Preliminary draft: do not quote

Impact of EPA's Voluntary 33/50 Program on Toxic Releases

Xiang Bi
Department of Agricultural and Consumer Economics
University of Illinois at Urbana Champaign
326 Mumford Hall
1301 Gregory Drive
Urbana, IL 61801
Email : Xiangbi2@uiuc.edu
Phone: (217)-766-5578

and

Madhu Khanna
Department of Agricultural and Consumer Economics
University of Illinois at Urbana Champaign
301A Mumford Hall
1301 Gregory Drive
Urbana, IL 61801
Email: Khanna1@uiuc.edu
Phone: (217)-333-5176

[JEL Codes: Q58, Q53, L60
Keywords: 33/50 program, Toxic release inventory, Releases, Program evaluation

Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Orlando, FL, July 27-29, 2008.

Impact of EPA's Voluntary 33/50 Program on Toxic Releases

I. INTRODUCTION

Environmental regulations in the US have typically relied on command-and-control approaches that focus on end-of-pipe measures instead of source reduction for pollution control. Since the 1990s there has been greater emphasis on voluntary programs to reduce releases of unregulated pollutants and on pollution prevention as the preferred approach for environmental protection. The emphasis on pollution prevention follows from the view that pollution can be viewed as an outcome of inefficient use of resources and that pollution prevention is a more cost effective way to protect the environment as compared to end-of-pipe pollution control. While not mandated by the National Pollution Prevention Act of 1990, adoption of pollution prevention techniques for reducing toxic releases has been encouraged by voluntary means and by requiring firms to report their activities to the Toxics Release Inventory (TRI).

The earliest voluntary program that sought to encourage a pollution prevention ethic among firms was the 33/50 program initiated by the US EPA in 1991 with the aim of reducing aggregate releases of 17 toxic chemicals by 33% by 1993 and by 50% by 1995, relative to their 1988 levels. However, firms had flexibility in the extent of reduction they achieved and in the methods they chose to reduce their releases. Observed data indicate that the program was successful in attracting participation from 17% of eligible firms that accounted for 61% of releases of 33/50 chemicals (hereafter referred to as 33/50 releases) in 1988. The program exceeded its goals and reduced these releases by 55% by 1995 relative to 1988 with 72% of this reduction occurring after 1991 (EPA, 1997). Empirical evidence on the extent to which this reduction can be attributed to program participation is mixed (see Khanna, 2006) and there has been no systematic

examination of the effectiveness of pollution prevention techniques in reducing 33/50 releases.

There are several reasons why the impact of the program on 33/50 releases could be questioned despite the observed reductions. First, two of the 17 chemicals were considered ozone depleting substances (ODS) and were being phased out by 1996 under the Montreal Protocol. Second, the 33/50 chemicals were classified as Hazardous Air Pollutants (HAP) in the Clean Air Act Amendments of 1990 and were expected to be subject to Maximum Available Control Technology standards starting in 2000. This could have created incentives for some firms to achieve early reductions even in the absence of the 33/50 program. Third, by using 1988 as the baseline for measuring emissions reductions the program created incentives for firms that had already achieved reductions prior to the 33/50 program to participate and obtain credit for those reductions. These firms may have initiated actions prior to program participation following negative publicity accompanying the public disclosure of TRI data that led to a downward trend in 33/50 releases and was independent of their program participation decision. Fourth, the program sought to encourage adoption of pollution prevention, firms may have simply reduced 33/50 releases by increasing recycling (Gamper-Rabindran, 2006).

The purpose of this paper is to re-assess the impact of 33/50 program on 33/50 releases. Specifically we examine if this impact differed for ODS and the rest 15 chemicals. Second, we examine if such impact differed for earlier participants and late participants. Third, we look at the extent to which any reduction in 33/50 releases can be attributed to pollution prevention techniques. In undertaking these analyses we control for any time trend in emissions, for the effect of anticipated regulations on Hazardous Air

Pollutants (HAP) that include 33/50 chemicals and for the synergistic effects of other regulations.

We conduct our analysis at the facility level, using facility level participation information and emissions data for the 1988-1995 period for 12,463 facilities from 48 states in the U.S that were eligible to participate in the program starting in 1991 because they reported emitting 33/50 releases prior to 1991 to the TRI. These facilities belonged to 4,861 parent companies. Of these, 1033 facilities belonging to 1268[1] parent companies that committed to the 33/50 program. We apply a GMM framework suitable for dynamic panel data models that incorporates facility specific unobserved effects, timing of participation and controls for endogeneity of program participation and pollution prevention adoption decisions. This approach allows us to determine the program's effect on the change in releases over time and to examine if the effect of program participation differed for late joiners as compared to early joiners.

We find that the 33/50 program led to a reduction of 33/50 releases. Despite the downward trend in emission reduction for most facilities during the program period, the annual rate of reduction was 35% higher for participating facilities than non-participating ones. Phasing out of the ODS chemicals had caused large reduction in ODS releases, but the program's effect was extended to the other 15 chemicals. Among participating facilities, those that participated in the first year of the program i.e. 1991 had undertaken largest reduction throughout the program; whereas facilities that participated later did not significantly reduce their releases as compared to the first group and those that did not

[1] Since some parent company names changed over time or because some facilities did not report parent company names in the TRI database, we are not able to match all 1294 firms in the EPA's program participants list with parent companies reported to TRI.

participate. Furthermore, pollution prevention technology adopted for specific chemicals had led to reduction of releases after controlling for program participation.

II. LITERATURE REVIEW

Several papers have sought to explain the incentives for participation in the 33/50 program (see review in Khanna, 2006 and Alberini and Sergerson, 2002; also Arora and Cason, 1995; Khanna & Damon, 1999; Vidovic and Khanna, 2007; Rivera et al., 2006). A few studies (Khanna and Damon, 1999; Vidovic and Khanna, 2007; Gamper-Rabindran, 2006; Sam and Innes, forthcoming; Sam et al., 2008) have examined the effectiveness of the 33/50 program in reducing releases and find mixed evidence.

Khanna and Damon (1999) find that program participation has a statistically significant negative effect on 33/50 releases in the chemical sector over the period of 1989-93. Vidovic and Khanna (2007) examine the effects of the program over the period 1991-95 for a broader set of sectors and argue that this finding vanishes if prior reductions in pollution achieved before the start of the program and time fixed effects are taken into account. However, even after controlling for time and industry effects and examining a broad array of manufacturing firms, Sam and Innes (forthcoming) find that 33/50 participation significantly reduces related emissions. Sam et al. (2008) find that even after controlling for other voluntary activities a firm might undertake, such as adoption of Total Quality Environmental Management (TQEM), program participation had a statistically significant negative impact on 33/50 releases. Gamper-Rabindran (2006) focus only on the 15 non-ozone depleting chemicals, arguing that the two ozone depleting 33/50 chemicals were due to be phased out anyway under the Montreal Protocol. She finds that the impact of the program varied by industry and media with some industries and media experiencing significant release reductions due to the 33/50

program effect, and others did not. The broad conclusion from this literature appears to be that, at least in some sectors, the 33/50 program led to reduction in releases.

These studies use two-step estimation methods. A discrete choice model of program participation is estimated in the first step; the second step uses the probability of participation to estimate the impact of participation on emissions with fixed/random effect estimators (an exception is Gamper-Rabindran (2006) that uses cross sectional change of emissions before and after the program) with bootstrapping methods to obtain consistent standard errors (Vidovic and Khanna, 2007; Sam and Innes, forthcoming).

However there are several draw backs related to this method. Such two-step estimation requires that the first-step probit model is correctly specified and correction of standard errors when using predicted probability as a variable (Wooldridge, 2002). Moreover, fixed effect estimation might still be biased if explanatory variables like program participation are affected by time varying factors or if they include lagged dependent variables and the dependent variable has an autoregressive structure. The latter is likely since emissions can be expected to be path dependent with adjustments in the production process occurring gradually over time.

With the exception of Gamper-Rabindran (2006) all studies have examined the impact of participation using firm level data that considers a firm as a participant if even one facility of that firm participates in the program. Due to lack of participation data at the facility level, even Gamper-Rabindran assumes that all facilities belonging to a participating parent company participated in the program. Additionally, these studies have modeled participation decisions using Probit models with cross sectional information about participation in the beginning of the program, i.e. year 1991/1992 (Gamper-Rabindran, 2006; Sam and Innes, forthcoming). They therefore do not

incorporate differences in the timing of participation by firms (EPA, 1997; EPA, 1992; EPA, 1991). Exceptions are Vidovic and Khanna (2007) who include information on program participation in each year of the program with random effect panel probit model and Khanna and Damon (1999) who estimate a cross sectional probit model for the period from 1991 to 1993. None of these papers however, distinguish between firms based on the timing of their participation decision. These studies also consider the effects of participation in a given year on emissions in that year with the exception of Sam and Innes (forthcoming) who examine the impact of the 33/50 program during the program years (1992-1995) and after the program (1996-1998) and find significant negative impacts in both periods. Lastly, these studies have typically focused on impact of participation only and disregarded other voluntary activities a firm might be undertaking that could also impact its 33/50 releases. Sam et al. (2008) consider the effects of both 33/50 program and adoption of TQEM and show that 33/50 participating firms are more likely to adopt TQEM, which further contributes to emission reduction.

