put these figures into context, the estimated increase in pollution is equivalent to the effect of switching a plant from the 25th percentile industry in terms of pollution to the median industry, holding all else equal.

Our results on the average effects of RC are robust to the inclusion of the additional variable of plant-level inspections by the EPA under the CAA. This addition reduces our sample by about 30% as only a subset of TRI plants require operating permits under the CAA.[29] We find

[29] Studies of TRI pollution focus on inspections under the CAA because most TRI releases are into the air (Potoski and Prakash, 2005).

that inspections do not have a statistically significant impact on pollution and the inclusion of the inspection variable does not qualitatively change our estimates of the impact of RC. Our analysis is robust to numerous checks, including the use of subsets of instruments, alternative specifications for the instruments, and alternative measures of pollution (Online Appendix I: Tables A1 and A2). We find comparable results on pollution measured in pounds, i.e., RC raises pounds of pollution by 6.1% in the multi-plant sample and 9.8% in the full sample.

We provide estimates of the impact of RC using the PSM method, which does not rely on exclusion restrictions required for consistent estimation under our IV specifications (Rosenbaum and Rubin, 1983).[30] Our preferred specifications, (i) kernel matching and (ii) nearest neighbor matching with common support and with replacement, yield similar estimates that range from one third to the full magnitude of the GMM estimates (0.159 to 0.204). Our estimates from kernel matching, 5-nearest neighbors and 1-nearest neighbor matching are 0.147, 0.169 and 0.068, respectively, but these PSM estimates are not statistically significant (Online Appendix II: Table A3).

As an additional check, we examine if RC reduces plant-level pollution intensity. Such reductions would mean that all else equal, the same amount of production would result in less pollution (Cole et al., 2005). The dependent variable is the log of (toxicity-weighted TRI releases into the air divided by the number of employees). We find that RC raises pollution intensity by 15.1% in the multi-plant sample and by 12.6% in the full sample (Online Appendix III: Table A4).

5.22 Validity tests for instruments

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[30] The drawback of the PSM method is its assumption that program effects can be identified by matching on observables alone (Heckman et al., 1997). However, as revealed in section 5.1, it is likely that firms self-select into RC on unobserved factors that are also related to plant pollution. As the GMM and PSM models have their strengths and limitations (Wooldridge, 2010), we present results from both models.

Our analysis applies instruments to address two types of endogenous variables; first, our main variable of interest, the RC participation variable, and second, the lagged dependent variables. While no tests can positively determine that an instrument is valid, we run a number of tests to check if they are conclusively invalid. The first condition for valid instruments is that they are not correlated with the error term in the second stage. Based on the p-value of the Hansen-J statistics for over-identification, seen in Table 3, we fail to reject the null that the instruments are exogenous in any of the specifications. Given that our main contribution to the empirical estimation of the RC program is to address firms' self-selection into RC, we also conduct tests specifically for the RC instruments. The Difference-in-Hansen statistics provide support for the exogeneity of the RC instruments that are used to address self-selection (Table 3, columns 1-4).

The second condition for valid instruments is that they are correlated with the endogenous regressors. The instruments for the lagged dependent variables fulfill this condition because by construction, the lagged differences of the dependent variable are correlated with the lagged levels. To examine this condition for the instruments for the RC participation variable, we conduct tests based on the relationship between the instruments and RC-status. We run a Probit regression, regressing the RC participation variable on the instruments and other covariates (Table 4). We use likelihood ratio tests to examine whether the instruments are correlated with RC participation. For the multi-plant sample, we conduct three separate likelihood ratio tests for three sets of instruments: (i) the excluded variables defined for all plants, (ii) the additional instruments defined for plants belonging to multi-plant firms only, and (iii) the entire set of instruments. In each of these three cases, the null hypothesis that the instruments have no effect on RC participation is rejected at the 1% statistical significance level (Table 4, columns 1 and 2). In the full sample, the likelihood ratio test, comparing the fit of models with and without the excluded variables, rejects the null that the two excluded variable have no effect on RC participation (Table 4, column 3 and 4).

We briefly describe the relationship of the instruments to the RC participation variable. We calculate the marginal effects from the Probit estimates from Table 4 with the values of covariates set at their sample means. We note that a statistically (in)significant coefficient on any one instrument does not necessarily imply that the instrument is (in)valid. First, we consider the instruments defined only for plants belonging to multi-plant firms (Table 4, column 1 and 2). As expected, ownership by firms with a high HAP to TRI ratio is positively related with RC participation. A one standard deviation larger HAP to TRI ratio at the firm-level raises participation by 6.3 percentage points. Firms whose plants are located in one standard deviation more urban areas are less likely to participate in RC by 5.4 percentage points, but surprisingly firms with plants located in poorer neighborhoods are more likely to participate by 5.5 percentage points. Second, we consider instruments that can be defined for single-plant firms (Table 4, columns 3 and 4). Firms' membership in ACC prior to the creation of RC exhibits the expected sign and is statistically significant. Ownership by a firm that was a member of the ACC prior to the creation of RC raises participation by 68.0 to 89.6 percentage points. Participation by rival plants is negatively correlated the participation of a plant's parent firm conditional on the other covariates and industry controls. This could result from the benefits of membership declining with the number of rival facilities that are members.

5.23 System GMM test statistics

A crucial assumption of the system GMM estimator is that the error terms are not serially correlated. In each of our four main specifications, we include two lags of the dependent variable to ensure the errors are not serially correlated (Table 3, columns 1-4). For these specifications, we cannot reject the null of no serial correlation based on the Arellano-Bond AR(2) test.

5.3 RC effects over time

We examine if RC's effects have varied over time. In particular, we ask if the increased pollution of RC participants relative to non-participants, revealed in our main analysis, occurred predominantly during RC's early years. This may occur for two reasons. First, firms recognize that with time, their failure to meet their commitments is more likely to be detected. Second, the RC program gradually introduced refinements that can discourage rising pollution. RC's codes of conduct, including pollution prevention, were developed over the first five years of the program. Beginning in 1999, firms were required to establish their own performance goals and publicly report progress toward those goals (Rees, 1997).

In these specifications, which omit the RC participation dummy, the coefficient on the interaction variable between the RC participation dummy and the year(s) dummy provides a comparison of the pollution from RC participants and non-RC participants for the given time period. As seen in Table 5, columns 3-6, we find in most specifications that RC raises pollution by a greater amount in the earlier period of our study than in the latter period. For example, RC raises pollution by 20.2% and 24.4% in the multi-plant and all-plant samples, respectively, between 1990 and 1995, but no statistically significant increases attributable to RC are detected between 1996 and 2001. In no time period is there evidence that RC reduces pollution. These results are consistent with the view that refinements to the RC program implemented over time (Rees, 1997) discouraged participants from raising their pollution. We also examine whether the impact of RC varies with the firm's length of membership in RC. It is plausible that longer membership in RC is associated with larger reductions in pollution because the installation of pollution abatement equipment or changes in the production process to reduce pollution requires time. However, we find that the impact of RC does not vary with the firm's length of membership in RC (Table 5, columns 7 and 8).

