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Beyond regulations: Industry voluntary ban in arsenic use

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A B S T R A C T

Firms play a key role in pollution abatement and control by engaging in beyond-compliance actions without the force of law in voluntary programs. This study examines the effectiveness of a bilateral voluntary agreement, one type of voluntary programs, negotiated between the U.S. Environmental Protection Agency (EPA) and the pressure-treated wood industry to phase-out the use of chromated copper arsenate (CCA), a poisonous arsenic compound. Arsenic is ranked number one on the EPA's priority list of hazardous substances. Unlike a majority of earlier studies on voluntary programs, dynamic panel estimation and structural break analysis show that while a technological innovation in semiconductors is associated with arsenic use increases, the CCA voluntary agreement is associated with a reduction in arsenic use to levels not seen since the 1920s. A voluntary ban in arsenic acid by pesticide manufacturers in the agriculture sector has also contributed to arsenic reductions. Furthermore, the results suggest that environmental activism has played a role in curbing arsenic use. Increasing stakeholder pressures, as measured by membership in the Sierra Club, improves voluntary agreement effectiveness.

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1. Introduction

Since the 1980s, President Ronald Reagan's "Environmental Federalism" has increased state and private sector involvement in environmental policy (*Economic Report of the President*, 1982, p. 44). Experimentation with alternative policy instruments that devolved regulation from the federal government continued into subsequent administrations. New governance approaches include information-based regulations (e.g., EPA's Toxic Release Inventory), collaborative partnerships (e.g., regional watershed partnerships), market-based approaches (e.g., SO_2 trading, catch shares in fisheries), and voluntary programs (e.g., EPA's 33/50 program, the Chemical Industry's Responsible Care).

Firms play a key role in pollution abatement and control by engaging in beyond-compliance actions without the force of law in voluntary programs. A majority of the literature points to modest or negligible impact on the effectiveness of such voluntary programs. That being said, when variation in voluntary programs is accounted for a more nuanced depiction of program efficacy emerges. Prior research shows that among the different types of voluntary programs, unilateral or industry sponsored voluntary programs are the weakest in their environmental performance (Gamper-Rabindran and Finger, 2012; King and Lenox, 2000). Evidence of the effectiveness of public voluntary programs or government initiated programs in reducing pollution has also been lackluster (Antweiler and Harrison, 2007; Gamper-Rabindran and Finger, 2012; Gamper-Rabindran, 2006; Glachant and Muizon, 2007; Morgenstern and Pizer, 2007; Takahashi et al., 2001; Vidovic and Khanna, 2007; Welch et al., 2000).[2] By contrast, third-party or non-governmental organization (NGO) sponsored voluntary programs (e.g., ISO 14001) and bilateral voluntary agreements (which is the subject of this paper) have fared considerably better in their efficacy (Arimura et al., 2008; Darnall and Kim, 2012; Dasgupta et al., 2000; Glachant and Muizon, 2007; Krarup and Millock, 2007; Morgenstern and Pizer, 2007; Potoski and Prakash, 2005; Wakabayashi and Sugiyama, 2007). Bilateral voluntary agreements are voluntary agreements to reduce pollution in specific industries that are negotiated between the government and the private sector (Borck and Coglianese, 2009; Morgenstern and Pizer, 2007). These negotiated agreements, which are entered into voluntarily often lead to legal binding contracts.

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[2] Notwithstanding, there is some evidence that the EPA's 33/50 program has had direct pollution reduction benefits both during and after the program years (Innes and Sam, 2008; Khanna and Damon, 1999; Koehler, 2007).

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Compared to the other types of voluntary programs, there have been few studies on the efficacy of bilateral voluntary agreements. Existing studies on bilateral voluntary agreements suggest that the negotiated agreements between regulators and corporate actors have the potential to reduce pollution by a substantial amount. Three studies of bilateral voluntary agreements to reduce CO_2 emissions in Japan, Denmark, and the United Kingdom (UK), respectively, are featured in Morgenstern and Pizer (2007). The authors report that in each case, negotiated targets were met within the first few years of inception (Glachant and Muizon, 2007; Krarup and Millock, 2007; Wakabayashi and Sugiyama, 2007). For example, in four years, participants of the 2001 Climate Change Agreements in the UK surpassed their 2010 targets (Glachant and Muizon, 2007). Similarly, participants of Japan's 1997 Keidanren Voluntary Plan achieved emissions below 1990 levels within the first 5 years of the program's 10 year CO_2 emission reduction goal (Wakabayashi and Sugiyama, 2007).

This paper examines the effectiveness of a bilateral voluntary agreement negotiated between the U.S. Environmental Protection Agency (EPA) and the largest industrial user of arsenic. The agreement, concluded at the end of 2003, delineated the terms of a voluntary phase-out of chromated copper arsenate (CCA) in residential uses by the pressure-treated wood industry. This is an important study because CCA is an arsenic compound, and arsenic is a poisonous chemical that continues to be ranked number one on the EPA's priority list of hazardous substances (ATSDR – Priority List of Hazardous Substances, 2011). Like the abovementioned bilateral voluntary agreements in Japan, Demark, and the UK, the CCA voluntary agreement was lauded as a success by the major stakeholders involved in the negotiated agreement. In fact, this paper's estimated models show that the CCA voluntary agreement led to a substantial reduction in arsenic use: aggregate arsenic use has been lowered to levels not seen since the 1920s.

The impact of the CCA voluntary agreement on the industrial use of arsenic in the U.S. is rigorously estimated using a unique U.S. Geological Survey (USGS) dataset spanning all industry sectors between 1975 and 2004 and aggregate arsenic use between 1975 and 2011. Arellano-Bond dynamic panel estimator is employed to estimate the impact models. Uniquely, Bai and Perron's (2003, 1998) structural break analysis is conducted on a longer aggregate time series to provide a robustness check to the panel estimation and to offer additional information about the long-run impact of the CCA voluntary agreement.

Empirical results show that factors *beyond* regulation are important drivers of arsenic use. While a technological innovation in semiconductor manufacturing is associated with increases in arsenic use, the CCA voluntary agreement has had a relatively large impact in reducing arsenic use in the immediate years following its negotiation and corresponds to a permanent downward structural shift in arsenic use trends. A voluntary ban in arsenic acid by pesticide manufacturers in the agriculture sector has also contributed to arsenic use reductions in the estimated models. Furthermore, the results suggest that environmental activism as measured by membership in the Sierra Club has played a role in curbing arsenic use. The effectiveness of the industry voluntary bans rises with the level of stakeholder pressures.

This paper contributes to the literature in several ways. First, the paper presents a U.S. case of a bilateral voluntary agreement—which is distinct from the three experiences of negotiated agreements in Japan, the UK, and Denmark that have been documented in the literature—to present new evidence that under certain conditions bilateral voluntary agreements have the potential to reduce pollution by a considerable amount.

Second, unlike a majority of the prior research in this area, this study focuses on toxic use rather than emissions. In fact, this study is the first comprehensive analysis of toxic chemical use data from the USGS. Interviews with federal regulators and corporate managers of arsenic-using sectors suggest that given technological constraints, firms have relatively less control over emissions while consumptive use is a matter of input management.[3] Another advantage of focusing on arsenic use rather than emissions is the fact that toxic chemical use data are a longer time series than emissions data; emissions data from the EPA's Toxic Release Inventory are restricted to 1988 and onwards.

Third, this study introduces structural break analysis to environmental policy evaluation. Structural break analysis is an advanced time series methodology commonly used in macroeconomic research and finance studies but seldom employed in public policy research. Available industry-level panel data ends in 2004, which is two years after the negotiation of the CCA agreement. By contrast, aggregate arsenic use data are available through 2011, providing several more years of post-CCA voluntary agreement data for time series analysis.