This paper contributes to the literature in the following ways. First, we incorporate the dynamics process in our model and apply instrumental variables to correct for endogenous problems associated with self-selection and lagged dependent variable. Second, we study the impact of the 33/50 program using data on participation at the facility level. This allows for more accurate assessment of program impact since we do not incorrectly attribute participation to all facilities in a firm in which only one facility has participated. In our sample, the 1268 participating parent companies had a total 5832 facilities of which only 1033 facilities participated. Earlier papers have thus overestimated the number of participants by more than five fold. Third, we examine how timing of participation affects outcomes and to which extend pollution prevention

techniques have impacted on releases. Last, we compare the program's impacts on the two ozone deleting chemicals and the other 15 chemicals, to isolate the effectiveness of the program by controlling for the effect of other overlapping regulatory pressures.

III. MODEL FRAMEWORK & HYPOTHESIS

Conceptual Framework

We assume that a rational facility chooses its levels of pollution generation, the method of pollution reduction at each point in time and whether or not to participate in a voluntary program such as the 33/50 program to maximize its discounted net benefits over a specified time horizon. Since participating in the 33/50 program, adopting pollution reduction methods and reducing toxic releases are non-mandatory activities, incentives for any of these voluntary initiatives can arise due to regulatory pressure, the desire to preempt more stringent regulations, and desire to signal good public image or prevent adverse publicity. The commitment to reduce 33/50 releases is not binding, but the amount of releases by each facility and the count of pollution prevention techniques adopted for each chemical is publicly disclosed, regulators, environmental groups etc can observe the extent to which a firm is being environmentally responsible, making good faith efforts to improve environmental performance and being successful at doing so.

Specifically, the hypotheses we seek to test are as follow:

Hypothesis 1: Participation in the 33/50 program led to a reduction in 33/50 releases.

The first hypothesis we test is whether 33/50 program participation induced a reduction in 33/50 releases that was larger than that in the absence of the program. The extent to which such reductions can be attributed to the program is not as straightforward to determine. Some facilities might be making changes to their operations which would reduce their releases even in the absence of program participation. They might have

joined the program simply to get credit for reductions they were going to be making anyway. Other participants might simply join the program to get some reputational benefits without making any effort to make the changes needed to improve environmental performance.

Hypothesis 1a: the 33/50 program had a more significant impact on ODS than non -ODS chemicals

Facilities that participated in the program were those emitting more ODS and needed to phase them out anyway. As a result of the mandatory phasing out, at the facility level, we observe that the number of facilities that emitted ODS releases also reduced. In 1988, 30% facilities in TRI that were eligible for the program had emitted ODS, while in 1995, it reduced to 7%. Similarly, the percentage of ODS emitting facilities dropped from 30% to 4% among participating facilities.

Although the aggregated releases and transfers from the two ODS chemicals was about 14% in total 33/50 releases in 1988 (EPA,1999), it experienced the highest percentage reduction during the program, which was 86% reduction; while the other 33/50 program chemicals reduced by 40%. Since program only cared about aggregate reductions, these facilities could claim to reduce 33/50 releases while focusing only on reducing ODS. If this is the case, we expect to see stronger impact of the program on ODS chemicals than the other program chemicals. Such reduction in fact would be due to regulations rather than voluntary efforts. However 33/50 program might indeed have induced participants to further reduce emissions from other toxic chemicals beyond the two ODS chemicals. The program's effect on non-ODS chemicals could be larger than ODS chemicals because participants would have reduced more non-ODS releases than non-participants; while all facilities were going to reduce ODS anyway.

Hypothesis 1b: Early joiners in the 33/50 program achieved bigger reductions in 33/50 releases than late joiners.

We expect that incentives to reduce these releases might have differed by the timing of participation. The difference in time of participation is due to the following reasons: EPA sent invitation letters in five rounds in January 1991, July 1991, July 1992, Jan 1993 and 1994, to the top "600 firms" and other eligible firms. Companies can decide when to participate so some of them waited for a year or two to join the program after invitation. As the first invitation group includes the "top 600 firms", their emission level in 1988 was the highest. They had incentives to participate early in order to improve their reputation, show good faith efforts to be environmentally responsible to the EPA and mitigate adverse publicity from public disclosure of TRI since 1989. Compared to the second invitation group and the rest of the facilities, the first invitation group has reduced its emission by 66% (EPA, 1999).

Firms who had already begun to make reductions in emissions before the program was established (during 1988 to 1990) might also participate in the program early, to get credit for their earlier efforts. On the other hand, firms that were smaller polluters and not among the earlier invitees by the EPA may have joined later and made smaller reductions in pollution. They could benefit from the reputation that the 33/50 program had already achieved as being a successful program without making significant reductions and free-riding on the reductions achieved by earlier participants.

Hypothesis 2: Adoption of pollution prevention technologies reduced 33/50 releases

The 33/50 program emphasized pollution prevention at source as the preferred method for reducing 33/50 releases. It provided technical assistance and established a pollution prevention clearing house to provide information about pollution prevention

methods to firms. Information about these techniques was available to participants and non-participants. A facility can choose to reduce its releases using several different methods, prevention at source, end-of pipe abatement, reduction in production, and recycling, transfer to off-site disposal. A rational firm would pick the appropriate mix of methods for each chemical so as to maximize net benefits. The effectiveness of that method in improving environmental performance of the firm will depend on the choice of the method and its implementation. Since adoption of pollution prevention is also publicly disclosed as part of the TRI, facilities have incentives to adopt these for similar reasons as for participating in voluntary programs. The effectiveness of pollution prevention in reducing releases will depend on whether they are adopted simply to convey a visible signal of an environmentally responsible firm among external stakeholders without making meaningful changes that reduce pollution or if they are adopted to improve process efficiency, reduce waste and phase out toxic chemicals. By including the count of pollution prevention techniques adopted we examine the extent to which emissions were reduced using this particular method.

Hypothesis 3: A facility's current emissions of 33/50 releases will be influenced by its lagged emissions of 33/50 releases

Emissions are affected by managerial, technical and organizational features of a facility's operations which may change slowly over time and not always observable. The levels of pollution dependent on observable facility's production technology, level of output produced, input and output prices; as emissions are outputs of production. Since outputs are usually highly correlated with output prices. When output prices are likely to be autoregressive, current emissions levels are more likely to be dependent on previous emissions. Furthermore, emissions, program participation and pollution prevention

methods applied can all be influenced by unobserved heterogeneity which can be partially captured by lagged emissions. Therefore the emission process is path dependent. Facilities with higher emissions previously are more likely to take voluntary initiatives to reduce future releases; although, their releases are still likely to be relatively higher in the future.

Empirical Framework

We hypothesize that the *ith* facility's pollution level at time *t*, Y_{it}, is determined by a vector of observed of exogenous facility-specific variables, X_{it} (such as a facility's production technology, level of output produced, input and output prices), and it's program participation decision, P_{it} , its extent of adoption of pollution prevention technologies , T_{it} , and unobserved facility specific effects. In addition, if 33/50 releases are path dependent, and follow a first-order autoregressive process, the program outcome model is specified as:

(1) $y_{it} = \rho y_{it-1} + \beta_1 X_{it} + \gamma P_{it} + \beta_2 T_{it} + v_{it}$, t=1991,..., 1995

Where v_{it} is the error term, which can be composed of a facility-specific time-invariant unobservable and an idiosyncratic error, i.e. $v_{it} = \eta_i + u_{it}$. Program participation and P2 adoption could be correlated with unobserved error term v_{it}.

Our main interest is to correctly and consistently estimate coefficients γ and β_2 , which represents the partial effect of 33/50 program and P2, after controlling for other factors. There are several problems while estimating equation (1) using Pooled OLS. First the participation decision and P2 is likely to be correlated with the error term, either through η_i, or through u_{it} , or both. For example, Facilities with a greener manager are

more likely to participate in the 33/50 program and have lower emissions even in the absence of participation. Besides parent companies might have assigned a particular facility to participate in the program based on characteristics that we can not observe. A fixed effect model that controls for unobserved factors correlated with the explanatory variables could be used to estimate equation (1) and would control for endogeneity of participation and P2 if these variables are primarily determined by time invariant facility specific factors. Alternatively, we estimate a model by first differencing time varying variables in equation (1) as follows and estimating equation (2).

$$(2)\ \Delta y_{it} = \rho \Delta y_{it-1} + \beta_1 \Delta X_{it} + \gamma P_{it} + \beta_2 T_{it} + \Delta u_{it}\ ,\quad \text{t=1991,..., 1995}$$

where $\Delta y_{it} = y_{it} - y_{it-1}$, $\Delta y_{it-1} = y_{it-1} - y_{it-2}$ $\Delta X_{it} = X_{it} - X_{it-1}$, $\Delta u_{it} = u_{it} - u_{it-1}$, and the unobserved individual effect drops out. The binary participation variable here is defined as $P_{is} = 1$ for $t \geq s$ if facility started to join the program in year s , and $P_{is} = 0$ otherwise; and it is not first differenced in equation (2). The P2 variable is reported as the new P2 adopted each year by facility; it is already in first differenced form. The estimated coefficient γ shows the program's effect on the annual change in toxic releases between participants and non-participants. When y_{it} is taken log form, γ is the difference in rate of release reduction between participants and non-participants.

