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**A Natural Experiment on US Clean Water
Act Monitoring and Compliance**

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Abstract

In this paper we utilize the random treatment of reduction or complete stoppage of ambient water quality monitoring, to show that major polluters increase their pollution discharges relative to effluent limits in the 'post-treatment' period. We investigate this question using Pennsylvania, South Carolina and Virginia, 1990 to 2010, monthly biological oxygen demand (BOD) discharges and ambient dissolved oxygen (DO) data. More than a quarter of the 505 plants witnessed a 50% reduction in ambient monitoring. Communications with state officials served as anecdotal evidence that regulators stopped or reduced ambient monitoring based on budget concerns. We differentiated plants based on no ambient monitoring, or 3 out of 4 quarters drop in annual monitoring. Results show that these plants increased their relative concentration and quantity discharges by 30 percent in response to exogenous policy change in contrast to those that were regularly monitored for downstream water quality. We interpret the magnitude as high in the light of prior studies establishing plants' inflexibility in making costly abatement adjustments to changes in other incentives such as regulated levels of effluents. We find differential impact of plants at lower pollution percentiles i.e. those that are overcomplying substantially; especially for relative quantity loads. We do not find noteworthy differences in publicly owned treatment works versus privately owned manufacturing plants; especially for the diff-in-diff estimations.

Keywords: Clean Water Act, Water Quality Monitoring, U.S., Responsive Regulation, Natural Experiments

Resumen

En este documento abordamos el tratamiento aleatorio de reducción o interrupción total del monitoreo de la calidad del agua de los reguladores para mostrar que los principales contaminadores aumentan sus descargas en relación con los límites de efluentes en el período de "post-tratamiento". Investigamos este planteamiento utilizando las descargas mensuales de demanda biológica de oxígeno (DBO) y los datos de oxígeno disuelto (OD) en Pennsylvania, Carolina del Sur y Virginia en el período de 1990 a 2010. Los tres estados tienen 505 plantas y más de una cuarta parte de ellas experimentaron una reducción del 50% en el monitoreo ambiental. A través de comunicaciones con funcionarios estatales pudimos evidenciar de forma anecdótica que los reguladores detuvieron o redujeron el monitoreo ambiental basados en preocupaciones presupuestarias. Diferenciamos las plantas en función de la falta total de monitoreo ambiental, o aquellas con reducciones significativas en el monitoreo anual (de 4 revisiones a 1 anual). En comparación con las industrias que fueron monitoreadas regularmente, los resultados muestran que ciertas industrias aumentaron su concentración relativa y de descargas un 30% en respuesta a un cambio de política exógena. Interpretamos la magnitud de este cambio como alta al tomar en cuenta estudios previos que establecen la inflexibilidad de las industrias para realizar ajustes costosos de mitigación a cambio de incentivos como niveles más estrictos en la regulación de efluentes. Encontramos un diagnóstico diferencial en las industrias con niveles de contaminación más bajos, es decir, aquellas que cumplen sustancialmente por encima de las normas; especialmente para cargas de cantidad relativa. No encontramos diferencias notables en las plantas de tratamiento de agua de propiedad pública versus las plantas de propiedad privada; especialmente para las estimaciones de "diff-in-diff".

Palabras claves: Clean Water Act, Control de la calidad del agua, EEUU, Regulación receptiva, Experimentos

Introduction

In this era of rolling back of environmental regulations, the Clean Water Act (CWA) of the United States has been largely spared, so far, with major focus on air and related industries. In the academic literature however there are heavily cited policy pieces that outline the significant benefits of the CWA as well as substantial costs of compliance and monitoring and enforcement incurred by the federal and state EPAs. In this paper, I propose a new mechanism for improving environmental compliance behavior by exploiting the exogenous change in ambient water quality monitoring station networks. Changes in monitoring networks are mostly due to budgeting constraints of the state EPAs that are in charge of implementing the CWA under federal guidelines. I argue that the states should not fold back their resources for ambient monitoring as it has implications for costly enforcement and lawsuits even in the realm of water pollution (Kitzmueller and Shimshack 2012).