2. Background

Industrial toxic chemicals are an issue area that has seen much experimentation with voluntary programs (Morgenstern and Pizer, 2007). Examples include the EPA's 33/50 program, a public voluntary program, and the Chemical Industry's Responsible Care program, a unilateral or industry sponsored voluntary program. A chief challenge facing toxic chemical regulation is the rapid speed of technological development in toxic chemical-using sectors. It has been challenging for regulators to understand the toxicology of currently available toxic chemicals and their impact on human health and the environment before the next new chemical is on the market (GAO, 2007). Thus, the EPA, the chief regulator of industrial chemical use and emissions, has increasingly worked with the private sector to curb toxic chemical use through voluntary programs, notably public voluntary programs and bilateral voluntary agreements. Government regulators have on occasions negotiated with private industry to reduce toxic chemical use, as in the case of the CCA voluntary agreement, which is the subject of this paper.

Bilateral voluntary agreements are unique in that they are a type of "cooperative regulation" (Harrison, 1998) in which government attempts to "exhort" or persuade organizations to alter their behavior. Specifically, the government preserves a significant threat of punishment (i.e., legal sanctions) in the case of voluntary failure. Moreover, the government can indirectly induce behavioral change by proactively inviting or at least allowing multiple stakeholder participation. This creates multiple social–political and economic pressure points for encouraging behavioral change by the private sector. At the same time, the private sector retains varying flexibility in the negotiation process. In many cases, as with the CCA voluntary agreement, the private sector is free to determine the level of detail and extent of commitment in the agreement, as long as regulators acquiesce.

At the center of the CCA voluntary agreement is the controversy over the pressure-treated wood industry's use of CCA, an arsenic compound, as a wood preservative in residential products, such as residential decks, picnic tables, and playground equipment. Initial public concerns surfaced in the 1960s, which centered on employees falling ill upon handling CCA. In the 1980s, voluntary labels by manufacturers about toxic exposures for workers were encouraged by the EPA. Fifteen years later, when CCA was due for a

[3] That being said, arsenic use and emissions correlate each other considerably well for available data; the two series exhibit a Pearson's correlation coefficient of about 0.90.

routine pesticide renewal public concern expanded to include children's exposure to CCA-treated wood on the playground.[4]

In the face of persistent advocacy and protest by a coalition of environmental NGOs, both the EPA and the Consumer Product Safety Commission (CPSC) began separate but coordinated investigations. Both the EPA and the CPSC invited technical experts, private industry, as well as third-party stakeholders for public commenting. An explosion of media attention ensued. The activities of the environmental NGOs and the investigations by the EPA and CPSC were widely reported by the news media.[5]

In early 2002, the EPA announced that the manufacturers of CCA had requested that the pesticide registrations for CCA be canceled for all residential uses, effective December 31, 2003 (EPA, 2002). According to the terms of the agreement, CCA-treated residential wood products prior to year-end 2003 would remain in circulation. Furthermore, the EPA accepted the pressure-treated wood industry's claim that children's exposure to CCA-treated wood used for nonresidential purposes (e.g., highway utility poles) was relatively negligible, thus CCA registration was permitted for nonresidential uses (EPA, 2003).

At critical dosages, arsenic causes a variety of cancers, including cancer of the lung, bladder, skin, and liver (ATSDR – Toxic Substances – Arsenic, 2011). In addition to ranking first on the EPA's priority list of hazardous substances, arsenic ranks among the top 10 most toxic substances according to the CRC Handbook of Chemistry and Physics. Finally, arsenic is a "controlled" substance under the Basel Convention on the Control of Transboundary Movements of Hazardous Wastes and their Disposal (Protocal on Liability and Compensation for Damage Resulting From Transboundary Movements of Hazardous Wastes and Their Disposal, n.d.).

Notwithstanding, arsenic is a key ingredient in the manufacturing of wood preservatives, as well as agriculture pesticides, glass, and electronics. For the past three decades, wood preservative uses had surpassed any other applications. Between 1975 and 2004, close to 90 percent of all arsenic used in the U.S. was consumed by manufacturers who treated wood with CCA to prevent the wood from decay. The electronics, glass, and agriculture industries together make up the other 10 percent of total arsenic use.

3. Did the CCA voluntary agreement lower arsenic use?

The CCA voluntary agreement was lauded as a success by regulators, industry representatives, and environmental activists involved in its development. It was considered a landmark decision by all major stakeholders because the largest arsenic-using industry's voluntary compliance ensured that the industrial use of arsenic, a poisonous chemical that is ranked number one on the EPA's priority list of hazardous substances, would be lowered. By how much did the CCA voluntary agreement reduce arsenic use in the U.S.?

3.1. Data and measures

This paper quantifies the effect of the CCA voluntary agreement on the industrial use of arsenic using a unique dataset on arsenic use across all arsenic-using industry sectors from the mineral statistics publication of the U.S. Bureau of the Mines and the USGS. Arsenic use data are a combination of published and calculated industrial use data.[6] Arsenic use is estimated by the USGS using the following equation for most years: Chemical Use = Production + Imports − Exports ± Stock Changes. Data for the other years come from published data from the USGS Mineral Facts and Problems and the Mineral Yearbook. Aggregate arsenic use data are available through 2011.

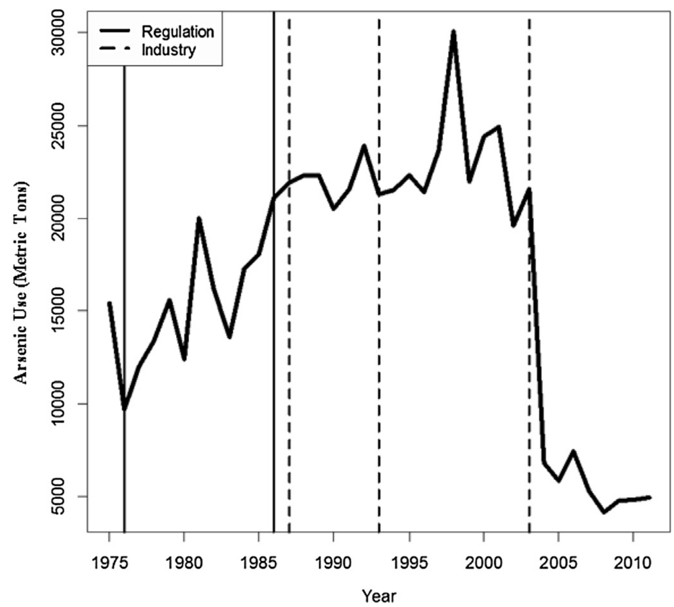

Fig. 1. Arsenic use in the U.S., 1975–2011.

Data between 1975 and 2003 are available for the following arsenic end-use sectors: agricultural chemicals, glass, and semiconductors. Data are available through 2004 for the pressure-treated wood industry. The USGS estimates for the end-use distributions are based on apparent demand information collected from industry contacts and Internet sources.[7] End-use figures sum up to total use figures.

Fig. 1 shows aggregate arsenic use between 1975 and 2011. The solid vertical lines represent the federal regulations that pertain to arsenic use: the Toxic Substances Control Act (TSCA) of 1976 and the Comprehensive Environmental Response, Compensation, the Emergency Planning and the Community Right-to-Know Act (EPCRA) of 1986 (which established the Toxics Release Inventory). The dotted vertical lines represent the discovery of gallium arsenide, a key arsenic compound in the manufacturing of semiconductors, in 1987; a voluntary ban on arsenic acid by agriculture users in 1993; and the CCA voluntary agreement in 2003.

Fig. 2 Panels A and B present arsenic use by major industrial users. Fig. 2 Panel A plots arsenic use by the pressure-treated wood and the agriculture industries from 1975 to 2004, respectively. In

[4] As a restricted pesticide, CCA must be renewed every fifteen years by the EPA for the use in commercial applications by the pressure-treated wood industry. A Consumer Product and Safety Commission study (CPSC, 2003) found that the principle exposure to arsenic from CCA-treated wood in playground equipment occurs through the transfer of wood surface residues to a child's hands and subsequent hand to-mouth transfer that can occur when children put their hands or fingers in their mouths.