In order to differentiate the program effect among early joiners and late joiners, we break the participation variable into two binary variables: $P_{it,1991} = 1$ for $t \geq 1991$ if a facility participated in the program in the first year and $P_{it,1991} = 0$ otherwise; $P_{it,1992}$ =1 for $t \geq 1992$ if a facility participated in the program in either 1992, 1993 or 1994, and $P_{it,1992}$ =0 otherwise. The coefficient of the first binary participation variable indicates the differences in change of releases between first joiners and non-participants and late

joiners. The coefficient of the second binary variable indicates the different program's impact between late joiners and first joiners and non-participants on change of releases.

Although first differencing removes the individual time invariant unobserved effect η_i; two potential problems remain. First, when $E(P_{it}\Delta u_{it}) \neq 0$ and $E(T_{it}\Delta u_{it}) \neq 0$ (possible due to unobserved heterogeneity), estimation of the coefficients of (2) is biased. To avoid this problem, we could use valid instruments for program participation and P2 in equation (2). These instruments could be a predicted value obtained from a first stage model or variables that can be hypothesized to influence participation and are uncorrelated with emissions.

The second problem is associated with the dynamic feature of our model. In the presence of a lagged dependent variable as an explanatory variable, the fixed effects method will lead to biased results (Anderson and Hsiao, 1981) because the first differenced Δy_{it-1} is correlated with Δu_{it} in equation (2). One can use 2SLS by Anderson and Hsiao (1981) to estimate equation (2), where y_{it-2} is used as instrument, because $E(y_{it-2}\Delta u_{it}) = 0$ but y_{it-2} is correlated with Δy_{it}. Additional instruments are available when the panel has more than 3 period observations. Thus, $(y_{it-2}, ...y_{i1})$ can be used as instruments in the first-differenced equation for period t=T. However, 2SLS is not asymptotically efficient, even if the complete set of instruments is used for each equation at each time (Arellano and Bond, 1991).

Instead, we use the GMM framework proposed by Arellano and Bond (1991) where instrument matrix Z_i is used for each individual. The GMM conditions are such that $E(Z_i'\Delta u_i) = 0$, for each individual i; where $\Delta u_i = (\Delta u_{i3}, \Delta u_{i4}, ...\Delta u_{iT})'$. The GMM estimator is obtained by minimizing the criterion

function $J_N = (\frac{1}{N}\sum_{i=1}^{N}\Delta u_i' Z_i) W_N (\frac{1}{N}\sum_{i=1}^{N} Z_i' \Delta u_i)$, where W_N is the weighting matrix. Using identity matrix and the weighting matrix yields one-step GMM estimator. The efficient GMM estimator is such that $W_N = \left[\frac{1}{N}\sum_{i=1}^{N}(Z_i' \Delta\widehat{U}_i \Delta\widehat{U}_i' Z_i)\right]^{-1}$, where $\Delta\widehat{U}_i$ are consistent estimates of the residuals obtained from a consistent estimation on the first differenced equations. We explain how the instruments for GMM estimation are constructed in the next section.

The validity of the entire set of over identifying conditions can be tested by Hansen's J statistic, when the model is over identified, i.e. the number of instruments excluded from the equation is larger than the number of included endogenous variables (Baum, Schaffer and Stillman, 2003; 2007). The J statistic measures the value of GMM criterion function at the efficient GMM estimator under the null. It follows a chi-squared distribution with degrees of freedom equal to the number of over identifying restrictions under the null. Rejection of the null hypothesis implies that instruments are not satisfying the orthogonality conditions, possibly because they are not truly exogenous or because the are incorrectly excluded from the regression. In addition, we can use a GMM distance test (C test) to test a subset of the original set of orthogonality conditions. The C-statistic is calculated as the "difference between two J statistics: that for the restricted and fully efficient regression using the entire set of overidentifying restrictions, versus that for the unrestricted, inefficient but consistent regression using a smaller set of restrictions , in which a specified set of instruments are removed from the set" (Baum, et al. 2003,p18). Under the null that the suspect orthogonal conditions are satisfied, it follows a chi-squared distribution with degree of freedom equals the number of suspected IVs. It can be used to test if an instrument is exogenous; or if a endogenous regressor can be treated

as exogenous. We use both tests to evaluate and select proper instruments to estimate equation (2) in the next section.

Besides the orthogonality conditions, a weak identification problem may be present, even when the parameters are identified. If instruments are only weakly correlated with the endogenous regressors, biased estimation will arise. Staiger and Stock (1997) suggested that the F-test statistics on the joint significance of all the excluded IVs in the first stage regression should be larger than 10 as a "rule of thumb". In our case, there will be multiple endogenous variables (program participation, P2 adoption and lagged dependent variable); therefore, we can not make a judgment on the instruments based on any one of the first-stage F statistics. Stock and Yogo (2005) have tabulated the critical values based on the F-statistic of Cragg & Donald (1993) in finite sample, which includes cases up to three endogenous variables and 100 excluded instruments under i.i.d assumption. The null hypothesis is that the estimator is weakly identified and is subject to bias that is unacceptably large. Cragg-Donald F statistic is not robust to non-i.i.d error. Instead Kleibergen-Paap rk Wald F statistic is robust to herterskedasticity, autocorrelation and clustering. However there have not been any studies testing weak instruments in the presence of non-i.i.d errors. In that case, one can still refer to the critical values by Stock and Yogo (2005) or refer to the "rule of thumb" with caution (Baum, Schaffer and Stillman, 2007).

Construction of Explanatory Variables and Instruments

The 33/50 releases include onsite releases to air, water, land, etc. and transfers to treatment and disposals. There are three endogenous variables: program participation, lagged releases, and P2 adoptions. The valid instruments need to be correlated with participation, releases, and P2 adoption but not with change of release. The exogenous

variables included in X_{it} however influence both the dependent variables and endogenous variables.

All earlier studies have used the first invitation group as one of the excluded IVs in the first step probit modeling. Start from March 1991, July 1991, July 1992, Jan 1993 and 1994, EPA sent out invitation letters in five groups to the top "600 firms" and other eligible firms. The first invitation group represents the big polluters, and 64% of the companies in the first invitation group had participated in the program. At the facility level, however, we find that using the first invitation solely as IV cannot reject weak identification test. Although only 15% of the parent companies in the second group had participated in the program, at the facility level however, 69% of the 33/50 facilities belong to the second invitation group. Therefore, we use the dummy variable indicating those parent companies who were invited by EPA in the first and second round in early and June 1991 as one of the IVs in the instrument set of the GMM condition.

Earlier studies also have used the prior reduction of 33/50 releases to program participation, which is defined as the change of 33/50 releases from 1988 to 1990, as one of the excluded IVS from their first-step probit model (Khanna and Damon, 1999; Gamper, 2006; Sam and Innes, forthcoming). Vidovic and Khanna (2007) include this variable as one of the regressors in their second step fixed effect model on 33/50 releases and find that after taking into account of this reduction, 33/50 program's effect is not significant anymore. In our case, once it is included as one of the excluded IVs in the GMM instrument set described above, both of the test statistics (J-statistic=58.159; C-

statistic=55.803) are significant at 1%, which implies that prior reduction of 33/50 releases is endogenous to equation (2)[2].

Facilities were required to report the number of additional P2 activities adopted by each chemical annually. Such reporting became formalized only after 1991 and there were very few facilities reporting P2 before 1991. P2 is reported as the count of new practices adopted that year; thus it is already in the form of a first difference. While estimating equation (2) we treat lagged P2 as predetermined, and can be used as one of the instruments together with other instruments specified above in the GMM framework[3].

To estimate equation (2) consistently with a lagged dependent variable, Arellano and Bond (1991) uses the value of the dependent variable lagged two or more years as an instrument. Since the program started in 1991 and lasted until 1995, releases between 1991 and 1995 could be potentially endogenous to program participation. For example, releases in 1993 might not be orthogonal to change in releases in 1995 if facilities participated in the program before 1993. We therefore use emissions in 1988 and in 1989 as instruments to avoid this problem.