5.4 Heterogeneous program effects

We test Dawson and Segerson's (2008) hypothesis that sub-groups of firms have incentives to reduce their pollution, even if other firms free-ride. For example, firms that have larger operations, measured by their number of plants or their number of employees, may derive greater benefit from a credible industry self-regulation program, and thus they may face sufficient incentives to reduce their pollution. However, we find that program effects do not vary significantly with the number of plants owned by the firm or their number of employees (Table 6, columns 3-5). Indeed, our results in Table 6 indicate that there are no sub-groups of firms in our sample for which RC leads to statistically significant reduction in pollution.

We find some evidence, in support of environmental justice concerns, that RC firms whose plants are located in poor neighborhoods are less inclined to reduce their pollution. As seen in Table 6, columns 7 and 9, RC firms whose plants are located in poorer areas increase their pollution to a greater extent than RC firms whose plants are located in richer areas. Nevertheless, we note that plants belonging to RC firms raise their pollution even if they are located in neighborhoods where none of the population lives below the poverty line.

Our analysis of heterogeneous program effects uses predicted probabilities of RC participation to instrument for the RC participation variable. Our estimation of the predicted probabilities uses excluded variables, and thus the identification is not based solely on functional form. We also compare the estimated impact of RC on pollution in specifications using predicted probabilities of RC participation as instruments (Table 3, columns 2 and 4) and in specifications using excluded variables as instruments (Table 3, columns 1 and 3). The similarity in these two sets of results gives us confidence in our use of predicted probabilities of RC participation as instruments.

5.5 Other factors that influence participation in RC

We describe briefly other covariates that influence participation in RC (Online Appendix IV, Table A6). These marginal effects are calculated from the Probit estimates (Table 4) with the values of covariates set at the sample mean. Firm size exerts a sizeable influence on plant participation. One standard deviation increase in the number of plants owned by the firm is associated with an increase of 15.8 to 23.6 percentage points in the probability of RC participation. Ownership by a firm whose mean number of employees per plant is one standard deviation more than the average is associated with an increase of 10.5 to 11.0 points in the likelihood of RC participation.

We find that neighborhood characteristics exert only a weak influence on participation, and plants located in poorer neighborhoods are more likely to participate in RC. Comparing a plant with another located in a neighborhood that has one standard deviation higher share of poverty, the latter is more likely to participate in RC by 2.3 percentage points. Plausibly firms are more likely to derive benefits from industry self-regulation and therefore join the program in more concentrated industries where the problem of collective action is less difficult to overcome. However, we find that plants whose primary operations are in more concentrated industries have lower likelihood of RC participation.

6. Conclusion

Our study provides robust evidence that, controlling for self-selection, RC participants pollute more than non-participants. Our preferred estimates from our multi-plant sample indicate that RC raises pollution by 15.9%. This increase in pollution attributed to RC is large relative to the yearly 4% reduction in pollution among all plants in our sample between 1988 and 2001. Based on our estimates, RC participation would eliminate at least 3 years of this trend. These results are robust to the use of subsets of instruments and the measurement of pollution in pounds. We find comparable results that RC reduces pollution by 16.1% in the full sample (in which we use imperfect instruments). Importantly, our estimation using PSM, a method whose consistency does not rely on exclusion restrictions, yields estimates that range from one third to the full magnitude of the GMM estimates (6.8% to 16.8%), though these PSM estimates are not statistically significant. Finally, we also find that RC raises pollution intensity by 15.1% in the multi-plant sample.

Our results that RC participants pollute more than statistically equivalent non-participants, particularly in the earlier years of the program, are consistent with Glachant's (2007) theory and descriptions of RC's institutional history (Rees, 1997; Gunningham, 1995; Givel, 2007). Glachant (2007) suggests that under specific circumstances, firms strategically enter a self-regulation program without any intention to comply with their commitments of that program. Firms enter the program to postpone legislation, and they are able to not comply with their commitments because their failure to comply is not immediately observable. Meanwhile, firms undertake lobbying efforts to weaken the final legislation. In the early years of the RC program, participants were able to not reduce their pollution, as key refinements to the program had not yet been implemented. The ACC developed codes of conduct over the first five years of the program and only in 1999 required firms to establish performance goals and publicly report progress toward those goals (Rees, 1997). Drawing on ACC's documents, Givel (2007) argues that avoiding strict regulation had been one policy goal of the ACC in adopting RC and that the

ACC had engaged in efforts to weaken legislation. Similarly, Gunningham (1995) narrates examples that exemplify ACC's efforts in weakening legislation.

Our results are consistent with most studies to date which find that self-regulation or voluntary programs do not significantly reduce pollution (Morgenstern and Pizer, 2007). Our results, while not directly comparable, complement the results in King and Lenox (2000)s. Our approach of comparing the pollution *levels* of participants to non-participants, rather than their relative *rates* of improvement, follows the method used in Lyon and Kim (2011) and Pizer et al., (2011). King and Lenox (2000) examine the rate of improvement of RC firms relative to a normalized level of toxicity-weighted pollution based on plant size, industry, and year.[31] They find that RC participants have slower rates of improvement relative to normalized levels by 5% in their GLS specification and by 7% in their fixed-effects specification, though the fixed effects estimates are not statistically significant at conventional levels. Their conclusion of RC's poor performance, however, is limited by their GLS method which does not address self-selection. As is evident in the comparison of our GMM and OLS models, it is the firms that are less likely to reduce their pollution that self-select into the program and thus the failure to address self-selection leads to an overstatement of the adverse effects of RC.[32] In our GMM models that address self-selection, we find that RC participating plants *raise* their pollution relative to non-participants by 15.9%. Therefore, our results point firmly to the failure of the pre-2002 RC program to improve environmental performance.

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[31] We use the RSEI toxicity weights as in Brouhle et al. (2009) and Bae et al. (2010). Lenox and King (2000) use the inverse of Reportable Quantities, listed in the Comprehensive Environmental Response, Compensation and Liability Act, which they show correlates well to other measures of toxicity weights.
[32] Our OLS models and even FE models find much larger increases in participants' pollution relative to non-participants than do the GMM models (Table 2).

From a policy perspective, we conclude that it would be premature to rely on industry self-regulation programs which mirror the pre-2002 RC program, i.e., without third party verification or enforceable penalties for non-performance, as a tool to reduce pollution. Industry self-regulation programs that do not require certification, e.g., the petroleum industry's program, are not likely to improve environmental performance. Finally, regulators and firms in the oil and gas industry, which are drawing lessons from RC for self-regulation in that sector, should exercise caution. Third party certifiers in oil and gas have limited independence (Bea, pers. comm.; Pettit, 2010). The ineffectiveness of the pre-2002 RC program, without third party certification, counsels against relying on self-regulation as the primary policy tool for improving environmental performance.

We note that our study may understate RC's impact on reducing pollution if RC reduces the pollution of non-participants (Lyon and Maxwell, 2007; Lange, 2009). One potential channel for this to occur is if RC prompted innovations in pollution abatement technology and this technological spillover reduced the pollution abatement costs and thus reduced pollution for all plants. However, we argue this estimation concern is mitigated. These spillover effects are likely to be larger among RC members, as they share pollution abatement information and technology (Prakash, 2000).