[5] In an August 1, 2011 interview with the author, the EPA Branch Chief of Risk Assessment described it this way: "[It] felt like everything was happening at the same time. There was news every day about CCA [in the media]."

[6] To my knowledge, there is no other source of comprehensive industrial chemical use data. Data are publically available on the USGS website (http://minerals.usgs.gov/ds/2005/140/). The USGS houses data on the production, trade, and commercial use of over 80 mineral commodities (many of which are elemental chemicals) in the U.S., including arsenic dating back to 1900, albeit the current analysis is concerned only with industrial chemical use during the post-1975 environmental regulatory era.

[7] This information was provided by Dr. William E. Brooks, the commodity specialist at the USGS for Silver, Mercury, and Arsenic, in an email exchange with the author on May 11, 2009.

1975, the agricultural sector was the leading user of arsenic; arsenic has been used as a pesticide and cotton desiccant in agriculture (Loebenstein, 1994). By the early 1980s, the pressure-treated wood industry exceeded the agriculture sector in arsenic use. This rise coincided with the expansion of CCA as a major ingredient in wood preservatives. By contrast, arsenic use in the agriculture sector has been on a decline since 1975 and hastened in the 1990s.

Arsenic use by the glass and the semiconductors industries since 1975 is plotted in Fig. 2 Panel B. The two sectors have been relatively small but consistent users of arsenic. Arsenic is used in the compound form of gallium arsenide in semiconductor manufacturing and as a key ingredient in glass purification.

It is the interest of public policy to be concerned about how regulatory or voluntary actions in specific sectors impact aggregate environmental performance. As such, my empirical objective is to illustrate how a voluntary action to reduce the use of a poisonous chemical by the largest industrial user of arsenic could have had a "landmark" effect on the total use of arsenic use in the U.S. To achieve this, I pool data across the four industry sectors in the dynamic panel regression analysis. In this study, the success of the CCA voluntary agreement is assessed by whether or not it generates discernible impact on aggregate arsenic use.

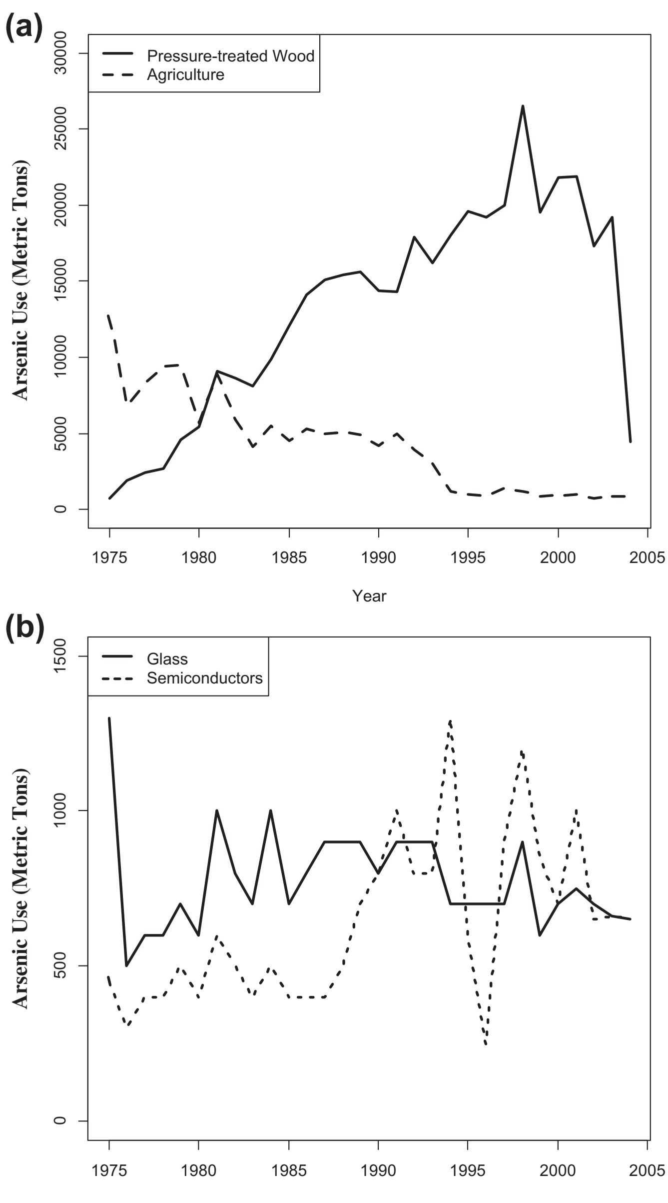

Fig. 2. Panel A: arsenic use in pressure-treated wood and agriculture industries. Panel B: arsenic use in semiconductors and glass industries.

In the following regression analysis, the dependent variable or outcome variable of interest is the natural log-transformed arsenic use. The log transformation of arsenic use retains the structure of the data but reduces fluctuations and facilitates the interpretation of results without changing the results.

The key independent or explanatory variable is *CCAvoluntaryban* (CCA voluntary agreement), which is hypothesized to exhibit a statistically significant negative relationship with arsenic use, i.e., CCA voluntary agreement should be associated with a reduction in arsenic use. While the CCA voluntary agreement did not take effect until the end of 2003, the pressure-treated wood industry approached the EPA at the beginning of 2002 to negotiate the cancellation of CCA. It is likely that private industry began altering behavior and substituting away from CCA in 2002. Thus, *CCAvoluntaryban* is constructed as an indicator variable that equals 0 between years 1975 and 2001 and 1 in years 2002, 2003, and 2004 (the end of the industry-level data).

The choice of the control variables is guided by the need to account for factors in the political economy that could potentially "cause" or at least "correlate" with an increase or decrease in arsenic use, which are not directly related to the CCA voluntary agreement. A parsimonious set of variables that include industry developments and political economy factors, along with year fixed effects serve as controls.

With respect to industry developments, an indicator variable is used to represent the 1987 discovery of gallium arsenide (*GaAs87*) in semiconductor manufacturing. *GaAs87* is equal to 1 starting in 1987 and there on after. There has been rapid adoption of gallium arsenide by electronic manufacturers because GaAs's higher saturated electron velocity and higher electron mobility relative to silicon have allowed transistors made from it to function at high frequencies. Moreover, unlike silicon, GaAs devices are relatively insensitive to heat and tend to have less noise than silicon devices especially at high frequencies. Thus, the advent of GaAs should be positively correlated with arsenic use since the demand for arsenic necessarily increases given that GaAs has become a key ingredient in electronic production.

Another industry development is the 1993 voluntary cancellation of inorganic arsenic acid in agriculture for treating cotton by the two major agricultural pesticide manufacturers that dominated the market. Before the 1993 voluntary ban (*AsAcidvoluntaryban*), cotton growers in the U.S. used arsenic acid to dry out the bolls of their cotton plants prior to harvesting them.

Like the CCA voluntary agreement, the arsenic acid ban is referred to as an industry-led "voluntary" ban by both policymakers and industry representatives as opposed to a government directive (Arsenic Acid Cancellation Order 4/93, 1993). That being said, one major difference between the two voluntary bans is that for arsenic acid the threat of a government-driven directive was notably greater on the eve of the voluntary ban: the EPA had formally issued a "Notice of Preliminary Determination to Cancel Registration" a year prior to the manufacturers' voluntary cancellation, which made provisions for the distribution, sale, or use of existing arsenic acid stocks. By contrast, the EPA had not taken any formal action against CCA at the time of the CCA voluntary agreement.

AsAcidvoluntaryban is an indicator variable that equals 1 starting in 1992, the year in which the EPA had issued a warning to private cotton producers before the agriculture industry voluntarily banned the chemical, and hereon after and 0 otherwise. I hypothesize that the 1993 voluntary ban is negatively correlated with arsenic use.

The ebb and flow of the business cycle and the economy is measured by each industry's gross output (*sectorGDP*), as appraised by each industry's value added, respectively. The sector GDP data are obtained from the U.S. Bureau of Economic Analysis. Sector GDP is expected to be positively correlated with arsenic use: a rise in industrial development necessitates increases in productive inputs, all else equal.