After checking for the test statistics of orthogonality conditions and weak identifications, we choose the following instrument set: $Z_i = \left[y_{i1}' \quad y_{i2}' \quad P2_{i,1991}' P2_{i,1990}' mail' \right]$, where each column corresponds to a vector of

[2] Appendix Table 1 show the estimated results from Probit model on program's participation. Prior reduction of 33/50 release and the invitation groups (first and second groups) are significantly influencing program's participation. However, prior reduction of 33/50 release cannot be used as excluded IVs because it is endogenous to 33/50 release. Including it as a regressor in the equation (2) directly does not change the conclusion of our model.

[3] We assume the P2 reported in 1991 is not correlated with change of releases in 1991 but is impacting on change of releases in 1992. We have also tried to use τ_{it-2} as instruments for each period from 1992-1995, but they are shown not to be orthogonal according to J statistics.

instruments[4]; and each row corresponds to the first differenced dependent observation for periods t=1991,1992, ..1995. The first period starts in 1988; y_{i1} and y_{i2} represent the 33/50 releases in 1988 and 1989; "mail" represents a dummy variable indicating facilities belonging to the first and second invitation group.

We include several explanatory variables to control for the effects of regulatory pressures on releases. These include the numbers of inspections for checking compliance with air pollution regulations and the percentage of releases of HAP[5] chemicals in total TRI releases (HAP-TRI ratio). As HAP chemicals were expected to be regulated from 2000 onwards, the higher the ratio is, the more likely that the facility would join the 33/50 program and reduce emission to reduce compliance costs in the future. The dependent variable in (2) is first difference of the natural log of emissions. Both HAP/TRI and AFS inspections are lagged by one year in equation (2) then first differenced[6]. We also include the attainment status of the county, reported by EPA since 1992[7] for six "criteria pollutants". Areas where air pollution levels consistently stay below ambient standards are designated "attainment". Facilities that are located in a more polluted county may be more likely to reduce releases or participate in the program if they anticipated more stringent regulatory pressures.

[4] The instruments are generated this way: all previous lags of y from 1988 up to year t-2 are generated for each year t (1991-1995). We have un-balanced data set, not all observations of a particular year have observations in 1988 or 1989. For example, a facility that had 33/50 releases in 1993 did not appear in 1989's TRI, then the missing value in 1989 is replaced with zero in order to be used in the instrument matrix.

[5] 189 toxic chemicals are identified by the congress as Hazard Air Pollutant Chemicals. The 17 33/50 chemicals are among them. Emissions of these 188 chemicals by air will be subject to the first major maximum control technology standards by year 2000.

[6] Lagged HAP/TRI ratio and AFS inspection can be treated as exogenous given the instrument sets we specified above[6].

[7] http://nsdi.epa.gov/oar/oaqps/greenbk/anay.html, we assumed that attainment in 1991 was the same as 1992, due to lack of data in 1991.

Scores[8] on the environmental-friendly actions made by the state legislature from 1991 to 1995 (LCV scores) and per capital membership of Sierra club by state from 1991 to 1995 are also included (Sam and Innes, forthcoming), to control for state specific effect. If facilities locate in a state with higher per capital membership and LCV score, it will have negative impact on the releases. The industry specific effect is controlled by including ten industry dummies, classified by facility's primary 4-digit SIC code. All of these control variables are strictly exogenous and since they do not vary much over time, all of them are kept in levels in equation (2).

IV.DATA DESCRIPTION

TRI data set contains facility specific information on 33/50 releases, P2 adoptions, HAP releases and all TRI chemical releases, SIC codes and locations. Participation status of facility is merged with TRI data set by the unique TRI-identifier for each facility[9]. Using the unique TRI identifier, this data set is merged with EPA's AFS data set, where numbers of violations, penalties and inspections for compliance with mandatory regulations at the individual facility level are recorded. The reported location of facilities is used to merge the above data with a county's attainment status (EPA,[10] 2008), state level scores on environmental legislations[11] (League of Conversation Voters, 2007), and Sierra club membership (Sam and Innes, forthcoming),

We compile this data to create an unbalanced panel data for 33/50 emissions, adoption of P2 techniques and program participation for 16618 (93344 observations)

[8] League of Conversation Voters calculate these scores according to votes on environmental and energy related bills, by states. http://www.lcv.org/

[9] Facility's participation status is obtained from Catherine Miller, Hampshire Research, www.hampshire.org

[10] http://nsdi.epa.gov/oar/oaqps/greenbk/anay.html

[11] http://www.lcv.org/scorecard/

eligible[12] facilities from 1988 to 1995 in 48 U.S states. Among those, 11907 facilities can be identified as belonging to 4861 parent companies. According to EPA, 1294 companies committed to 33/50 program (hereafter 33/50 companies). We are able to identify 1268 parent companies by their names in our dataset. 328 firms among the 600 invitees that were first contacted by EPA in march 1991 confirmed their participation; 819 firms among 5400 invitees that were contacted in July 1991 participated in the program (EPA, 1999). Our data set is able to identify 327 out of 328 parent companies in the first group; and 810 out of 819 in the second group. For the rest of the invitation groups, we identify 132 out of 140 participating companies

The 1268 participating parent companies had 5852 facilities but only 1033 facilities participated in the 33/50 program (hereafter 33/50 facilities). The participation percentage at the facility level was therefore as low as 8.7 %. An assessment of the program based on the assumption that all facilities belonging to a participating parent company is therefore inaccurate.

Our data show that total 33/50 releases dropped by 57.6% from 1988 to 1995 and by 29.5% from 1988-1991 (this is also the trend reported in EPA's final report (EPA, 1999). The reduction of 33/50 releases was not confined to facilities in 33/50 participating companies. Nor did such decrease only happen for ozone depleting chemicals. Total releases of ODS reduced by 36% for 33/50 facilities, although participating facilities had larger average releases in the base year than non-participating facilities, by the end of the program, the average ODS releases had fallen by 17 thousand pounds for 33/50 facilities (Figure 1a).

[12] If a facility had positive emissions of 33/50 chemicals in 1988, 1989 or 1990, we consider it as eligible of participating in 33/50 program.

Similarly, releases for the other 15 chemicals decreased over time for both participating and non-participating facilities (Figure 1b). Although facilities from 33/50 companies had almost twice emission level on the average than the facilities that did not belong to 33/50 companies in 1988, by the end of the program, the average releases for the facilities from the participating firms dropped by about 50%. The average releases from 33/50 facilities became slightly smaller than non-participating facilities.

V. ESTIMATION & RESULTS

Estimation

Although the dataset is un-balanced, the average length of period for each facility in the data set is 3.89 years; 77% observations have remained in the dataset for at least 3 years. For the modeling period of 1991- 1995, there are 13206 eligible facilities (520702 observations). After taking first differencing and instrumenting, the size of the sample is reduced to 12463 facilities (48529 observations) and 860 33/50 facilities are left, as facilities that did not have complete time series dimension are dropped. Table 1 shows the sample descriptive statistics of the main variables in regression and the distribution of facilities across various industries in the regression; in which 82% facilities in chemical and 76% in fabricated metal industry participated in 33/50 program.

Results

Feasible efficient GMM estimates that are robust to heteroskedasticity and clustering are reported in Table 2-Table 5[13]. The last two rows of each table report Hansen's J statistics indicating the validity of the entire set of over-identifying conditions and Kleibergen-Paap rk statistic[14] (robust to heteroskedasticity, autocorrelation and clustering) which will be compared with Stock-Yogo critical values (derived for Cragg-Donald F-statistic under i.i.d. errors) for to determine if parameters are only weakly

[13] Estimations are obtained from Stata's User Written Command, ivreg2, by Baum et.al. 2007.
[14] It is reported automatically in stata when feasible efficient 2-step GMM estimates are called.

identified. Since, those critical values[15] are not tabulated for rk statistic; we apply those critical values with caution in the presence of heteroskedasticity and auto-correlated errors (from first differencing).

Table 2 shows the estimated results for equation (2), where the impact of program participation on 33/50 releases are measured using GMM. The first column only includes facility level variables and time dummies. Including control variables in the second column yields similar results as the first one: the program's effect on the change of 33/50 release is negative and significant at 1%[16]. The coefficient of the 33/50 participation variable is -0.35 in column 2. Since the 33/50 releases are included in natural log form, the coefficient on program participation indicates that with program participation the reduction rate of 33/50 releases is 35% higher for participating facilities than non-participating facilities for each year the facility stayed in the program, after controlling for time and industry effect. For example, a representative facility emitted 109 thousand pounds (mean releases of all participating facilities) in 1990. The regression result implies that if this facility started the program in the first year (1991), by 1995, it would reduce its emission by 87%; and the emission would drop to 19 thousand pounds. If this facility followed the same reduction as non-participants, it would reduce its release to 39 thousand pounds in 1995, which is around 36% less than what it achieved as a participant.

The last column of Table 2 provides the results obtained by assuming that if a parent company participated in the program, all its subsidiary facilities also participated

[15] There are two types of Stock-Yogo critical values generated: one is for the maximal IV relative bias (ratio of IV estimator bias vs. bias of OLS) and the other is for the maximal IV size (under the weak IV, Wald test on the coefficient of the endogenous regressor rejects too often; the size test refers to a rejection rate 10%, 20% etc that one is willing to tolerate if the true rejection rate is 5%).