Our assessment of RC comes with two caveats: (i) we examine only one RC code, i.e., pollution prevention; and (ii) we examine the RC institutional structure pre-2002, i.e., the absence of third party certification. We leave for future work, should data become available, (i) the evaluation of RC's Process Safety code (ACC, 1990) that aims to prevent Bhopal-type industrial accidents; and (ii) the evaluation of the third party certification requirement which was implemented in 2002 in the RC14001 program (Moffet et al., 2004).

References

American Chemistry Council (ACC) [formerly known as the Chemical Manufacturers' Association.] 1990.Responsible Care: Codes of Management Practices. Archived at the International Labor Organization Corporate Codes of Conduct. Retrieved from: http://actrav.itcilo.org/actrav-english/telearn/global/ilo/code/responsi.htm

American Petroleum Institute (API). 2005. *Toxic Release Inventory Burden Reduction Proposed Rule; TRI-2005-0073; RFL-7532-8;70 Federal Register 57822-57847*. October 4. Washington DC: Office of Environmental Information Docket, U.S. Environmental Protection Agency, Docket ID No. TRI-2005-0073.

Arellano, Manuel and Stephen Bond. 1991. “Some Tests of Specification for Panel Data: Monte Carlo Evidence and An Application to Employment Equations.” *The Review of Economic Studies* 58 (2): 277-297.

Arellano, Manuel and Olympia Bover. 1995. “Another Look at the Instrumental Variable Estimation of Error Components Models.” *Journal of Econometrics* 68 (1): 29-51.

Arora, Seema and Timothy N. Cason. 1995. “An Experiment in Voluntary Environmental Regulation: Participation in EPA’s 33/50 Program.” *Journal of Environmental Economics and Management* 28 (3): 271-286.

Arora, Seema and Timothy N. Cason. 1999. “Do Community Characteristics Influence Environmental Outcomes? Evidence from the Toxics Release Inventory.” Southern Economic Journal 65(4): 691-716.

Bae, Hyunhoe, David Popp, and Peter Wilcoxen. 2010. “Information Disclosure Policy: Does States’ Data Processing Efforts Help More than the Information Disclosure Itself?” *Journal of Policy Analysis and Management* 29(1): 163-182.

Barnett, Michael and Andrew King. 2008. “Good Fences Make Good Neighbors: a Longitudinal Analysis of an Industry Self-Regulatory Institution.” *Academy of Management Journal* 51 (6): 1150–1170.

Baron, David P. 2001. “Private Politics, Corporate Social Responsibility, and Integrated Strategy.” *Journal of Economics and Management Strategy* 10 (v):7-45.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. “Automobile Prices in Market Equilibrium.” *Econometrica* 63 (4): 841-890.

Blundell, Richard and Stephen Bond. 1998. “Initial Conditions and Moment Restrictions in Dynamic Panel Data Methods.” *Journal of Econometrics* 87 (1): 111-143.

Blundell, Richard and Stephen Bond. 2000. “GMM Estimation with Persistent Panel Data: an Application to Production Functions.” *Econometrics Reviews* 19(3): 321-340.

Brouhle, Keith, Charles Griffiths, and Ann Wolverton. 2009. ”Evaluating the Role of EPA Policy Levers: An Examination of a Voluntary Program and Regulatory Threat in the Metal-finishing Industry.” Journal of Environmental Economics and Management, 57(2): 166-181

Calcott, Paul. 2010. “Mandated Self-regulation: the Danger of Cosmetic Compliance.” *Journal of Regulatory Economics* 38(2): 167-179.

Cohen, Mark A., Madeline Gottlieb, Joshua Linn, and Nathan Richardson. 2011. “Deepwater Drilling: Law, Policy, and Economics of Firm Organization and Safety.” Resources for the Future Discussion Paper 10-65

Cole, Matthew A., Robert J.R. Elliott and Kenichi Shimamoto. 2005. “Industrial Characteristics, Environmental Regulations and Air Pollution: An Analysis of the UK Manufacturing Sector.” *Journal of Environmental Economics and Management* 50(1): 121-143

Dawson, Na Li and Kathleen Segerson. 2008. “Voluntary Agreements with Industries: Participation Incentives with Industry-Wide Targets.” *Land Economics* 84 (1): 97-114.

DeCanio, Stephen J. and William E. Watkins. 1998. “Investment in Energy Efficiency: Do the Characteristics of Firms Matter?” *Review of Economics and Statistics* 80 (1): 95-107.

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

Environmental Protection Agency (EPA). 2007. *Green Book: The Green Book Nonattainment Areas for Critical Pollutants*. Retrieved from http://www.epa.gov/oar/oaqps/greenbk.

Environmental Protection Agency (EPA). 2009. *EPA’s Risk Screening Environmental Indicators (RSEI).* February. Methodology Office of Pollution Prevention and Toxics.

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

General Accounting Office (GAO). 2011. “Private Fund Advisers: Although a Self-regulatory Organization Could Supplement SEC Oversight, It Would Present Challenges and Trade-offs. Report to Congressional Committees. GAO-11-623.

Givel, Michael. 2007. “Motivation of Chemical Industry Social Responsibility through Responsible Care.” *Health Policy* 81 (1): 85-92.

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

Greenstone, Michael. 2003. “Estimating Regulation-Induced Substitution: The Effect of the Clean Air Act on Water and Ground Pollution.” *American Economic Review Papers and Proceedings* 93(2): 442-448.

Gunningham, Neil. 1995. “Environment, Self-Regulation and the Chemical Industry: Assessing Responsible Care” *Law and Policy* 17 (1): 57-109

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

Hamilton, James T. 2005. *Regulation through Revelation: The Origin, Politics, and Impacts of the Toxics Release Inventory Program*. Cambridge, UK: Cambridge University Press.

Hartman, Raymond S. 1988. “Self-Selection Bias in the Evaluation of Voluntary Energy Conservation Programs.” *Review of Economics and Statistics* 70 (3): 448-458.

Heckman, James J, Hidehiko Ichimura, and Petra E. Todd. 1997. "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme." *Review of Economic Studies* 64(4): 605-54

Hoffman, Andrew. 2000. *Competitive Environmental Strategy: A Guide to the Changing Business Landscape*. Washington, DC: Island Press.

Innes, Robert and Abdoul G. Sam 2008. “Voluntary Pollution Reductions and the Enforcement of Environmental Law: an Empirical Study of the 33/50 Program.” *Journal of Law & Economics* 51 (2): 271-296.

International Council of Chemical Associations (ICCA). 2008. Responsible Care Status Report 2008 Retrieved from http://www.icca-chem.org/ICCADocs/Status_Report_2008.pdf

King, Andrew and Michael Lenox. 2000. “Industry Self-regulation Without Sanctions: the Chemical Industry’s Responsible Care program.” *Academy of Management Journal* 43 (4): 698–716.