Moreover, the extent to which the public is aware of arsenic's harm to human health and the environment could shape consumer demand for products containing arsenic. As mentioned above (see Background section), media attention appeared to have played a critical role in the formation of the CCA voluntary agreement by raising public awareness, including the attention of policymakers and public officials. I measure the change in public awareness over time regarding the adverse human health and environmental effects of arsenic use by a count of the number of media reports published by the *New York Times* (*mediaNYT*). An increase in media attention about arsenic's harm to human health and environment should reduce arsenic use.

Another control variable included in the regression analysis is the number of Sierra Club members per one thousand people in the U.S. population (*sierra*). *sierra* is a proxy for the role of environmental NGOs in encouraging and at times pressuring for beyond-compliance activities by businesses.[8] It is potentially an important explanatory factor to account for because of the prominent role that environmental NGOs had played in waging an activist campaign against CCA-treated wood on playgrounds. Environmental pressure could impact the negotiation of the CCA voluntary agreement as well as the level of arsenic use more generally. An increase in Sierra Club membership should reduce arsenic use.

Two federal regulations that address toxic chemical use, including arsenic use by U.S. manufacturers were passed since 1975.[9] The first legislation, the Toxic Substances Control Act (TSCA) of 1976, is a command-and-control regulation that authorizes the EPA to regulate the manufacture and use of toxic chemicals, including arsenic and arsenic compounds that pose an unreasonable risk to human health or the environment.

The second federal legislation is the 1986 Emergency Planning and Community Right-to-Know Act (EPCRA), which created the Toxics Release Inventory (TRI). The TRI is an information disclosure rule that stipulates mandatory reporting of toxic emissions and transfers by manufacturers in specific industries, including arsenic-using sectors. Both the TSCA and the TRI have the authority to prosecute end-users in multiple if not all arsenic-using sectors. As such, these regulations, along with changes in other contemporaneous institutional, macroeconomic, and macro-political characteristics are accounted for as part of the year fixed effects included in the regression analysis.

Table 1
Summary statistics.[a]

Variable	Obs.	Mean	Std. dev.	Min	Max
Pressure-treated wood industry					
arsenic (metric tons)	30	13,198.330	6978.569	700	26,500
CCAvoluntaryban (0/1)	30	0.1	0.305	0	1
AsAcidvoluntaryban (0/1)	30	0	0	0	0
GaAs87 (0/1)	30	0	0	0	0
sectorGDP (bil. $)	28	28.463	3.772	18.028	34.576
mediaNYT	30	5.4	4.319	0	20
sierra (per thous. pop)	23	2.107	0.367	1.480	2.670
Agriculture industry					
arsenic (metric tons)	30	4290.333	3205.562	750	12,700
CCAvoluntaryban (0/1)	30	0	0	0	0
AsAcidvoluntaryban (0/1)	30	0.433	0.504	0	1
GaAs87 (0/1)	30	0	0	0	0
sectorGDP (bil. $)	28	101.341	15.115	77.877	137.299
mediaNYT	30	2.767	2.254	0	9
sierra (per thous. pop)	23	2.107	0.367	1.480	2.670
Semiconductors industry					
arsenic (metric tons)	30	633.667	262.094	250	1300
CCAvoluntaryban (0/1)	30	0	0	0	0
AsAcidvoluntaryban (0/1)	30	0	0	0	0
GaAs87 (0/1)	30	0.6	0.498	0	1
sectorGDP (bil. $)	28	134.783	32.464	72.556	194.138
mediaNYT	30	5.367	5.480	0	19
sierra (per thous. pop)	23	2.107	0.367	1.480	2.670
Glass industry					
arsenic (metric tons)	30	775.330	162.560	500	1300
CCAvoluntaryban (0/1)	30	0	0	0	0
AsAcidvoluntaryban (0/1)	30	0	0	0	0
GaAs87 (0/1)	30	0	0	0	0
sectorGDP (bil. $)	28	39.806	5.232	28.305	50.135
mediaNYT	30	0.066	0.253	0	1
sierra (per thous. pop)	23	2.107	0.367	1.480	2.670

[a] All data are based on sector-year observations.

The inclusion of the time indicator variables in the model is based on a theoretical conjecture that in each passing year, there are contemporaneous events in the political economy that affect in some unobserved way all the sectors that use arsenic as an input.[10] These exogenous events also include commodity price changes, the oil crisis, changes in presidential administrations, as well as changes in monitoring and enforcement activities at the EPA that address toxic chemical use more generally rather than any one particular sector specifically.

Table 1 provides summary statistics for the regression analysis.

3.2. Analytical method: Arellano–Bond dynamic panel estimator

This paper employs the Arellano–Bond dynamic panel estimator (Arellano and Bond, 1991) to rigorously identify the impact of the CCA voluntary agreement. The Arellano–Bond estimator exploits the time dimension of the industry-level arsenic use data and resolves a potential endogeneity problem associated with a dynamic model by using lagged values of the dependent variables as instrumental variables. The Arellano–Bond estimator is estimated in the Generalized Methods of Moment (GMM) framework.

[8] The Sierra Club is the oldest, largest, and most influential grassroots environmental organizations in the U.S. Per capita Sierra Club membership has been used by other researchers to proxy for the proportion of a population (e.g., at the state level) with a high preference for environmental activism (e.g., Daley, 2007; Gallagher and Muehlegger, 2011; Innes and Sam, 2008).

[9] Since the 1970s, the federal government has played an increasingly active role in environmental regulation (Revesz, 2001; Stavins, 2004). From 1970 through 1990, eight major federal statutes pertaining to toxic substances were passed. These federal statutes are the Occupational Health and Safety Act of 1970, the Clean Water Act of 1972, the Safe Drinking Water Act of 1974, the Resource Conservation and Recovery Act of 1976, the Toxic Substances Control Act of 1976, the Comprehensive Environmental Response, Compensation, and Liability Act of 1980, the Emergency Planning and Community Right-to-Know Act of 1986 (which established the Toxics Release Inventory), and the Clean Air Act of 1990. While arsenic is listed as a priority chemical by all these federal rules, only the TSCA and TRI regulate arsenic use and production.

[10] A dummy has been omitted for one of the years to avoid perfect multicollinearity.

The following setup of the Arellano–Bond estimator highlights key features of the estimator. To begin, equation (1) is a conventional panel data model with sector fixed effects.

$$\begin{aligned}\ln arsenic_{it} = {} & CCAvoluntaryban_{i,t-1}\beta + AsAcidvoluntaryban_{i,t-1}\gamma_1 \\ & + GaAs87_{i,t-1}\gamma_2 + \ln(sectorGDP)_{it}\gamma_3 \\ & + \ln(mediaNYT)_t\gamma_4 + \ln(sierra)_t\gamma_5 + T'\theta_i + \alpha_i + v_{it}\end{aligned} \tag{1}$$

CCAvoluntaryban lagged by one period is the key explanatory variable of interest. The indicator variable for the CCA voluntary agreement is lagged by one period in order to allow for the fact that the impact of the pressure-treated industry's voluntary ban could be delayed. A similar logic applies to lagging *AsAcidvoluntaryban* and *GaAs*87 by one period. Several of the control variables, namely *sectorGDP*, *mediaNYT*, and *sierra* have been logged for the ease of interpretation in percentage terms. *T* is a vector of time fixed effects that control for contemporaneous shocks such as commodity price changes and changes in any economic, political, or institutional characteristics that affect all arsenic-using sectors, including government regulation. α_i represents a whole host of not readily observed factors that could shape an industry's arsenic use, which are unrelated to government mandates or time varying economic and political factors. v_{it} is an idiosyncratic disturbance that varies with time and sector.

Equation (1) is converted to its dynamic form by lagging $lnarsenic_{it}$, the dependent variable, by one year and adding it to the right-hand side of equation (1) as another regressor. The logic is that an industry sector's consumption of arsenic in one period is likely to be correlated with that sector's consumption in the previous period. For example, manufacturers regularly purchase commodity chemical inputs via long-term contracts, and as a result production planning horizons are lengthened. This stickiness in arsenic use is captured by including lagged arsenic use as a regressor.