[16] In the appendix we show the estimation results of determinants of program participation, fixed effect estimation of the release model and alternative two-step estimation. The conclusion that program participation led to reduction of 33/50 releases does not change.

in the program in that year. With the same instrument set, the program effect is attenuated from -35% to around -6%. This would imply that the amount of reduction achieved by participating facilities that started the program in the first year was only 26% higher ($1-e^{-0.06*5}$) than by non-participants.

All three models in Table 2 pass the overidentification test since the J statistics are not significant at 5%. The critical values for maximum relative bias at 5% and maximum size at 10% are all smaller than the rk statistics reported in the last row, which validates the null that the these IVs do not suffer from weak identification problem.

Next we are testing if the reduction has come from ODS chemicals only. The first two columns in Table 3 model the change of releases of 15 non-ODS chemicals; while the third and forth columns model the change in releases of two ODS chemicals, using an instrument set constructed in a similar manner to that in Table 2. The first model only includes facility level variables that failed to pass the overidentification test (J statistic is significant at 5%). With control variables however, model (2) satisfies tests for overidentification and weak identification. It shows that the annual reduction rate of 15 chemicals releases is 30% higher for the 33/50 facilities than non-participating ones (coefficient for program participation is -0.3). Thus the program has led to reduction to chemicals not only ozone depleting chemicals but also the other 15 chemicals (Table 3, row 2). These 15 chemicals are included among the HAP chemicals. Facilities with a higher HAP/TRI ratio in the past achieved greater reduction in 33/50 releases in the next period (Table 3, row 3).

We hypothesize that that the program had a bigger impact on ODS than the rest of the 15 chemicals. However the results indicate the opposite (coefficients for program participation are -0.3 for 15 chemicals and -0.287 for ODS). This implies that participants

did not simply reduce ODS chemicals but all 33/50 chemicals. In fact the program's effect was smaller for the ODS because non-participants were reducing their ODS too due to the phase out mandated by the Montreal Protocol.

The third hypothesis we are testing is whether participants in the beginning of the program have led larger reduction than later ones. We generate two binary variable for program participation: $P_{91i,t} = 1$, for $t >= 1991$, if facilities joined the program in 1991; otherwise $P_{91i,t} = 0$. $P_{91b,it} = 1$ for $t >= S$, S is any year after 1991 that the facilities joined the program; otherwise $P_{91b,it} = 0$. Unlike the coefficients shown in earlier tables that indicate the program's impact on the annual change of releases, the coefficient of the first binary variable implies the impact of program participation on the change of 33/50 release for facilities that joined the program in 1991 comparing to facilities that joined later or did not join at all; while the second coefficient indicate the program effect for later participants in comparison to facilities that participated earlier or did not participate at all.

Table 4 shows that facilities that joined the program in 1991 had undertaken larger reduction throughout the program, as compared to later participants and non-participants (row 2). The annual rate of reduction for first group of participants is 88% higher than other facilities. By the end of the program, those facilities reduced by 100% more releases than the other facilities. As facilities that participated in the first year belong to the top 600 firms, those facilities were more likely to be larger polluters or under higher pressure to reduce emissions. On the other hand, facilities that participated later during the program were either more likely to be smaller polluters. Or some of them had already undertaken reduction before they were invited. The same pattern is seen for both ODS chemicals and the other 15 chemicals (column 2 and 3) where program

participation in 1991 had led to 77% more reduction for 15 chemicals and 70% more for ODS chemicals. All three models in Table 4 have insignificant J statistics at 5% and quite high rk statistics for weak identification test (although the critical values are not generated for 4 endogenous variables estimated in this model, the large rk statistics are somewhat comforting) .

The last hypothesis we are interested in is whether pollution prevention activities by program participants and non-participants led to further reduction of 33/50 releases after controlling for program participation effect. This analysis only covers year 1992 to 1995 because reporting of P2 was not required until 1991. We undertake the analysis for all 33/50 releases (Table 5, Column 1), the 15 non-ODS chemicals (Column 2) and two ODS chemicals (Column 3). In column 2 and 3, P2 activities are separated by two groups of chemicals accordingly (15 chemicals and 2 ODS chemicals). We find that in addition to program participation, P2 adoption contributed to reduction of 33/50 releases for ODS and non-ODS chemicals. The results show that each additional P2 activity adopted for the 15 non-ODS chemicals, change of releases were reduced by 5.6%. For five years, one extra P2 adopted would reduce 25% emissions. The P2 adopted for ODS chemicals had a much stronger impact on releases (-100%), which implies that the phasing out the ODS chemicals was achieved through reduction at the source (replacing chemicals, modification of production process, etc). However, results for model (3) in this table should be taken with grain of salt. As more facilities stopped emitting ODS over time, our instruments for endogenous P2 adoption of ODS chemicals, program participation and lagged ODS releases seem to be weak. The weak identification test is significant at 10% (last row, column 3).

Conclusion

Previous studies on the effects of 33/50 program have found mixed evidence of program impact. This study analyze emission, P2 adoption and program participation at the facility level and recognizes the path dependence in emission production and takes it into account while modeling change of release. We also examine the impact of the program separately for two ODS under mandatory phase out and the rest of 15 chemicals that were expected to be regulated in 2000. In addition, introducing two participation variables in the model allows us to draw contrasts between early participants and late joiners in terms of program's impact.

Our results show that 33/50 program led participating facilities to reduce more releases than non-participating facilities. Regulatory pressure to comply with Montreal protocol motivated firms to reduce ODS emissions. Nevertheless, the program also led reduction in the other 15 chemicals that are target of HAP pollutants control. In fact the effect is slightly larger for the 15 chemicals than two ODS. At the time of the 33/50 program, those pollutants were not directly subject to emission regulations, facilities might have anticipated that more stringent regulations such as Maximum Available Control Technology would take into place by 2000. These standards were to be based on emissions levels already being achieved by the best-performing similar facilities. By participating in the 33/50 program and reducing releases, facilities could avoid future compliances costs and establish themselves as environmental leaders in the industry.

The effect of the program varied across time possibly because firms committed to the program with different agendas. We find facilities that participated in the first year of the program had the most reduction; while facilities that joined later did not significantly reduce their releases compared to non-participants and the first participants. Facilities that

were larger polluters were more likely to participate early in the program and make real efforts to improve environmental performance, gain goodwill from regulators and improve public adversity associated with disclosure of TRI.

33/50 program had sought to encourage facilities to reduce emissions at source. By including the count of new P2 activities in our models, we find that pollution prevention technologies had significant negative impact on releases of ODS and the rest 15 chemicals. Specifically, ODS chemicals had the larger reduction due to P2 adopted.

In conclusion, this paper provides more accurate assessment on the effectives of 33/50 program by using facility level participation information. Our approach enables us to control for endogeneity associated with program participation, P2 adoption, and dynamics of emission production. The results show that the program and P2 adoption had caused further reductions in releases for both ozone depleting chemicals and other 15 chemicals. We also discover that the program's effect varied by time of participation i.e. the first groups of participants significantly reduced their releases than other facilities.

References

Alberini A. and K. Segerson. 2002. "Assessing Voluntary Programs to Improve Environmental Quality", Environmental and Resource Economics 22: 157-184.

Arora, S. and T. Cason. 1996 "Why Do Firms Volunteer To Exceed Environmental Regulations? Understanding Participation in EPA's 33/50 Program." Land Economics 72 (1996): 413-432.

Arora, S. and T. N. Cason. 1995. "An Experiment in Voluntary Environmental Regulation: Participation in EPA's 33/50 Program', Journal of Environmental Economics and Management 28: 271–286.

Arellano, M., and O. Bover. 1995. "Another look at the instrumental variables estimation of error components models". Journal of Econometrics 68: 29–51.

Arellano, M., and S. Bond. 1991. "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations". Review of Economic Studies 58: 277–97.

Baum, C. F., M. E. Schaffer, and S. Stillman. 2007. " ivreg2: Stata module for extended instrumental variables/2SLS, GMM and AC/HAC, LIML, and k-class regression". Boston College, Department of Economics, Statistical Software Components S425401. Downloadable from http://ideas.repec.org/c/boc/bocode/s425401.html.

Blundell, R. & S. Bond. 2000. “GMM Estimation with persistent panel data: an application to production functions”. Econometric Reviews, 19 (3), 321-340.

CDC. 1997. "1990 Census Data on Housing and Population”, Center For Disease Control and Prevention. http://www2.cdc.gov/nceh/lead/census90/house11/housdesc.htm

EPA. 2008.“ The Green Book Nonattainment Areas for Criteria Pollutants”, http://nsdi.epa.gov/oar/oaqps/greenbk/anay.html

EPA. 1997. “33/50 program, the final records”, EPA, USA.

EPA. 1992. “EPA’s 33/50 Program Second Progress Report”, EPA , USA.