Kleindorfer, Paul R. and Eric Orts. 1998. “Informational Regulation of Environmental Risks” *Risk Analysis* 18(2): 155-170

Konar, Shameek and Mark A. Cohen. 2001. “Does the Market Value Environmental Performance? ” *Review of Economics and Statistics* 83 (2): 281-289.

Lange, Ian. 2009. “Evaluating Voluntary Measures with Treatment Spillovers: The Case of Coal Combustion Products Partnership.” *B.E. Journal of Economic Analysis & Policy* 9 (1), article 36.

Lenox, Michael and Jennifer Nash. 2003. “Industry Self-Regulation and Adverse Selection: A

Comparison Across Four Trade Association Programs." *Business Strategy and Environment* 12 (6): 343-356.

Levinson, Arik. 2004. "Review of *New Tools for Environmental Protection: Education, Information, and Voluntary Measures*, Dietz and Stern (Eds.)." March 24. *Journal of Economic Literature* 42 (1): 171-231.

Lyon, Thomas P. and Eun-Hee Kim. 2011. "Strategic Environmental Disclosure: Evidence from the DOE's Voluntary Greenhouse Gas Registry." *Journal of Environmental Economics and Management* 61(3): 311-326.

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

Lyon, Thomas P. and John W. Maxwell. 2007. "Environmental Public Voluntary Programs Reconsidered." *Policy Studies Journal* 35 (4): 723–750.

Lyon, Thomas P. and John W. Maxwell. 2011. "Greenwash: Corporate Environmental Disclosure under Threat of Audit." *Journal of Economics and Management Strategy* 20(1): 3-41.

Maxwell, John W. and Christopher Decker. 2006. "Voluntary Environmental Investment and Responsive Regulation." *Environmental & Resource Economics* 33 (4): 425-439.

Maxwell, John W., Thomas Lyon, and Steven Hackett. 2000. "Self-regulation and Social Welfare: the Political Economy of Corporate Environmentalism." *Journal of Law and Economics* 63 (43): 583-617.

Moffet, John, Francois Bregha and Mary Jane Middelkoop. 2004. "Responsible Care: A Case Study of a Voluntary Environmental Initiative." (pp. 177–208). in K. Webb (Ed.), *Voluntary Codes: Private Governance, the Public Interest and Innovation*. Ottawa, Canada: Carleton Research Unit for Innovation, Science and Environment.

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.

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*. Committee for the Analysis of Causes of the Deepwater Horizon Explosion, Fire, and Oil Spill to Identify Measures to Prevent Similar Accidents in the Future.

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.

Nevo, Aviv. 2000. “Mergers with Differentiated Products: The Case of the Ready-to-Eat Cereal Industry.” *RAND Journal of Economics* 31 (3): 395-421.

Nickell, Stephen. 1981. “Biases in Dynamic Models with Fixed Effects.” *Econometrica* 49 (6): 1417–26.

Oehlert, Gary W. 1992. “A Note on the Delta Method” *The American Statistician* 46 (1): 27-29.

O'Rourke, Dara. 2003. “Outsourcing Regulation: Analyzing Nongovernmental Systems of Labor Standards and Monitoring.” *Policy Studies Journal* 31 (1): 1-29.

Pettit, David. 2010. “The more things change at MMS …” David Pettit’s blog at the Natural Resources Defense Council, June 14, 2010. Retrieved from http://switchboard.nrdc.org/blogs/dpettit/the_more_things_change_at_mms.html

Pizer, William A, Richard Morgenstern and Jhih-Shyang Shih. 2011. “The Performance of Industrial Sector Voluntary Climate Programs: Climate Wise and 1605 (b).” *Energy Policy* 2011

Potoski, Matthew and Aseem Prakash. 2005. “Covenants with Weak Swords: ISO 14001 and Firms’ Environmental Performance.” *Journal of Policy Analysis and Management* 24 (4): 745-769.

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

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

Roodman, David. 2008. “How To Do xtabond2: An Introduction to “Difference” and “System” GMM in Stata.” Center for Global Development working paper, Washington DC.

Rosenbaum, Paul R. and Donald B. Rubin. 1983. “The Central Role of the Propensity Score in Observational Studies for Causal Effects.” *Biometrika* 70 (1): 41-55.

Rosenthal, Isadore and Howard Kunreuther. 2010. “Roles for Third Parties in Implementing USDA Food Safety and Inspection Service (FSIS)’s Food Safety Process Management Programs” Risk Management and Decision Processes Center, The Wharton School of the University of Pennsylvania.

Van Asten, Mike and Charles Martinson. 2005. "MON MACT Impact." *Products Finishing* 70 (3): 54-59

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

Windmeijer, Frank. 2005. “A Finite Sample Correction for the Variance of Linear Two-Step

GMM Estimators." *Journal of Econometrics* 126 (1): 25-51.

Table 1: Summary statistics: means for various subsets of plants

	[1]	[2]	[3]	[4]		[5]	[6]	
	All Plants		Plants owned by			Plants owned by		
			RC	Non-RC		Multi-plant	Single-plant	
	Mean	Std. Dev.	Participants	Participants		Firms	Firms	
Responsible Care (RC) participation dummy	0.356	0.479	1	0	***	0.514	0.035	***
Membership in the American Chemistry Council in 1988 and 1989	0.347	0.470	0.882	0.051	***	0.495	0.046	***
Plant's number of employees	157	415	254	103	***	196	78	***
Number of plants owned by a firm	8.849	11.44	17.0	4.350	***	12.7	1.000	***
Single-plant firm dummy	0.329	0.470	0.032	0.493	***	0	1	***
Toxicity-weighted air pollution by industry [% plants in sample]	2.8×10^{7}	5.7×10^{8}	6.2×10^{7}	9.7×10^{6}	***	3.9×10^{7}	6.7×10^{6}	***
Modal Industry: SIC 2851 - Paints, Varnishes [18.7%]	2.2×10^{6}	9.7×10^{6}	5.7×10^{6}	1.7×10^{6}	***	2.6×10^{6}	1.7×10^{6}	***
Most Polluting Industry: SIC 2812 - Alkalies & Chlorine [1.3%]	1.8×10^{8}	6.8×10^{8}	2.3×10^{8}	1.9×10^{7}	***	2.0×10^{8}	1.1×10^{6}	***
Least Polluting Industry.: SIC 2835 - Diagnostic Subs. [0.4%]	1.3×10^{5}	4.5×10^{5}	1.1×10^{3}	1.8×10^{5}	***	1.2×10^{5}	1.6×10^{5}	***
SIC 2821 - Plastics Materials and Synthetic Resins [11.5%]	1.5×10^{7}	5.8×10^{7}	1.7×10^{7}	1.1×10^{7}	***	1.7×10^{7}	6.8×10^{6}	***
SIC 2869 - Industrial Organic Chemicals, n.e.c. [11.1%]	3.1×10^{7}	1.1×10^{8}	4.3×10^{7}	1.3×10^{7}	***	3.3×10^{7}	2.5×10^{7}	***
SIC 2819 - Industrial Inorganic Chemicals, n.e.c. [9.6%]	1.6×10^{8}	1.8×10^{9}	2.6×10^{8}	7.1×10^{7}	***	2.1×10^{8}	2.4×10^{7}	***
SIC 2899 - Chemicals and Chemical Preparations, n.e.c. [7.8%]	4.7×10^{6}	2.5×10^{7}	9.3×10^{6}	2.5×10^{6}	***	6.4×10^{6}	2.6×10^{6}	***
Toxicity-weighted air pollution/employees	3.1×10^{5}	4.0×10^{6}	5.5×10^{5}	1.8×10^{5}	***	3.7×10^{5}	2.0×10^{5}	***
Toxicity-weighted HAP/TRI	0.746	0.400	0.767	0.734	*	0.738	0.762	**
Plant's neighborhood's characteristics								
% white	0.759	0.289	0.771	0.753	**	0.761	0.756	**
% < high school education	0.327	0.169	0.329	0.326		0.326	0.327	
% poor	0.158	0.152	0.158	0.158		0.160	0.154	*
% urban	0.736	0.397	0.679	0.767	***	0.717	0.775	***
County in non-attainment status under the Clean Air Act (CAA)	0.641	0.480	0.614	0.655	***	0.619	0.685	***
SIC-4 Industry Pollution index:	3.63	9.60	5.04	2.85	***	3.97	2.93	***
(Pollution in SIC-28xx / Pollution in SIC-28)^{2}								
SIC-4 Value of Shipment Index	94.8	12.71	93.7	95.5	**	94.9	94.6	
SIC-4 Producer Price Index	92.5	8.69	92.8	92.3		92.9	91.6	*
SIC-4 Herfindahl-Hirschman Index	695	539	744	667	***	728	626	***