Estimating this model by OLS gives us inconsistent estimates because the explanatory variables now include a lagged dependent variable. Anderson and Hsiao (1981) suggest taking the first difference of equation (1) and then estimating the resulting transformed model, equation (2), using an instrumental variable approach[11]:

$$\begin{aligned}\Delta\ln arsenic_{it} = {} & \delta\Delta\ln arsenic_{i,t-1} + \Delta CCAvoluntaryban_{i,t-1}\beta \\ & + \Delta AsAcidvoluntaryban_{i,t-1}\gamma_1 + \Delta GaAs87_{i,t-1}\gamma_2 \\ & + \Delta\ln(sectorGDP)_{it}\gamma_3 + \Delta\ln(mediaNYT)_t\gamma_4 \\ & + \Delta\ln(sierra)_t\gamma_5 + T'\theta_i + \Delta v_{it}\end{aligned} \tag{2}$$

The first differenced model remains inconsistent when estimated by OLS because $lnarsenic_{i,t-1}$ is correlated with $v_{i,t-1}$, so that the regressor $\Delta lnarsenic_{i,t-1}$ is correlated with the error Δv_{it}. To remedy this, the second lag of the dependent variable, $lnarsenic_{i,t-2}$, is employed as an instrument for $\Delta lnarsenic_{i,t-1}$. $lnarsenic_{i,t-2}$ is a valid instrument because it is uncorrelated with Δv_{it} but correlated with $\Delta lnarsenic_{i,t-1}$.[12]

In effect, the exogenous dependent variable of two periods ago is used as an instrument for the endogenous dependent variable in the current time period.[13] This allows for the possibility that past shocks to arsenic use have feedback effects on current values of the explanatory variables, whether it is government mandates, sector GDP growth or negative media reports highlighting children's exposure to poisonous chemicals.

Finally, equation (2), along with the instrumental variables, is estimated in the GMM framework, which allows for a more efficient estimator than a standard panel data model.[14] The standard errors are adjusted with panel-robust standard errors to correct for heteroskedasticity and serial correlation.

3.3. *Results and discussion*[15]

Table 2 reports the results of the regression analysis.[16] Model 1 is the base model (see equation (2)) and Model 2 and Model 3 are alternative specifications, which supplement Model 1 with additional information about the possible causal pathways of sector GDP, media attention, and Sierra Club membership (as opposed to the robustness check in the next section, which is based on a different underlying model).[17]

Model 2 is a replication of Model 1 plus quadratic terms of *sectorGDP*, *mediaNYT*, and *sierra*. The quadratic terms allow for these variables to enter the model nonlinearly; the assumption is that the time paths of these variables have a U or inverted-U shape; a threshold or turning point exists, at which point a decreasing trend becomes an increasing trend or vice versa. Model 3 is a replication of Model 1 plus quadratic terms, as well as interaction terms involving *sierra* and *CCAvoluntaryban*, and *sierra* and *AsAcidvoluntaryban*. These interaction terms focus on how environmental activism mediates the impact that the industry voluntary bans have on arsenic use. The conjecture is that the more intense the stakeholder pressures are (as measured by increases in Sierra Club membership) the more *negative* are the effects of *CCAvoluntaryban* and *AsAcidvoluntaryban* on arsenic use. Generally, Models 2 and 3 are preferred over Model 1 because the alternative specifications contain additional information about how the explanatory variables may influence arsenic use.

In all models, the regression coefficients for *sectorGDP*, *mediaNYT*, and *sierra* represent percentages. Coefficients on the

[11] Time-invariant industry-specific characteristics (fixed effects) are removed, because it does not vary with time. This is not unreasonable since they are likely correlated with the explanatory variables.

[12] Cameron and Trivedi (2005) posit that for moderate length *T* (which is what we have) there may be a maximum lag of the dependent variable that is used as an instrument, such as $y_{i,t-4}$. The sargan test indicates that our set of overidentifying instruments is valid, namely that the instruments are uncorrelated with the contemporaneous error term.

[13] The Levin-Lin-Chu unit panel unit root test has been conducted on the arsenic use industry panel data to confirm that the Arellano–Bond estimator is an appropriate estimator. If unit roots exist, the Arellano–Bond estimator is biased because the twice-lagged variable will be a poor instrument for the lagged differenced data (Bond et al., 2005). A statistically significant test statistics of −4.995 indicate that the null hypothesis of panel unit roots is rejected at *p*-value of 0.0003.

[14] Holtz-Eakin et al. (1988) and Arellano and Bond (1991) recommend estimating in the GMM framework particularly when the instrument set is unbalanced, i.e., when there are more instruments than there are endogenous variables. In GMM estimation, sample moment conditions (e.g., the mean, variance, and so on, which are functions of the model parameters and the data) are used to estimate parameters. The GMM method minimizes a certain norm of the sample averages of the moment conditions to obtain parameter estimates.

[15] The regression analysis has been conducted in *Stata*.

[16] The three models are run on 88 observations despite the 120 observations from the original USGS toxic chemical data (30 years × 4 industries). The "missing" observations are accounted for this way: 1) Four observations are differenced out as part of the four lags in the models in accordance to the dynamic panel model structure of the Arellano–Bond estimator; 2) 28 sector-year observations (seven from each of the four sectors) are dropped because data for Sierra Club members per one thousand people in the U.S. population are not available between 1975 and 1981.

[17] *sierra* has been dropped from Models 2 and 3 by *Stata* due to collinearity, while $sierra^2$ remains in the regression models.

Table 2
Dynamic panel estimation results.

	Model 1[a]			Model 2[a,b]			Model 3[b]		
	Coef.	Robust std. err.	Impact (%)	Coef.	Robust std. err.	Impact (%)	Coef.	Robust std. err.	Impact (%)
Last year's arsenic use									
Log (one lag of arsenic use)	0.505**	0.103	0.50	0.477**	0.099	0.47	0.445	0.099	0.45
Industry voluntary agreement									
2003 Pressure-treated wood CCA voluntary agreement	−0.486**	0.075	−38.5	−0.517**	0.090	−40.4	−0.650**	0.054	−47.8
Control variables									
Industry developments									
1993 Arsenic acid voluntary ban	−0.750**	0.133	−52.8	−0.770**	0.135	−53.7	−0.580**	0.158	−44.0
1987 Discovery of GaAs	0.246**	0.104	27.9	0.347**	0.098	41.5	0.352**	0.098	42.2
Log (sector GDP)	0.049	0.152		1.162**	0.665	1.62	1.727	0.707	1.73
Media attention and environ. activism									
Log (media attention)	−0.046**	0.011	−0.05	−0.136	0.076		−0.119	0.084	
Log (sierra members per thous. pop)	−2.132	1.526							
Quadratic terms									
Log (sector GDP)^2				−0.185**	0.071	−0.19	−0.193**	0.076	−0.19
Log (media attention)^2				0.029	0.023		0.022	0.024	
Log (sierra members per thous. pop)^2				−0.287**	0.144	−0.29	−0.033	0.021	
Interaction terms									
Log (sierra members per thous. pop) × 2003 Pressure-treated wood CCA voluntary agreement							0.154	0.098	
Log (sierra members per thous. pop) × 1993 arsenic acid voluntary ban							−0.296**	0.076	−0.30
Year fixed effects	Yes			Yes			Yes		
N	88			88			88		
Prob > chi^2	0.004			0.015			0.016		
Adj. R^2	0.95			0.95			0.95		

** Indicates statistical significance of ≥5% level.
[a] Model 2: Model 1 + Quadratic Terms; Model 3: Model 1 + Quadratic Terms + Interaction Terms.
[b] *sierra* has been dropped from Models 2 and 3 by *Stata* due to collinearity.

industry voluntary ban and technology dummies represent log-points; percentages have been computed for the ease of interpretation for the statistically significant coefficients (see Table 2 Columns 3, 6, and 9). Moreover, estimated coefficients represent long-run impact (10 or more years) for *AsAcidvoluntaryban* and *GaAs87*, while the coefficient for *CCAvoluntaryban* represents a short-run impact measure of two years (2002–2004).