33/50 Program office, EPA, 1991. “Progress Report on EPA’s 33/50 Program: Reducing Toxic Risks Through Voluntary Action”, Total Quality Environmental Management, Vol (1), Issue (2): 159-166.

Gamper-Rabindran, S. 2006. “Did the EPA’s voluntary industrial toxics program reduce emissions? A GIS anaylsis of distributional impacts and by-media analysis of substitution”, Journal of Environmental Economics and Management, 52, 391-410.

Khanna, M., G. Deltas and Donna R. Harrington 2007. “Adoption of Pollution Prevention Techniques: The Role of Management Systems, Demand-Side Factors an Complementary Assets”, working paper, University of Illinois at Urbana Champaign

Khanna, M. , 2006. “The U.S. 33/50 Voluntary Program: Its Design and Effectiveness”. In Richard D. Morgenstern and William A. Pizer (Ed.), *Reality Check : The Nature and Performance of Voluntary Environmental Programs in the United States, Europe, and Japan (pp.15-42),* Resource for Future Press,2006.

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

League of Conversation Voters. 2007. “National Environmental Scorecard. http://www.lcv.org/scorecard/

Rivera, J., Leon, P.,and Koerber, C. 2006. “Is Greener White yet? The Sustainable Slope Program after 5 years’, the Policy Studies Journal Vol (34), Number 2.

Roodman, D. 2006. “How to do Xtabond2: An Introduction to Difference and System GMM in Stata”, Center for Global Development, Working paper No.103. Washington D.C.

Sam, A. G., and R. Innes. Forthcoming. “Voluntary Pollution Reductions and the Enforcement of Environmental Law: An Empirical Study of the 33/50 Program,”, Journal of Law and Economics.

Sam, A. G., M. Khanna and R. Innes, 2008.“Voluntary Pollution Reduction Programs, Environmental Management, and Environmental Performance: An Empirical Study, Working paper, Department of Agricultural, Environmental & Development Economics, Ohio State University, Ohio.

Stock, J.H., and M. Yogo(2005). “Testing for Weak Instruments in Linear IV Regression. In Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg”, ed. D.W.Andrews and J.H.Stock, 80-108. Cambridge University Press.

Videras, J. and A. Alberini. 2000. “The Appeal of Voluntary Environmental Programs: Which Firms Participate and Why.” Contemporary Economic Policy 18 (2000): 449-461.

Vidovic, M. and N. Khanna. 2007. "Can Volutary Pollution Prevention Programs Fulfill Their Promises? Further Evidence from the 33/50 Program." Journal of Environmental Economics and Management 53 (2007): 180-95.

Windmeijer, F. 2005. "A finite sample correction for the variance of linear efficient two-step GMM estimators". Journal of Econometrics 126: 25-51.

Wooldridge, J. 2002. "Econometric analysis for Cross Section and Panel data", MIT Press.

Tables and Figures

Table 1 Descriptive Statistics (1991-1995)

	All Facilities	33/50 facilities	Non-33/50 facilities
Facility level variables	Mean	Mean	Mean
33/50 releases	70.68	84.68	69.64
(1000 pounds)	(260.79)	(244.85)	(261.91)
ODS releases	7.39	14.58	6.86
(1000 pounds)	(42.04)	(80.79)	(37.51)
Non-ODS releases	63.28	70.10	62.78
(1000 pounds)	(255.54)	(231.60)	(257.24)
	76.95	77.71	76.89
HAP/TRI ratio	(31.24)	(30.50)	(31.30)
Number of Inspections	0.37	0.43	0.36
(EPA AFS)	(1.04)	(1.24)	(1.02)
	1.23	1.84	1.19
Number of P2 adopted	(2.52)	(3.09)	(2.47)
Control variables			
County	0.57	0.65	0.57
non-attainment status	(0.98)	(1.01)	(0.98)
State per capita sierra	9.32	9.44	9.31
membership(log)	(1.12)	(1.02)	(1.13)
	99.75	104.42	99.40
State LCV scores	(39.36)	(36.10)	(39.57)
Number of facilities	12463	860	11603
Total observations	48529	3379	45150

Industry Dummies	Percentage in total obs.	Percentage in 33/50 facilities	Percentage in non 33/50 facilities
SIC 26: Paper	3.58	14.42	3.51
SIC 28: Chemical	21.42	82.44	21.11
SIC 29: Petroleum	2.65	2.21	2.79
SIC 30: Rubber	8.86	26.05	8.92
SIC 33: Primary metal	13.28	44.42	13.25
SIC 34: Fabricated metal	21.43	75.58	21.29
SIC 35: Machinery & Computer	8.59	17.21	8.84
SIC 36:Electronics	8.40	32.91	8.27
SIC 37:Transportation	9.66	22.33	9.86
SIC 38: Instruments	2.13	6.16	2.15

Standard errors in parentheses

Table 2. Program's Effect on 33/50 Releases, 1991-1995.

	(1)	(2)	(3)
COEFFICIENT	33/50 releases	33/50 releases	33/50 Releases
LD.33/50 releases	0.465***	0.459***	0.466***
	[0.057]	[0.057]	[0.056]
Program Participation	-0.342***	-0.351***	-0.057***
	[0.087]	[0.085]	[0.014]
LD.HAP-TRI ratio	-0.011***	-0.010***	-0.011***
	[0.001]	[0.001]	[0.001]
LD.Number of inspections	-0.004	-0.004	-0.005
	[0.010]	[0.010]	[0.010]
State per capita sierra membership		-0.005	-0.006
		[0.005]	[0.005]
State LCV scores		0	0
		[0.000]	[0.000]
County non-attainment status		-0.002	-0.003
		[0.006]	[0.006]
Year Dummy			
Year 1991	-0.224***	-0.178***	-0.162***
	[0.021]	[0.050]	[0.049]
Year 1992	-0.082***	-0.036	-0.026
	[0.019]	[0.049]	[0.049]
Year 1993	-0.133***	-0.089*	-0.079
	[0.019]	[0.051]	[0.050]
Year 1994	-0.059***	-0.015	-0.007
	[0.020]	[0.050]	[0.050]
Year 1995	-0.203***	-0.160***	-0.152***
	[0.023]	[0.052]	[0.052]
SIC Dummy			
SIC 26: Paper		0.044*	0.054**
		[0.024]	[0.024]
SIC 28: Chemical		0.062***	0.068***
		[0.016]	[0.016]
SIC 29: Petroleum		0.007	0.034
		[0.030]	[0.029]
SIC 30: Rubber		0.041*	0.044**
		[0.021]	[0.021]
SIC 33: Primary metal		0.01	0.01
		[0.021]	[0.021]
SIC 34: Fabricated metal		0.008	0.005
		[0.019]	[0.019]
SIC 35: Machinery & Computer		-0.050*	-0.037
		[0.026]	[0.025]
SIC 36:Electronics		-0.099***	-0.092***
		[0.024]	[0.024]
SIC 37:Transportation		-0.014	0.003
		[0.020]	[0.020]
SIC 38: Instruments		-0.108**	-0.093**
		[0.044]	[0.043]
Observations	48529	48529	48529
R-squared	-0.349	-0.342	-0.348
Hansen J Statistic	2.092	2.045	2.205
Weak identification test	98.12	100	101.2

Robust(clustered) standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1

Table 3. Program's Effect by Groups of Chemicals, 1991-1995

	(1)	(2)	(3)	(4)
COEFFICIENT	15 releases	15 releases	ODS releases	ODS releases
LD.15 releases	0.629***	0.534***	0.892***	0.861***
	[0.078]	[0.039]	[0.043]	[0.046]
Program Participation	-0.306***	-0.300***	-0.251**	-0.287***
	[0.101]	[0.093]	[0.109]	[0.103]
LD.HAP-TRI ratio	-0.009**	-0.010***	-0.006***	-0.006***
	[0.004]	[0.001]	[0.001]	[0.001]
LD.Number of inspections	0.008	0.007	-0.012	-0.012
	[0.013]	[0.013]	[0.024]	[0.024]
State per capita sierra membership		-0.007		-0.004
		[0.006]		[0.007]
State LCV scores		0		0
		[0.000]		[0.000]
non-attainment status		0.004		-0.001
		[0.007]		[0.007]
Year Dummy				
Year 1991	-0.182***	-0.160***	-0.173***	-0.09
	[0.031]	[0.058]	[0.024]	[0.062]
Year 1992	-0.005	-0.014	-0.057***	0.023
	[0.027]	[0.058]	[0.021]	[0.060]
Year 1993	0.117***	0.134**	-0.369***	-0.290***
	[0.025]	[0.060]	[0.031]	[0.064]
Year 1994	-0.045*	-0.014	-0.054	0.014
	[0.027]	[0.059]	[0.038]	[0.068]
Year 1995	-0.210***	-0.176***	0.239***	0.305***
	[0.028]	[0.060]	[0.034]	[0.065]
SIC Dummy				
SIC 26: Paper		0.004		0.047
		[0.027]		[0.033]
SIC 28: Chemical		0.009		0.025
		[0.018]		[0.017]
SIC 29: Petroleum		-0.016		-0.117***
		[0.029]		[0.043]
SIC 30: Rubber		0.021		-0.082***
		[0.026]		[0.030]
SIC 33: Primary metal		0.019		-0.003
		[0.023]		[0.022]
SIC 34: Fabricated metal		0.084***		-0.092***
		[0.021]		[0.021]
SIC 35: Machinery & Computer		0.003		-0.058*
		[0.029]		[0.034]
SIC 36:Electronics		-0.051*		-0.096***
		[0.030]		[0.032]
SIC 37:Transportation		-0.007		-0.102***
		[0.026]		[0.033]
SIC 38: Instruments		0.095**		-0.231***
		[0.045]		[0.062]
Observations	48529	48529	48529	48529
R-squared	-0.615	-0.469	-0.955	-0.893
Hansen J Statistic	5.441*	1.911	2.344	2.255
Weak identification test	40.69	173	177	151.6