Notes: Means are statistically significantly different at the ***1%, ** 5% and * 10% level, respectively. The term HAP/TRI denotes the ratio of hazardous air pollutants to Toxic Release Inventory pollutants released into the air. The term n.e.c. denotes not elsewhere classified.

Table 2: Preliminary regressions on the relationship between RC participation and pollution.								
	[1]	[2]	[3]	[4]		[5]	[6]	
	Plants owned by multi-plant firms					All pla		
	No. obs.=14,434. No. plants=2,162					No. obs.=22,82		
	OLS	FE	IV, FE	Lag Dep., FE		OLS	FE	IV
RC participation dummy	0.634***	0.264***	0.139	0.195***		0.881***	0.262***	-0
	(0.090)	(0.096)	(0.270)	(0.053)		(0.080)	(0.088)	(0
R-squared (within plant for FE)	0.455	0.085	0.085	0.272		0.422	0.079	0
Test Statistics								
Durbin-Wu-Hausman statistic	4.590**	0.243	-	0.549		2.909*	2.605*	
i.e., endogeneity of RC participation								
F Test of fixed effects	-	23.03***	23.02***	2.29***		-	22.27***	22.

Notes: FE denotes fixed effects; IV denotes instrumental variables; Lag Dep. denotes lagged dependent variables.
Each specification includes control variables as in the main regression (see Table 3). IV specifications instrument fo
using excluded variables, discussed in section 3.5, that are applied in our system GMM model (Table 3). Specificatio
include 1st and 2nd order lagged dependent variables. Robust standard errors are in parentheses. Statistiscally signifi
** 5% and * 10% level, respectively.

Table 3: System GMM estimation of the impact of RC participation on plant-level pollution

	[1]	[2]	[3]	[4]
Sample	Plants owned by multi-plant firms		All plants	
Instruments for the RC participation dummy	Excluded Variables	Predicted Probability of RC Participation	Excluded Variables	Predicted Probability of RC Participation
RC participation dummy	0.159**	0.160**	0.161**	0.204**
	(0.079)	(0.081)	(0.078)	(0.090)
1st order lagged dependent variable	0.855***	0.858***	0.782***	0.777***
	(0.097)	(0.099)	(0.101)	(0.104)
2nd order lagged dependent variable	0.031	0.030	0.060	0.062
	(0.072)	(0.071)	(0.067)	(0.068)
Arellano-Bond AR(2) Test	0.79	0.80	0.07	0.04
p-value	0.43	0.42	0.94	0.97
Hansen J-Statistic p-value	88.10	79.50	78.01	78.15
p-value	0.11	0.09	0.13	0.11
Difference-in-Hansen Statistic (RC instrument)	72.39	63.99	71.48	71.60
p-value	0.15	0.12	0.16	0.15
No. of Instruments	128	119	120	119
Obs.	14,434	14,434	22,822	22,822
No. of plants.	2,162	2,162	3,278	3,278

Notes: The dependent variable is the plant-level toxicity-weighted air pollution. The specification includes lagged dependent variables (1st and 2nd order) as right hand side variables, in order to address potential serial correlation. These lagged variables are instrumented using second order and higher lagged levels in the differences equations, and lagged differences in the levels equations. Robust standard errors in parenthesis. Statistically significant at the *** 1%, ** 5% and *10% level, respectively.

Table 3 (continued): System GMM estimation of the impact of RC participation on plant-level pollution

	[1]	[2]	[3]	[4]
Sample	Plants owned by multi-plant firms		All plants	
Instruments for the RC participation dummy	Excluded Variables	Predicted Pr(RC)	Excluded Variables	Predicted Pr(RC)
Plant's HAP/TRI (t-1)	0.070	0.032	0.200	0.215
	(0.283)	(0.306)	(0.322)	(0.338)
Plant's SIC-4 Industry Pollution index	0.005*	0.005	0.007***	0.007***
	(0.003)	(0.003)	(0.003)	(0.003)
Plant's relative pollution (t-1)	0.0005	0.0005	0.001	0.0011
	(0.001)	(0.001)	(0.001)	(0.001)
No. of plants owned by firms	-0.005**	-0.005**	-0.005**	-0.005***
	(0.002)	(0.002)	(0.002)	(0.002)
Log (firm's mean employees)	0.031	0.036	0.036**	0.033**
	(0.029)	(0.029)	(0.017)	(0.017)
Single-plant firm dummy			-0.014	-0.0174
			(0.070)	(0.070)
Plant-level neighborhood characteristics				
% white	0.075	0.069	0.086	0.087
	(0.098)	(0.099)	(0.079)	(0.079)
% < high school education	0.021	0.043	0.066	0.072
	(0.158)	(0.160)	(0.121)	(0.122)
% poor	0.149	0.127	0.186	0.185
	(0.194)	(0.196)	(0.150)	(0.151)
% urban	-0.084	-0.082	-0.147***	-0.146***
	(0.059)	(0.060)	(0.053)	(0.054)
Non-attainment under the CAA	-0.002	-0.003	-0.007	-0.007
	(0.041)	(0.042)	(0.035)	(0.036)
Value of Shipment Index	-0.0003	-0.001	-0.001	-0.0005
	(0.002)	(0.002)	(0.002)	(0.002)
Producer Price Index	-0.010***	-0.009**	-0.009***	-0.009***
	(0.004)	(0.004)	(0.003)	(0.003)
Herfindahl-Hirschman Index	-1×10^4	-1×10^4	-1×10^4	-1×10^4
	(1×10^4)	(1×10^4)	(8×10^5)	(9×10^5)

Predicted Pr(RC) denotes the predicted probability of RC participation. The dependent variable is the plant-level toxicity-weighted air pollution. The specification includes lagged dependent variables (1st and 2nd order) as right hand side variables, in order to address potential serial correlation. These lagged variables are instrumented using second order and higher lagged levels in the differences equations, and lagged differences in the levels equations. The plant's SIC-4 Industry Pollution index denotes the average pollution of other plants in the same SIC-4 industry relative to the entire chemical sub-sector. Each specification includes year and SIC-4 dummies. Robust standard errors in parentheses. Statistically significant at the ***1%, ** 5% and *10% level, respectively.