Across all models the key result is that, as hypothesized, the pressure-treated wood industry's voluntary agreement to phase-out CCA in residential uses yields a statistically significant negative impact on arsenic use. The base model indicates that the CCA voluntary agreement is associated with 38.5 percent reduction in arsenic use. When *sectorGDP*, *mediaNYT*, and *sierra* are allowed to enter the model nonlinearly (Model 2) and *sierra* is interacted with the industry voluntary ban indicator variables (Model 3), the CCA voluntary agreement is estimated to exert an even larger negative effect on arsenic use (40–48 percent). The relative impact of the CCA voluntary agreement is substantial considering that this indicator variable measures short-term rather than long-run impact. In fact, this estimated reduction suggests that the CCA voluntary agreement has lowered arsenic use to levels not since the 1920s.

On sectoral developments, the 1993 voluntary ban on arsenic acid is associated with a statistically significant decline of 53–55 percent in arsenic use across the three models; slightly larger coefficient estimates are observed in Models 2 and 3 than in the base model.[18] Model 3 shows that the effect of *AsAcidvoluntaryban* is mediated by environmental NGO activism. The more intense is NGO activism (i.e., the higher is Sierra Club membership), the larger is the *negative* association between arsenic use and the arsenic acid voluntary ban in agriculture.

On balance, the results show that *sectorGDP* has had very little, if at all discernible impact on arsenic use—Models 2 and 3 report that a one percent increase in industry gross output is associated

[18] The author computes the marginal effect of *AsAcidvoluntaryban* in Model 3, centered at the mean of the log of Sierra Club membership, as follows.

$$\text{Model 3: } \frac{\Delta \ln arsenic}{\Delta AsAcidvoluntaryban} = \beta + 2\beta \times \text{mean}(\ln sierra) = 0.58 - (0.30)(0.73)$$
$$= -0.80 \text{ log points} = -55\%.$$

with a less than a one-fourth of a percent decline in arsenic use.[19] Of note, when nonlinear and interaction effects are accounted for, *sectorGDP* takes on an inverted-U shape: Industry gross output is positively correlated with arsenic use to some point. Beyond this point, industry gross output is associated with declines in arsenic use. This could be because at some point in time (perhaps after economies of scale have been exploited) it becomes economically feasible to use a more expensive but arsenic-free substitute to generate additional output value.

In all three models, the discovery of GaAs in 1987 by the semiconductor industry yields statistically significant increases in arsenic use. The industry innovation is associated with a close to 30 percent increase in arsenic use in the base model. When we allow for quadratic and interaction terms, *GaAs87* is associated with a considerably larger rise in arsenic use, yielding approximately a 42 percent impact since its discovery in both Models 2 and 3.

According to the regression analysis, *sierra* exerts statistically significant effect on arsenic use Model 2. In Model 2, where *sectorGDP*, *mediaNYT*, and *sierra* are allowed to enter the model nonlinearly, a one percent increase in Sierra Club membership leads to close to a 0.5 percent decrease in arsenic use. Moreover, in Model 3, *sierra* is associated with additional declines (although small) when it is interacted with *AsAcidvoluntaryban*. After accounting for quadratic and interaction terms, the marginal impact of *sierra* is modest in Model 3.[20]

Moreover, media attention yields essentially no discernible effect on arsenic use across the three models; at best a one percent increase in media attention leads to close to a one-tenth of a percent decrease in arsenic use (Model 1).

Finally, as predicted, arsenic use is positively associated with last period's arsenic use. A one percent increase in last year's arsenic use leads to about half a percent rise in this year's arsenic use.

3.3.1. Discussion

Overall, the regression results across all models suggest that over the past several decades the private sector and civil society actors have played a critical role in curbing arsenic use. When we allow for nonlinear and interaction effects, many of the statistically significant coefficients become larger in magnitude, suggesting that the causal pathways of the explanatory factors are complex.

While a technological discovery is associated with increases in arsenic use, the voluntary agreement by the pressure-treated wood industry to phase-out CCA in residential uses has had a relatively large impact in reducing arsenic use in the immediate years following its negotiation. The relatively large short-run impact of the CCA voluntary agreement is not surprising: it is in line with existing studies that show that negotiated targets of voluntary agreements to reduce CO_2 emissions in Japan, Denmark, and the UK were met within the first few years of inception (Glachant and Muizon, 2007; Krarup and Millock, 2007; Wakabayashi and Sugiyama, 2007).

A voluntary ban in arsenic acid by pesticide manufacturers in the agriculture sector also contributed to arsenic use reductions in the estimated models. The fact that the EPA had issued a "Notice of Preliminary Determination to Cancel Registration" a year prior to the manufacturers' voluntary cancellation suggests that the agriculture sector's ban on arsenic acid was closer to coercive regulation than the CCA voluntary agreement, although private industry preempted the government's formal pesticide recall.

While the EPA has the authority given by the TSCA and the FIFRA to suspend immediately the registration of pesticides and other toxic chemicals on the market, in practice the agency has generally sought non-coercive means whereby industry is encouraged to voluntarily recall products and reformulate or repair potential hazards when the said pesticide or toxic chemical does not pose "imminent hazard" (GAO, 2007, 2005, 1994). Consequently, the fact that the CCA voluntary agreement and the industry voluntary ban on arsenic acid are both associated with sizeable reductions in arsenic use bode well for the overall effectiveness of U.S. toxic chemical policy.

Moreover, the fact that both variants of voluntary agreements are estimated to have been effective in reducing arsenic use suggests that there is not a one size fits all. Variation to voluntary program design is to be expected, particularly for voluntary agreements that are often negotiated on a chemical-by-chemical basis. Of note, the two voluntary bans do have in common the feature that both become legally binding once the terms of agreement have been negotiated.

The statistically significant and positive effect of GaAs, a technological innovation on arsenic use suggests an important implication: arsenic use will continue as the private sector discovers new ways to exploit the physical properties of arsenic to create commercial products that benefit consumers.

Finally, the role of environmental activism cannot be underestimated. When nonlinear and interaction effects are accounted for in the regression analysis, environmental activism as measured by membership in the Sierra Club becomes a nontrivial even if not a major factor in curbing arsenic use. This suggests that activist campaigns and stakeholder engagement more generally influence how voluntary agreements to curtail toxic chemical use are negotiated: the effectiveness of the industry voluntary bans is contingent on stakeholder pressures. This result is consistent with prior empirical studies which find that the third-party stakeholders play a critical role in the pollution reduction potential of Canada's Voluntary Challenge Registry program (Takahashi et al., 2001) and the EPA's 30/50 program (Bi and Khanna, 2012; Innes and Sam, 2008).[21]

[19] The author computes the marginal impact of *sectorGDP* on arsenic use in Models 2 and 3, centered at the mean of the log of *sectorGDP*, as follows.

$$\text{Model 2: } \frac{\Delta\ln arsenic}{\Delta\ln sectorGDP} = \beta + 2\beta \times \text{mean}(\ln sectorGDP) = 1.62 + 2(-0.19)(0.11) = 0.10\%$$

$$\text{Model 3: } \frac{\Delta\ln arsenic}{\Delta\ln sectorGDP} = \beta + 2\beta \times \text{mean}(\ln sectorGDP) = 1.73 + 2(-0.19)(0.11) = 0.14\%$$

[20] The author computes the marginal impact for *sierra* in Model 3 centering at the mean of the log of *sierra* and *AsAcidvoluntaryban*, as follows.

$$\text{Model 3: } \frac{\Delta\ln arsenic}{\Delta\ln(sierra)} = 2\beta \times \text{mean}(\ln sierra) + \beta \times \text{mean}(AsAcidvoluntaryban) = 2(0.03)(0.73) - (0.30)(0.11) = 0.02\%$$

[21] The private governance literature highlights the prominent roles that external stakeholders play in motivating industry self-regulation across multiple issue areas, not just in environmental policy. Examples include the role of NGOs in sustainable forestry, Fair Trade coffee, "sweatshop free" apparel, and responsible recycling of e-wastes (Fung and O'rourke, 2000; Fung et al., 2001; O'Rourke, 2003; Cashore et al., 2004; Mayer and Gereffi, 2010; Cashore et al., 2011). In some cases NGOs are perpetrators of activist campaigns and in other cases NGOs are disinterested third-party monitors and auditors of firm and industry compliance with voluntary standards.