Robust(clustered) standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1

Table 4. Program's Effect by Time of Participation,1991-1995

	(1)	(2)	(3)
COEFFICIENT	33/50 releases	15 releases	ODS releases
LD.33/50 releases	0.487***	0.578***	0.868***
	[0.058]	[0.048]	[0.052]
Participation 1991	-0.882***	-0.770**	-0.702*
	[0.330]	[0.366]	[0.373]
Participation after 1991	0.184	0.225	0.051
	[0.144]	[0.162]	[0.156]
LD.HAP-TRI ratio	-0.011***	-0.010***	-0.006***
	[0.001]	[0.001]	[0.001]
LD.Number of inspections	-0.004	0.007	-0.012
	[0.011]	[0.013]	[0.024]
State per capita sierra membership	0	0	-0.000**
	[0.000]	[0.000]	[0.000]
State LCV scores	0	0	0
	[0.000]	[0.000]	[0.000]
non-attainment status	-0.001	0.002	
	[0.006]	[0.007]	
Year Dummy			
Year 1991	-0.192***	-0.195***	-0.108***
	[0.027]	[0.032]	[0.036]
Year 1992	-0.080***	-0.067**	-0.003
	[0.025]	[0.030]	[0.030]
Year 1993	-0.136***	0.073**	-0.322***
	[0.026]	[0.031]	[0.035]
Year 1994	-0.063**	-0.083***	-0.015
	[0.026]	[0.032]	[0.041]
Year 1995	-0.210***	-0.246***	0.275***
	[0.029]	[0.031]	[0.036]
SIC Dummy			
SIC 26: Paper	0.041	0.004	0.047
	[0.026]	[0.029]	[0.034]
SIC 28: Chemical	0.058***	0.005	0.022
	[0.017]	[0.018]	[0.017]
SIC 29: Petroleum	0.018	-0.006	-0.105**
	[0.030]	[0.030]	[0.042]
SIC 30: Rubber	0.047**	0.023	-0.076**
	[0.022]	[0.027]	[0.031]
SIC 33: Primary metal	0.024	0.027	0.007
	[0.022]	[0.025]	[0.022]
SIC 34: Fabricated metal	0.012	0.082***	-0.091***
	[0.019]	[0.021]	[0.021]
SIC 35: Machinery & Computer	-0.042	0.008	-0.054
	[0.026]	[0.030]	[0.035]
SIC 36:Electronics	-0.088***	-0.044	-0.088***
	[0.025]	[0.031]	[0.033]
SIC 37:Transportation	-0.014	-0.01	-0.102***
	[0.021]	[0.026]	[0.035]
SIC 38: Instruments	-0.098**	0.090*	-0.227***
	[0.045]	[0.046]	[0.063]
Observations	48529	48529	48529
R-squared	-0.38	-0.538	-0.908
Hansen J Statistic	5.972	2.997	2.233
Weak identification test	36.11	48.54	43.66

Robust(clustered) standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1

Table 5.Effect of P2 Adoption and Program Participation, 1992-1995

	(1)	(2)	(3)
COEFFICIENT	33/50 releases	15 releases	ODS releases
LD.33/50 releases	0.676***	0.269***	0.141
	[0.129]	[0.049]	[0.144]
Program Participation	-0.382***	-0.386***	-0.430***
	[0.102]	[0.100]	[0.146]
LD.HAP-TRI ratio	-0.012***	-0.005***	0
	[0.002]	[0.001]	[0.001]
LD.Number of inspections	-0.009	0.003	-0.015
	[0.013]	[0.012]	[0.017]
State per capita sierra membership	-0.013*	-0.024***	0.034**
	[0.007]	[0.008]	[0.013]
State LCV scores	0	0	-0.001**
	[0.000]	[0.000]	[0.000]
non-attainment status	-0.004	0.002	0.021*
	[0.008]	[0.009]	[0.011]
Number of P2	0.009	-0.056***	-1.015***
	[0.011]	[0.010]	[0.187]
Year Dummy			
Year 1992	0.057	0.156**	-0.127
	[0.066]	[0.072]	[0.095]
Year 1993	-0.032	0.326***	-0.465***
	[0.066]	[0.075]	[0.104]
Year 1994	0.063	0.228***	-0.498***
	[0.067]	[0.074]	[0.142]
Year 1995	-0.089	0.027	-0.261*
	[0.067]	[0.074]	[0.149]
SIC Dummy			
SIC 26: Paper	0.017	-0.047	-0.018
	[0.028]	[0.030]	[0.037]
SIC 28: Chemical	0.046**	0.02	0.044*
	[0.022]	[0.023]	[0.025]
SIC 29: Petroleum	0.006	0.031	-0.029
	[0.038]	[0.040]	[0.065]
SIC 30: Rubber	0.043	0.075**	-0.145***
	[0.027]	[0.034]	[0.044]
SIC 33: Primary metal	0.011	-0.009	-0.132***
	[0.026]	[0.028]	[0.038]
SIC 34: Fabricated metal	0.023	0.072***	-0.141***
	[0.026]	[0.026]	[0.033]
SIC 35: Machinery & Computer	0.02	0.052	-0.288***
	[0.038]	[0.036]	[0.065]
SIC 36:Electronics	-0.066*	-0.031	-0.254***
	[0.035]	[0.036]	[0.053]
SIC 37:Transportation	-0.003	0.026	-0.110**
	[0.028]	[0.033]	[0.048]
SIC 38: Instruments	-0.09	0.111*	-0.058
	[0.057]	[0.059]	[0.103]
Observations	37742	37742	37742
R-squared	-0.683	-0.174	-0.074
Hansen J Statistic	2.541	0.817	2.646
Weak identification test	15.04	78.96	8.64*

Robust(clustered) standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 1 Determinants of Program Participation, 1991-1995

COEFFICIENT	(1) Program Participation	(2) Program Participation	(3) Program Participation
Invitation group	2.799***	2.828***	2.815***
	[0.074]	[0.074]	[0.074]
Prior reduction in 33/50 releases	-0.000***		
	[0.000]		
Previous33/50 releases		-0.014	
		[0.010]	
HAP-TRI ratio	0	0.001	0
	[0.001]	[0.001]	[0.001]
Number of inspections	0.019	0.028	0.025
	[0.025]	[0.025]	[0.025]
SIC 26: Paper	-0.465**	-0.423**	-0.443**
	[0.186]	[0.187]	[0.186]
SIC 28: Chemical	-0.308***	-0.319***	-0.306***
	[0.108]	[0.109]	[0.108]
SIC 29: Petroleum	-1.996***	-1.972***	-1.984***
	[0.334]	[0.336]	[0.335]
SIC 30: Rubber	-0.366***	-0.365**	-0.371***
	[0.142]	[0.142]	[0.142]
SIC 33: Primary metal	-0.104	-0.095	-0.091
	[0.129]	[0.128]	[0.129]
SIC 34: Fabricated metal	0.081	0.072	0.078
	[0.110]	[0.110]	[0.110]
SIC 35: Machinery & Computer	-0.713***	-0.725***	-0.720***
	[0.157]	[0.157]	[0.157]
SIC 36:Electronics	-0.255*	-0.248*	-0.250*
	[0.136]	[0.135]	[0.136]
SIC 37:Transportation	-0.885***	-0.869***	-0.873***
	[0.143]	[0.144]	[0.143]
SIC 38: Instruments	-0.718***	-0.693***	-0.699***
	[0.254]	[0.255]	[0.254]
State LCV scores	0.003***	0.003***	0.003***
	[0.001]	[0.001]	[0.001]
State per capita sierra membership	0.073**	0.069**	0.071**
	[0.033]	[0.033]	[0.033]
County's non-attainment status	0.092**	0.091**	0.091**
	[0.037]	[0.037]	[0.037]
lnsig2u	1.288***	1.287***	1.287***
	[0.027]	[0.027]	[0.027]
Constant	-6.269***	-6.124***	-6.243***
	[0.322]	[0.333]	[0.322]
Observations	50911	50911	50911
Number of code	12898	12898	12898
Standard errors in brackets	*** p<0.01, ** p<0.05, * p<0.1		