Table 4: Probit regression of RC participation on instrumental variables (IV) and other covariates.

	[1]		[2]		[3]		[4]
	Plants owned by multi-plant firms				All plants		
	No obs.=14,434				No obs.=22,822		
	Coeff.		Robust Std.Err.		Coeff.		Robust Std.Err.
†% RC participation in the SIC-4 (SIC-ProbRC)	-14.06	***	2.118		-12.58	***	1.831
†ACC membership in 1988 and 1989 (ACC)	2.329	***	0.198		2.333	***	0.176
†Firm's HAP/TRI	0.588	**	0.231				
†Firm's SIC-4 Industry Pollution index	0.005		0.004				
†Firm's plants' relative pollution	-0.001		0.003				
†Firm's neighborhood characteristics							
% white	0.624		0.471				
% < high school education	-0.266		0.711				
% poor	1.729	**	0.812				
% urban	-0.584	*	0.299				
County in non-attainment status under the CAA	0.208		0.210				
Single-plant firm dummy					-0.111		0.247
No. of plants owned by firm	0.050	***	0.007		0.047	***	0.008
Log (firm's mean employees)	0.255	***	0.078		0.160	***	0.047
Plant's pollution (t-1)	0.007		0.012		0.021	*	0.011
Plant's HAP/TRI (t-1)	0.240	*	0.143		0.139		0.137
Plant's SIC-4 Industry Pollution index	-0.0001		0.003		0.001		0.003
Plant's relative pollution (t-1)	0.0003		0.000		0.001		0.001
Plant's neighborhood characteristics							
% white	0.089		0.176		0.008		0.162
% < high school education	-0.121		0.263		-0.309		0.238
% poor	0.437		0.307		0.514	*	0.306
% urban	-0.083		0.107		-0.128		0.094
Non-attainment county	0.120		0.078		0.078		0.077
Value of Shipment Index	-0.021	***	0.005		-0.018	***	0.004
Producer Price Index	-0.015	**	0.007		-0.009		0.006
Herfindahl-Hirschman Index	-0.001	***	0.000		-0.001	***	0.000
Constant	10.71	***	1.869		10.09	***	1.588
Log-Likelihood	-2,954				-3,834		
Likelihood Ratio Test - All Instruments	5,515	***					
Likelihood Ratio Test - SIC-ProbRC, ACC	5,204	***			6,340	***	
Likelihood Ratio Test - Multi-Plant IVs	147	***					

Notes: † denote variables that serve as the excluded variables in the main GMM specification. The plant's SIC-4 Industry Pollution index denotes the average pollution of other plants operating in the same SIC-4 industry relative to the entire chemical sub-sector. The firm's SIC Pollution index denotes the average SIC-4 Industry Pollution index of the subindustries in which the firm's plants operate. Each specification includes year and SIC-4 dummies. Statistically significant at the *** 1%, ** 5% and * 10%.

Table 5: GMM regression of pollution on RC participation interacted with a dummies for various years

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Specification	Main specification		3-year blocks		6-year blocks		No. of years in RC	
Sample	Plants owned by multi-plant firms	All Plants	Plants owned by multi-plant firms	All Plants	Plants owned by multi-plant firms	All Plants	Plants owned by multi-plant firms	All Plants
RC	0.204**	0.161**					0.159**	0.208**
	(0.090)	(0.078)					(0.080)	(0.091)
RC x I(yr='90-92)			0.250***	0.273***				
			(0.094)	(0.095)				
RC x I(yr='93-95)			0.154	0.217**				
			(0.098)	(0.103)				
RC x I(yr='96-98)			0.081	0.134				
			(0.099)	(0.100)				
RC x I(yr='99-01)			0.137	0.169*				
			(0.105)	(0.103)				
RC x I(yr='90-95)					0.202**	0.244***		
					(0.085)	(0.092)		
RC x I(yr='96-01)					0.109	0.151		
					(0.088)	(0.094)		
No. of years in RC.							-0.001	-0.002
							(0.008)	(0.008)
Observations	14,434	22,822	14,434	22,822	14,434	22,822	14,434	22,822
No of plants	2,162	3,278	2,162	3,278	2,162	3,278	2,162	3,278

RC denotes the RC participation dummy. These specifications (i) employ excluded variables as the instruments and (ii) covariates as in the main specification. Robust standard errors in parentheses. Statistically significant at the *** 1 %, ** 5% and * 10% level, respectively.

Table 6: GMM regression of pollution on RC participation: heterogenous program effects

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
	Plants owned by multi-plant firms	All Plants	Plants owned by multi-plant firms	All Plants	Plants owned by multi-plant firms	All Plants	Plants owned by multi-plant firms
RC	0.204**	0.161**	0.186*	0.193**	0.137*	0.203**	0.159*
	(0.090)	(0.078)	(0.112)	(0.085)	(0.082)	(0.090)	(0.082)
RC x no. plants in firm			0.003	-0.001			
that owns plant *j*			(0.006)	(0.005)			
RC x dummy for				-0.23			
single-plant firm				(0.312)			
RC x firm's #					-0.101		
employees (t-1)					(0.092)		
RC x % poor in plant's						0.370	0.458*
neighborhood						(0.234)	(0.265)
RC x % urban in plant's						-0.003	-0.077
neighborhood						(0.100)	(0.129)
Observations	14,434	22,822	14,434	22,822	14,434	22,822	14,434
No. of plants	2,162	3,278	2,162	3,278	2,162	3,278	2,162

Notes: RC denotes the RC participation dummy. The RC interaction variables are instrumented with the probit estimates of the
interacted with the de-meaned covariates. Other covariates as in the main specification are included. Robust standard errors are
Statistically significant at the *** 1%, ** 5%, and * 10% level, respectively.

Online Appendix I: Additional Robustness Checks

Robustness check #1: System GMM results using subsets of instruments
Table A1 shows that our main system GMM results on the effect of RC are robust to the use of subsets of instru specifications yield positive and statistically significant estimates that are similar in magnitude to our main result 1, 3, 4, 6, 7, 9). In no specifications, do we find that RC reduces plants' pollution (Table A1).