Table 3
Bai and Perron's simultaneous estimation of multiple structural breaks.

Series	Sample period	Number of breaks	Break estimates	95% Conf. intervals
ln(arsenic)	1975–2011	2	1985 2003	(1983, 1988) (2002, 2004)

3.4. Robustness check: structural break analysis[22]

The CCA voluntary agreement's substantial estimated impact on arsenic use is verified by a structural break analysis, which is based on a different underlying model of the data from the Arellano–Bond estimator. Structural break analysis is a regular tool of analysts and researchers in macroeconomic research and finance studies but seldom employed in public policy research.[23] The purpose of the structural break analysis is to show how "shocks" in the political economy, such as the CCA voluntary agreement, among other factors impact aggregate arsenic use. The CCA voluntary agreement and other political economy factors have a "permanent" effect if these interventions correspond to perturbations or structural shifts in the arsenic use trend path.

Specifically, I employ Bai and Perron's (2003, 1998) endogenous structural breaks estimation technique to verify whether the exogenously determined structural breaks, i.e., the voluntary ban and technology indicator variables in the regression analysis, do in fact correspond with the endogenous or actual changepoints in the data. In other words, do the regression results match up with what the data are telling us? The longer aggregate arsenic use time series (1975–2011) from the USGS allows us to determine whether the estimated short-term impact of the CCA voluntary agreement in the regression analysis is long-lasting.

The structural break analysis is concerned with assessing deviations from stability in the classical linear regression model, where changes concern divergence from the intercept/mean or the slope/trend of the data.[24] Specifically, the breakpoint estimates are the global minimizers of the sum of squared residuals determined using an algorithm based on dynamic programming. The optimal number of breakpoints is established based on the Bayesian Information Criterion (BIC) selection procedure. Technical details are provided in Appendix.

Table 3 presents the estimated breakdates along with their respective 95 percent confidence intervals. The changepoint test indicates two breakpoints in aggregate arsenic use between 1975 and 2011, which correspond to the following dates: 1985 and 2003.

Fig. 3 depicts graphically the two estimated structural shifts and their corresponding confidence intervals. Estimated breaks are designated by the solid line segment while the corresponding breakdates are shown by the dotted vertical lines in the figure. The 2003 breakpoint appears to be precisely estimated since the 95 percent confidence intervals cover only one year before and after

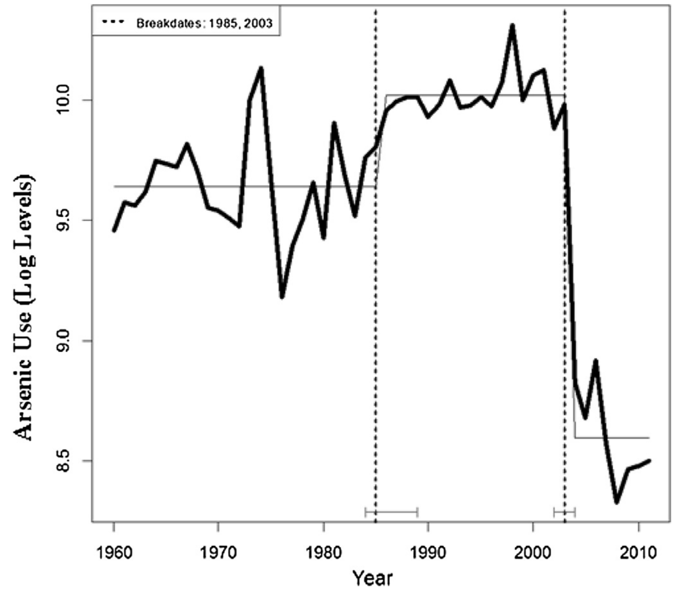

Fig. 3. Bai and Perron's multiple structural breaks.

the identified structural break. By contrast, the 1985 breakpoint is less certain with a 95 confidence region spanning the periods between 1983 and 1988.

How well do the results from the regression analysis match the endogenously determined breakpoints? The structural break analysis summarizes the bottom-line of the regression results, which is that major developments in arsenic-using sectors appear to have had "permanent" impact on altering the time dynamics of aggregate arsenic use. The estimated structural shifts ("shift up" for the first break and "shift down" for the second break) match two major events in the arsenic-using sectors: the 1987 discovery of GaAs in semiconductor manufacturing and the 2003 pressure-treated wood industry's voluntary agreement to ban CCA in residential uses. The narrow confidence interval around the 2003 changepoint corroborates that the CCA voluntary agreement, a nongovernment driven beyond-compliance pollution abatement effort, was a major driver of reductions in arsenic use in the U.S.

4. Conclusion

While the toxic chemical policy area and the environmental policy area more generally have witnessed a proliferation of voluntary programs, their efficacy remains disputed. This paper answers a retrospective question about voluntary program efficacy: by how much did the CCA voluntary agreement—a voluntary agreement negotiated between the EPA and the pressure-treated wood industry —reduce arsenic use in the U.S.?

Arellano–Bond dynamics panel estimation and the Bai and Perron endogenous structural break analysis find that the CCA voluntary agreement led to a substantial reduction in arsenic use: aggregate arsenic use has been lowered to levels not seen since the 1920s. Given data constraints, the industry panel regression analysis is only able to measure the CCA voluntary agreement's short-run impact. By contrast, the structural break analysis on a longer time series of aggregate arsenic use shows that the reductions associated with the pressure-treated wood industry's voluntary ban is longer-lasting: the CCA voluntary agreement corresponds to a permanent structural shift downwards in arsenic use in 2003, the year in which the CCA voluntary agreement took effect.

[22] The structural break analysis has been conducted by the author in the *R* statistical language.

[23] An exception in policy evaluation studies is Fomby and Lin (2006), which employs structural break analysis to estimate the effect of President Reagan's devolutionary policies (i.e., Environmental Federalism) on nitrogen oxides (NO_x), sulfur dioxides (SO_2) and volatile organic compounds (VOCs). While Fomby and Lin (2006) employ Bai's (1997a, 1997b) single break model, this study utilizes Bai and Perron's (2003, 1998) multiple breaks model.

[24] This paper employs a general structural break model; a more restrictive model allows for only changes in the mean or the trend of the data. Another application of the general model in examining toxic chemical use dynamics is Hsueh (2012); Hsueh identifies structural breaks involving mean and slope changes in more than a dozen highly toxic chemical use time series.

The empirical results more generally suggest that the private sector has been an important driver of arsenic use: a technological innovation in semiconductor manufacturing in the mid-1980s is associated with increases in arsenic use, while a 1993 voluntary ban in arsenic acid by pesticide manufacturers in the agriculture sector contributed to arsenic use reductions. The fact that both the CCA and the arsenic acid voluntary industry bans are associated with reductions in arsenic use bode well for arsenic use policy and toxic chemical policy more generally because in practice U.S. policymaking on toxic chemicals has centered on public voluntary programs or negotiated voluntary agreements with the private sector rather than legal mandates.

Results also highlight the importance of considering the role of environmental stakeholders in encouraging and at times pressuring for beyond-compliance activities by businesses. Reductions in arsenic use are associated with increases in Sierra Club membership; moreover, the regression results suggest the effectiveness of the industry voluntary bans is contingent on stakeholder pressures. This is in line with what Fung and O'Rourke (2000) term as "populist maximin regulation": the government's role is to set up a mechanism for information disclosure by firms such that maximum attention on minimum performers is reinforced by public pressures.