Appendix Table 2 Program's Effect, Fixed Effect, 1991-1995

	(1)	(2)
COEFFICIENT	33/50 releases	33/50 releases
Previous33/50 releases		0.194***
		[0.012]
HAP-TRI ratio	0.002***	0
	[0.001]	[0.001]
Program Participation*	-0.252***	-0.229***
	[0.075]	[0.071]
Number of inspections	-0.003	-0.002
	[0.012]	[0.011]
State per capita sierra membership	-0.144**	-0.130**
	[0.067]	[0.066]
State LCV scores	0	0
	[0.001]	[0.001]
non_attain	0.087	0.098
	[0.072]	[0.070]
Year 1992	-0.148***	-0.115***
	[0.018]	[0.018]
Year 1993	-0.345***	-0.288***
	[0.020]	[0.020]
Year 1994	-0.451***	-0.367***
	[0.021]	[0.020]
Year 1995	-0.725***	-0.614***
	[0.025]	[0.023]
Constant	10.139***	8.423***
	[0.639]	[0.634]
Observations	50911	50911
Number of code	12898	12898
R-squared	0.042	0.075

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

*Program partcipation was not instrumented by Ivs in this Table

Appendix Table 3. Alternative Estimation* on Program's Overal Effect, 1991-1995.

COEFFICIENT	33/50 releases
LD.33/50 releases	0.466***
	[0.056]
Program Participation	-0.236***
	[0.091]
LD.HAP-TRI ratio	-0.011***
	[0.001]
LD.Number of inspections	-0.005
	[0.010]
State per capita sierra membership	-0.005
	[0.005]
State LCV scores	0
	[0.000]
County non-attainment status	-0.002
	[0.006]
Year Dummy	
Year 1991	-0.177***
	[0.050]
Year 1992	-0.038
	[0.049]
Year 1993	-0.092*
	[0.050]
Year 1994	-0.019
	[0.050]
Year 1995	-0.164***
	[0.052]
SIC Dummy	
SIC 26: Paper	0.042*
	[0.024]
SIC 28: Chemical	0.061***
	[0.016]
SIC 29: Petroleum	0.011
	[0.030]
SIC 30: Rubber	0.040*
	[0.021]
SIC 33: Primary metal	0.009
	[0.021]
SIC 34: Fabricated metal	0.008
	[0.019]
SIC 35: Machinery & Computer	-0.047*
	[0.026]
SIC 36:Electronics	-0.099***
	[0.024]
SIC 37:Transportation	-0.011
	[0.020]
SIC 38: Instruments	-0.106**
	[0.044]
Observations	48529
R-squared	-0.349
Hansen J Statistic	2.252
Weak identification test	100.8
Robust(clustered) standard errors in brackets	*** p<0.01, ** p<0.05, * p<0.1

* We can modify the two-step estimation that had been done previously. In the first step, a probit model on program participation is estimated with valid instruments. In the second step, instead of replacing program participation directly with predicted probability in equation (3), one can use the predicted probability as instruments while estimating equation (3). This way, the standard errors obtained in the second step are asymptotically valid (Wooldridge, 2002, pp.623). The important robustness feature of this IV estimator is that we are using the predicted probability as an instrument for program participation, the model for participation does not have to be correctly specified. This model uses predicted probability from Model (3) in Appendix Table 1.

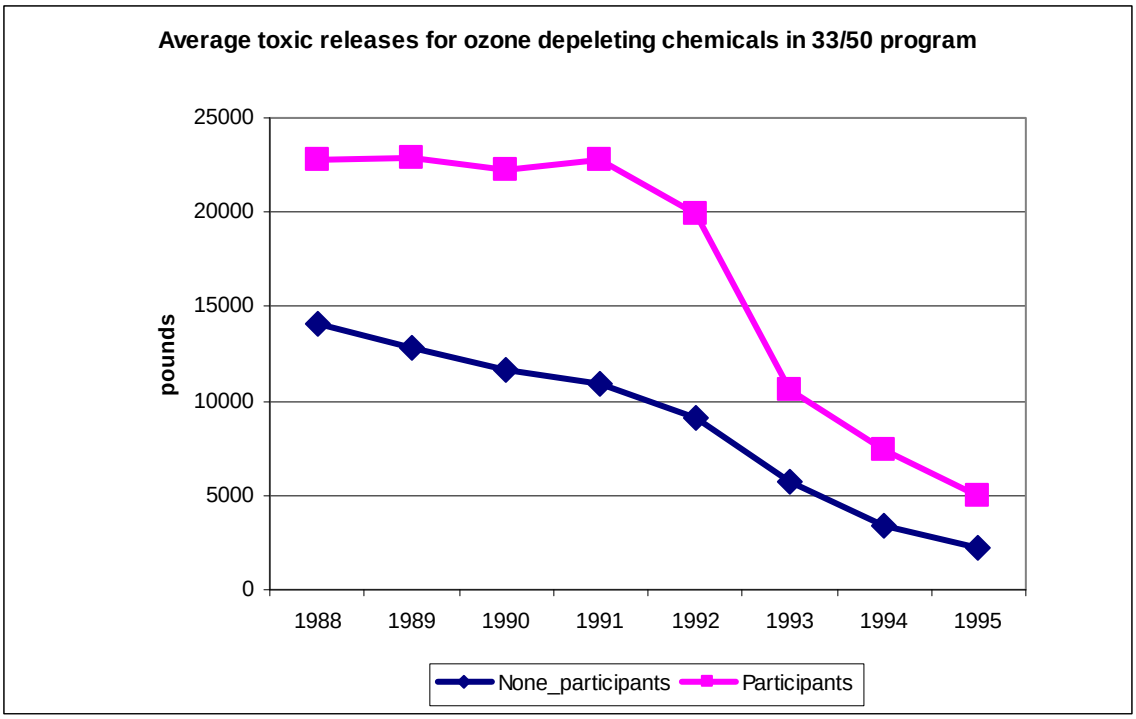

Figure 1a. Changes of Average Toxic Releases for ODS chemicals in 33/50 program

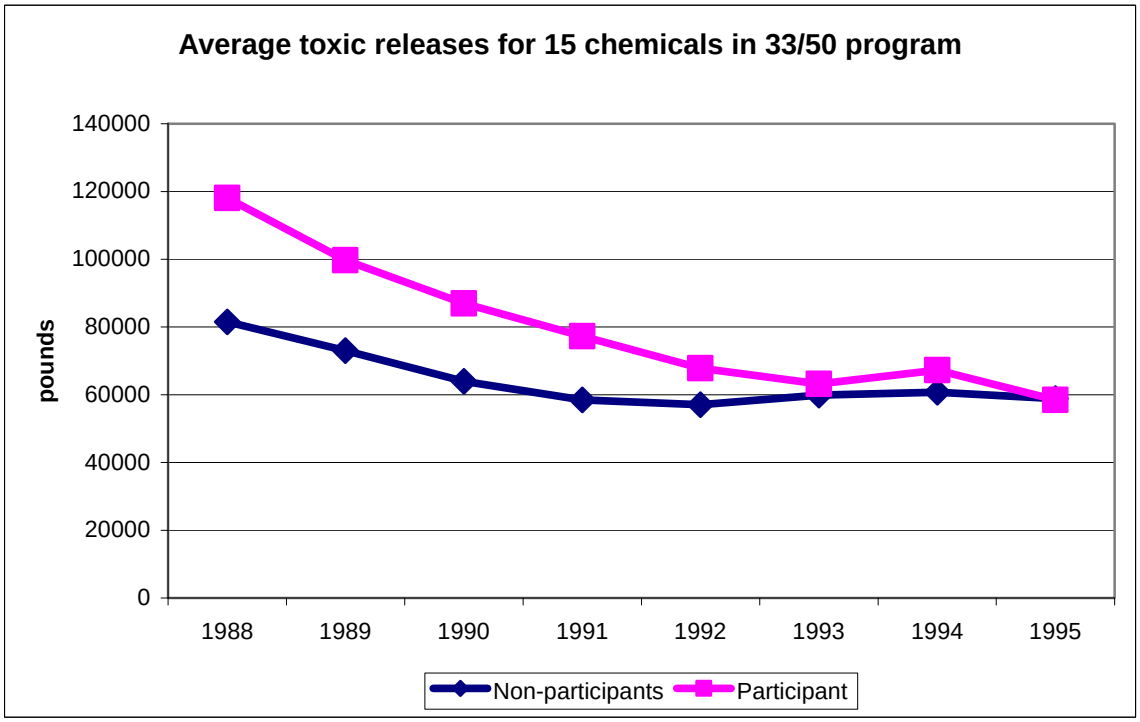

Figure 1b. Changes of Average Toxic Releases for 15 non-ODS chemicals in 33/50 program