Table A1: System GMM results using subsets of instruments								
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	
	Plants owned by multi-plant firms							
	No. obs.=14,434. No. plants = 2,162						No. obs.=22,82	
RC participation dummy	0.159**	0.317	0.711*	0.161**	0.201	0.152*	0.161**	
	(0.079)	(0.426)	(0.375)	(0.080)	(0.155)	(0.084)	(0.078)	(
Excluded Variables:								
Firm's plants' pollution attributes	√		√					
Firm's plants' neighborhood characteristics	√	√	√					
% RC participation in the SIC-4	√			√		√	√	
ACC membership in 1988 & 1989	√			√	√		√	
Arellano-Bond AR(2) Test Statistic	0.73	0.75	0.69	0.73	0.74	0.74	0.03	
p-value	0.47	0.45	0.49	0.46	0.46	0.46	0.98	
Hansen J-Statistic	88.2	85.2	84.6	79.9	80.1	79.7	78.0	
p-value	0.11	0.08	0.11	0.10	0.09	0.09	0.13	
Difference in Hansen	72.5	69.4	71.7	64.1	64.3	63.9	71.5	
p-value	0.15	0.21	0.22	0.24	0.22	0.22	0.15	
# of Instruments	128	123	126	120	119	119	120	

Notes: As our main instrumental variables (IV) specifications (Table 3), these specifications include (i) other control variab and SIC-4 dummies, and (ii) the first and second order lagged dependent variables (LDV). These lagged instrumental varia instrumented using second order and higher lagged levels in the differences equations and lagged differences in the levels e Robust standard errors are in parentheses. Statistically significant at the *** 1%, ** 5% and * 10% level, respectively.

Robustness check #2: Redefinition of instruments

We re-construct our BLP-type instruments) using plants owned by the same firm located in different stat potential spillovers across nearby plants. This strategy builds on findings in Shimshack and Ward (2005) and Gr (2007) that inspections at a plant can result in general deterrence at other plants in that state; but this general det within the state. This specification reduces our number of observations to plants owned by firms that operate in not qualitatively change our parameter estimates or our over-identification test statistics.

Robustness check # 3: Alternative dependent variables

Our results that RC raises pollution is robust to the alternative measure of air pollution i.e., pounds of air that RC raises pounds of air pollution by 6.1% in the multi-plant sample and by 9.8% in the all plant sample (Ta These estimates are about one third to two thirds the size of estimates for toxicity-weighted air pollution.

Table A2: System GMM regression of pollution on RC participation: alternative measures of pollution

	[1]	[2]		[3]	[4]
Pollution	Air			Air	
Toxicity-weighted	Yes			No	
Sample	Plants owned by multi-plant firms	All plants		Plants owned by multi-plant firms	All plants
RC participation dummy	0.159**	0.161**		0.061*	0.098***
	(0.079)	(0.078)		(0.036)	(0.034)
Obs.	14,434	22,822		14,434	22,822
No. of plants	2,162	3,278		2,162	3,278

Notes: These specifications employ (i) excluded variables as the instruments, and (ii) include control variables as in the main regression (Table 3). Robust standard errors are in parenthesis. Statistically significant at the *** 1%, ** 5% and * 10%, respectively.

Online Appendix II: Propensity Score Matching (PSM)

We use propensity score matching (PSM) as an alternative method to estimate the effect of RC. The PSM metho GMM method, does not rely on the IV exclusion restrictions. The PSM estimates the average treatment effects o We apply several matching procedures as a check for robustness, i.e., kernel matching (Table A3, column 1), 5-n matching (Table A3, column 2 and 3), 1-nearest neighbor matching (column 4 and 5). Our preferred estimates fr neighbor matching procedure are matches with common support restrictions (Smith and Todd, 2005)

The PSM estimates, particularly, those from kernel matching (0.147) and the 5-nearest neighbor matching with c (0.169) are fairly similar in magnitude to our GMM estimates (0.159 to 0.204). The PSM estimate from the 1-nea matching with common support (0.068) is about one third to almost one half the size of the GMM estimates. The however, are not statistically significant at conventional levels.

Table A3: Propensity Score Matching (PSM) estimate of the impact of RC on plant-level pollution

	[1]	[2]	[3]	[4]	[5]
Matching procedure	Kernel	5-Nearest Neighbors		1-Nearest Neighbor	
With replacement	-	Y	Y	Y	Y
Observations	All	Common Support	All	Common Support	All
RC Participation, i.e., average treatment on the treated	0.147	0.169	0.005	0.068	-0.139
	(0.199)	(0.167)	(0.204)	(0.198)	(0.223)
No. treated obs. (RC=1)	8,192	7,713	8,192	7,713	8,192
No. control obs. (RC=0)	15,908	15,007	15,908	15,007	15,908

Notes: Kernel matching uses all control observations in matching against the treated observations, but weights th closeness of the match using an Epanechnikov kernel. For the nearest neighbor procedures with the common sup exclude the treated observations whose estimated likelihood of treatment is greater than the highest estimated lik untreated observations. When matching is done with replacement, a control case can be used more than once, all precise matching. We use a probit specification to generate our propensity score estimates.

Online Appendix III: Impact of RC on plant-level pollution intensity

We examine the impact of RC on plant-level pollution intensity, defined as the ratio of toxicity-weighted number of employees. Lower pollution intensity would imply a more favorable trade-off between production anc al., 2005); i.e., the same production would result in lower pollution.

We find that RC raises pollution intensity by 15.1% in the multi-plant sample (Table A4, column 3). We raises pollution intensity by 12.6% in the all plant sample (though we note that the instruments for the all plant sa (Table A4 column 4). We also use the alternative denominator of plant-level employee squared. We continue to coefficients in both the multi-plant and all-plant samples, though these estimates are not statistically significant. fails to reduce pollution intensity.

Table A4: System GMM regression of pollution on RC participation: alternative normalizations for pollution-intensity

	[1]	[2]	[3]	[4]	[5]	[6]
Dependent variables are the ratio of toxicity weighted air pollution to different denominators						
Denominator	1		No. of employees		(No. of employees)^2	
Sample	Plants owned by multi-plant firms	All plants	Plants owned by multi-plant firms	All plants	Plants owned by multi-plant firms	All plants
RC participation dummy	0.159**	0.161**	0.151*	0.126*	0.111	0.052
	(0.079)	(0.078)	(0.078)	(0.074)	(0.074)	(0.072)
Obs.	14,434	22,822	14,293	22,640	14,293	22,640
No. of plants	2,162	3,278	2,145	3,253	2,145	3,253

Notes: These specifications employ (i) excluded variables as the instruments, and (ii) include control variables as in the main regression (Table 3). Robust standard errors are in parenthesis. Statistically significant at the *** 1%, ** 5% and * 10%, respectively.

The alternative normalization strategy addresses one potential estimation issue from using the number of denominator. This estimation issue arises if plants respond to RC by choosing a production process that is less la does not raise pollution per unit of production. Should larger plants increase their output at a faster rate than their denominator for large plants may be too small, resulting in too large a measure of pollution intensity. Given that typically have larger plants, this mismeasurement of pollution intensity could bias our estimates on the impact of when we address this potential source of bias using employee squared as a denominator, our conclusions that RC pollution intensity continues to hold.