That being said, the stipulations of command-and-control regulations passed in the 1970s will continue to be important. This is particular true for built-in-rules for periodic risk assessments whereby new information is requested and taken into account for pesticide reregistration, as well as process-oriented rules that call for external reviews and stakeholder participation and public commenting. In fact, the negotiation of the CCA voluntary agreement was preceded by investigations at the EPA and the CPSC; both investigations involved external expertise and stakeholder participation and the EPA's investigation was part of a periodic risk assessment enshrined in U.S. pesticide law.

Moreover, monitoring and sanctioning roles by the government continue to be important even as traditional regulations have made room for voluntary governance. The CCA voluntary agreement as well as the agriculture industry's voluntary ban on arsenic acid, and bilateral voluntary agreements more generally combine *ex ante* interactions with industry and other stakeholders with *ex post* legal sanctions for noncompliance. This supports Buthe's (2010) hypothesis that when governments explicitly delegate public authority to a private rule-maker, and when such delegation is accompanied by commitments to monitoring and enforcement by government agencies, this should result in higher levels of compliance.[25]

This paper raises several issues for future research and policy considerations. First, an issue not yet fully addressed by the voluntary program literature is: how "voluntary" are voluntary programs? There is a wide-ranging degree of "voluntariness" amongst the different types of voluntary programs. This variation in "voluntariness" has implications for program efficacy. Past efficacy studies indicate that studies which have found voluntary programs to have "no effect" on reducing pollution have all been impact analyses focused on public voluntary programs or unilateral initiatives by industry that do not combine voluntary industry self-regulation with some form of government monitoring and sanctioning.

By contrast, the few studies that have evaluated bilateral voluntary agreements have shown that these negotiated agreements—which give the government a greater role—generated at least modest if not substantial reductions in pollution (see Introduction for a brief literature review). These studies combined with the current study suggest that bilateral voluntary agreements are more likely than other types of voluntary programs to yield environmental outcomes desirable from a public policy perspective. Why this might be the case should be systematically investigated in future research.

One possible rationale could be that unilateral initiatives by industry and public voluntary programs are more focused on recruitment incentives and membership growth rather than actual environmental outcomes, thus leading to program obligations and compliance-related rules that lack real stringency. For example, Antweiler and Harrison (2007) find that the flexible terms of participation in the Canadian Voluntary Challenge and Registry (ARET), the option for participants to choose their own base years, the lack of transparency, and the absence of third-party validation of participants' reports ensured that ARET gained industry co-sponsorship, but also ultimately contributed to the ineffectiveness of ARET.

Second, this study answers the call by Prakash and Potoski (2012) in a symposium by the *Journal of Policy Analysis and Management* to identify aggregate country-level effects which could facilitate cross-country comparisons, rather than focus on facility-level analysis. This new direction toward the analysis of time series of aggregate effects merits experimentation with previously untried empirical methodologies in public policy. This paper employs the Arrelano–Bond dynamic panel estimator and the Bai and Perron structural break analysis, which is widely employed in macroeconomic research and finance studies but rarely used in policy evaluation studies to independently verify and validate that the CCA voluntary agreement is a plausible causal driver of substantial reductions in aggregate arsenic use.

Third, bilateral voluntary agreements that are undertaken for another toxic chemical, in another country, or in a different policy issue area will likely look very different from the CCA agreement. This is the case for the bilateral voluntary agreements on CO_2 emissions in Japan, Denmark, and the UK that have been mentioned in the introduction of the paper (Glachant and Muizon, 2007; Krarup and Millock, 2007; Wakabayashi and Sugiyama, 2007). The bottom-line is that bilateral voluntary agreements allow for flexibility and tailoring of policy based on the political economic contexts of the policy problem at hand. While multiparty negotiation may be variably costly, bilateral voluntary agreements could be cost effective in taking into account the specific needs of both the regulatory regime and the market.

Appendix. Multiple structural breaks model

Bai and Perron (2003, 1998) are concerned with assessing deviations from stability in the classical linear regression model:

$$y_t = x_t'\beta_t + \varepsilon_t \quad (t = 1, \ldots, T), \tag{A1}$$

where at time t, y_t is the observation of the dependent variable, x_t is a $k \times 1$ vector of regressors, with the first component usually equal to unity, and β_t is the $k \times 1$ vector of regression coefficients, which may vary over time. ε_t is the disturbance at time t.

In the general model, of interest are the presence of abrupt structural changes in both the mean and the trend/slope of the series. To the Bai and Perron's (2003, 1998) structural break test, a constant and a time trend are applied as the regressors, such that

[25] In fact, the voluntary program literature, notably Potoski and Prakash (2009), suggests that effective programs have rule structures that mitigate two central collective action problems: attracting firms and other entities to participate in the program and ensuring that participants adhere to program obligations. Without rule structures that overcome these challenges, voluntary programs are not likely to be effective in achieving desirable environmental outcomes.

$x_t = \{1 + t\}$. In this context, I am concerned with testing the hypothesis that the regression coefficients remain constant:

$$H_0 : \beta_t = \beta_0 \quad (t = 1, ..., T), \tag{A2}$$

against the alternative that at least one coefficient varies over time. In many applications, it is reasonable to assume that there are m breakpoints, where the coefficients shift from one stable regression relationship to a different one (Bai and Perron, 1998; Zeileis et al., 2003). Thus, there are $m + 1$ segments in which the regression coefficients are constant, and model (1) can be rewritten as:

$$y_t = x_t'\beta_t + \varepsilon_t \quad (t = t_{j-1} + 1, \ldots, T_j, \quad j = 1, \ldots, m+1), \tag{A3}$$

where j is the segment index, $T = \{T_1, \ldots, T_m\}$ denotes the set of breakpoints that are explicitly treated as unknown, and by convention $T_0 = 0$ and $T_{m+1} = T$. The purpose is to estimate the unknown regression coefficients together with the breakpoints when T observations on (y_t, x_t) are available.

Bai and Perron's procedure for the simultaneous estimation of multiple breakpoints is the minimization of the residual sum of squares (RSS) of equation (A3), with the following objective function:

$$\left(\widehat{T}_1, \ldots, \widehat{T}_m\right) = \arg\min_{(T_1, \ldots, T_m)} \mathrm{RSS}(T_1, \ldots, T_m) \tag{A4}$$

The breakpoint estimators are the global minimizers of the objective function. The regression parameter estimates are the estimates associated with the m-partition$\{\widehat{T}_j\}$, i.e., $\widehat{\beta} = \widehat{\beta}(\{\widehat{T}_j\})$. Since the breakpoints are discrete parameters and can only take a finite number of values they can be estimated by a grid search. This method becomes computationally burdensome for $m > 2$ (and any reasonable sample size T). As such, Bai and Perron (2003) present an algorithm for computing the optimal breakpoints given the number of breaks based on the principle of dynamic programming approach. The underlying idea is that of the Bellman principle. The optimal segmentation satisfies the recursion:

$$\mathrm{RSS}(T_{m,T}) = \min_{mT_h \le t \le T - T_h} \left[\mathrm{RSS}(T_{m-1,t}) + \mathrm{rss}(t+1, T)\right] \tag{A5}$$

Therefore, it suffices to know for each point t the "optimal previous partner" if t was the last breakpoint in an m-partition. This can be derived from a triangular matrix of $\mathrm{rss}(t,j)$ with $j - t \ge T_h$, the computation of which is again made easier by the recursive relation $\mathrm{rss}(t,j) = \mathrm{rss}(t, j-1) + r(t,j)^2$, where $r(t,j)$ is the recursive residual at time j of a sample starting at t (Brown et al., 1975).

Finally, the optimal number of breakpoints is established based on the Bayesian Information Criterion selection procedure. Bai and Perron (1998) to argue that the BIC is a suitable selection procedure in many situations whereas the Akaike's information criterion (AIC) tends to overestimate the number of breaks.

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