In defining pollution intensity, we use plant-level employee from Dun & Bradstreet to proxy for preferre plant-level output. This approach is used in other studies, given the absence of publicly available plant-level data provide evidence that plant-level employee can serve as a proxy for plant-level output. In the absence of publicly data, we examine the relationship between the number of employees and output, measured as value-added and va using data at the SIC-4 level from the NBER-CES Manufacturing Industry Database between 1988 and 2001 (Be 2009).

We restrict our analysis to industries in the chemical manufacturing sub-sector (SIC-28). We regress mea added or value of shipments, normalized to 1987 prices) on the number of employees and SIC-4 and year dumm positive relationship between the number of employees and both measures of output. We find positive and statist coefficients in regressions with either measure of output (Table A5, column 1 and 4). When we add the variable an additional explanatory variable, we continue to find strong positive relationships between the number of empl measures of output (column 2 and 5). In the regression with the number of employees squared, SIC-4 and year d strong positive relationship between the number of employees squared and both measures of output (column 3 ar

Table A5: Correlation between measures of output and employees at the SIC-4 industry level

	[1]	[2]	[3]		[4]	[5]	[6]
Dependent variable	Value Added ($1Million)				Value of Shipments ($1Million)		
Employees (1,000's)	98***	105***			162***	156***	
	(12.76)	(23.13)			(14.22)	(25.78)	
$Employees^2$ (1,000,000's)		-0.052	0.461***			0.044	0.803***
		(0.135)	(0.077)			(0.150)	(0.087)
Observations	406	406	406		406	406	406
R-squared	0.165	0.165	0.117		0.387	0.388	0.325

Notes: SIC-4 and year dummies are included. Statistically significant at ***1%, **5%, and *10%.

Online Appendix IV: Factors associated with RC participation

Table A6: Factors that influence RC participation: marginal effects from the RC probit estimation										
	[1]	[2]	[3]	[4]	[5]		[6]	[7]	[8]	
	Plants owned by multi-plant firms (no. obs.=14,434)						All plants (no obs.=22,			
	dPr(RC)	Std.	Mean	Std.	ΔPr(RC)		dPr(RC)	Std.	Mean	S
	dX	Error.		Dev.	due to 1		dX	Error		D
					Std. Dev.					
					increase					
% RC participation in the SIC-4	-5.408	0.862	0.291	0.165	-0.892	***	-3.668	0.518	0.269	
†ACC membership in 1988 and 1989	0.896	0.074	0.520	0.491	-	***	0.680	0.073	0.347	
Firm's HAP/TRI	0.226	0.090	0.847	0.278	0.063	**				
Firm's SIC-4 Industry Pollution index	0.002	0.002	4.642	9.552	0.019					
Firms' plants' relative pollution	-0.0003	0.001	2.189	10.13	-0.003					
Firms' plants' average neighborhood										
% white	0.240	0.182	0.761	0.157	0.038					
% < high school education	-0.102	0.273	0.320	0.089	-0.009					
% poor	0.665	0.317	0.158	0.082	0.055	**				
% urban	-0.225	0.115	0.720	0.239	-0.054	*				
Non-attainment under the CAA	0.080	0.080	0.619	0.283	0.023					
No. of plants owned by firms	0.019	0.003	13.32	12.34	0.236	***	0.014	0.003	8.849	
†Single-plant firm dummy							-0.032	0.070	0.329	
Log (firm's mean employees)	0.098	0.031	4.580	1.070	0.105	***	0.047	0.013	2.896	

Notes: The marginal effects are calculated from the probit regression in Table 4. The probability of RC participation with values c
sample mean is 0.21 for all plants and 0.60 for plants owned by multi-plant firms. The plant's SIC pollution index captures the pla
polluting sub-industries. Firms' plants' relative pollution is measured relative to other plants whose primary operations are in the sa
† Impact on participation resulting from a discrete change from 0 to 1. Robust standard errors are reported. Statistically significa
*** 1% level, ** 5% level and * 10% level, respectively.

Table A6 (continued): Factors that influence RC participation: marginal effects from the RC probit estimation										
	[1]	[2]	[3]	[4]	[5]		[6]	[7]	[8]	
	Plants owned by multi-plant firms (no. obs.=14,277)						All plants (no o			
	dPr(RC) dX	Std. Error.	Mean	Std. Dev.	ΔPr(RC) due to 1 Std. Dev. increase		dPr(RC) dX	Std. Error	Mean	S D
Plant's HAP/TRI (t-1)	0.092	0.056	0.747	0.394	0.036	*	0.041	0.039	0.752	
Plant's SIC-4 Industy Pollution index	-0.00003	0.001	4.764	12.81	-0.0004		0.0002	0.001	4.128	
Plant's relative pollution	0.0001	0.0002	2.477	27.61	0.003		0.0002	0.0002	1.886	
Plants' neighborhood characteristics										
% white	0.034	0.068	0.762	0.283	0.010		0.002	0.047	0.759	
% < high school education	-0.047	0.101	0.328	0.165	-0.008		-0.090	0.071	0.327	
% poor	0.168	0.118	0.160	0.151	0.025		0.150	0.090	0.158	
% urban	-0.032	0.041	0.714	0.406	-0.013		-0.037	0.027	0.736	
†Non-attainment under the CAA	0.046	0.030	0.617	0.486	-		0.023	0.022	0.641	
Value of Shipment Index	-0.008	0.002	94.9	12.94	-0.103	***	-0.005	0.001	94.82	
Producer Price Index	-0.006	0.003	92.9	8.869	-0.052	**	-0.003	0.002	92.49	
Herfindahl-Hirschman Index	-0.0004	0.0001	729	560	-0.204	***	-0.0002	0.0001	695	

Notes: The marginal effects are calculated from the probit regression in Table 4. The probability of RC participation with values o
sample mean is 0.21 for all plants and 0.60 for plants owned by multi-plant firms. The plant's SIC pollution index captures the pla
polluting sub-industries. Plant's relative pollution is measured relative to other plants whose primary operations are in the same SIC
Robust standard errors are reported. Statistically significant at the ***1% level, ** 5% level and * 10% level, respectively.

References for the Online Appendix

Becker, Randy A. and Wayne B. Gray. 2009. "NBER-CES Manufacturing Industry Database: Updated Data 1958-2005 - SIC and NAICS versions" Retrieved from http://www.nber.org/data/nbprod2005.html

Gray, Wayne B. and Ronald J. Shadbegian. 2007. "The Environmental Performance of Polluting Plants: A Spatial Analysis." *Journal of Regional Science* 47(1): 63-84.

Holladay, J. Scott. 2010. "Abate or Abscond: Polluters' Response to Environmental Regulation." presented at the Georgia Institute of Technology economics seminar, October 2010.

Shimshack, Jay and Michael Ward. 2005. "Regulator Reputation, Enforcement, and Environmental Compliance." *Journal of Environmental Economics and Management* 50(3): 519-540

Smith, Jeffrey A. and Petra E. Todd. 2005. Does Matching Overcome LaLonde's Critique of Nonexperimental Estimators? *Journal of Econometrics* 125 (1-2) 305-353.