Our main research question is whether plants that have downstream water quality monitors (within a reasonable distance) are systematically different from plants that do not have downstream water quality records. Of course, presuming that availability of downstream water quality is random occurrence i.e. states and the EPA randomly decide whether to monitor a segment of a river based on budgeting rather than water quality concerns. There is a vast literature on effectiveness of regulatory stringency both in terms of permitted effluent limits (Chakraborti and McConnell, 2012) and inspections (Magat and Viscusi, 1990; Earnhart 2004a, 2004b),

enforcement and sanctions (Shimshack and Ward, 2005, 2008; Gray and Shimshack, 2011) Earnhart 2004b; Gray and Shadbegian 2004). There is a parallel literature on compliance induced by citizen pressure such as citizen lawsuits (Shimshack and Langpap, 2010). Some recent papers have also looked at whether contributions to environmental groups have encouraged improved compliance behavior on the part of industries and treatment plants (Grant and Grooms 2012; Grant and Langpap 2013). I argue that all of the above mechanisms albeit effective are costlier than ambient water quality monitoring because the latter is a preventive measure while the remaining regulatory channels are responsive and hence most likely costly regulations.

The CWA regulations mandate that water bodies such as rivers, streams and lakes meet ambient water quality standards that are required to fulfill their designated uses such as boat-able, fish-able, maintenance of aquatic life, or swimmable. Every two years, the states are required to submit Water Quality Inventory Report to Congress (305(b) list) which determines the attainment status of various water bodies assessed for their designated uses. Unfortunately, limited resources mean that not 100% of all water bodies can be assessed. If a river or stream segment does not meet the ambient water quality standards, then it gets listed as an impaired segment under the 303(d) list. Regulators are required to establish TMDLS (Total Maximum Daily Loads) that assigns permitted levels of effluents for both point sources such as sewage treatment plants and industries as well as non-point sources such as farms and run-offs that discharge into these segments. Hence, the policy backdrop is that point sources are responsive to ambient water quality in the sub-watershed as well as monitoring frequency of downstream water quality. For example, if a biennial assessment reveals that designated use of that river segment is not met then TMDLS are assigned with more stringent effluent requirements for plants. On the other hand, if a water quality assessment reveals that designated uses are met then that stream segment can be de-listed from the 303(d) impaired streams list. For stream segments that meet ambient water quality standards, effluent limits might even be revised upwards due to costly abatement burden and especially if they are overcomplying with their original limits (Chakraborti and McConnell, 2012). Hence

we investigate whether plants increase their pollutant discharges once regular (monthly) monitoring protocol of their receiving stream segment is dropped.

Our empirical framework exploits the exogenous policy change of ambient monitoring stations that were dropped from active operation i.e. became inactive over the time period of 1990 to 2010. Stemming from a research project on assessing the accuracy of self-reported pollution data (Chakraborti and Shimshack, 2012), we gather ambient water quality data from downstream monitoring stations across the US and match them to self-reported monthly pollution data on major dischargers. We found about ten states in regions 3 and 4 of the EPA had reasonable ambient data for the relevant time period. We noticed patterns such as drop in monitoring data in the 2001 onwards period for South Carolina, and somewhat modest drop in 1999 onwards ambient monitoring for Pennsylvania, Georgia, Louisiana, and Alabama, 2001 onwards for Virginia, unlike monitoring in states like Maryland, Arkansas and North Carolina.

The experimental set up is that plants that pollute in a waterbody for which the state EPA stops monitoring falls in the treatment group and plants that do not witness a change in its downstream ambient monitoring falls in the control group. We ran a standard diff-in-diff analysis using monthly pollution reports from major plants and matching it with ambient water quality data from the nearest available downstream water quality data, within a reasonable distance (30 miles). Our future research plan is to extend this analysis to all 10 states for which we have matched plant level pollution to ambient monitoring data. The diff-in-diff would then treat all plants (irrespective of the state) for which ambient monitoring stopped after a certain time period as the treatment group and all other plants with no change in downstream ambient monitoring as the control group. We plan on robustness checks by utilizing the two most commonly studied water pollution measures of biological oxygen demand (BOD) and total suspended solids (TSS). The corresponding ambient water quality measures that are frequently monitored by the states are dissolved oxygen (DO) and ambient TSS.

Taking the self-reported pollution measurement data from major industries and treatment plants, at face value we find that environmental compliance

deteriorates once the downstream monitoring station stops or significantly reduces frequency of monitoring ambient water quality. This result can be validated from the sample of major dischargers in Pennsylvania, South Carolina, and Virginia between the 1990 and 2010 years. We utilize an exogenous change in statewide reduction (or stoppage) of ambient water monitoring for the period 1999 onwards for Pennsylvania and 2001 onwards for Virginia. South Carolina was notable in terms of the sharp decline in monitoring in 2001 onwards years (even compared to the other two states in this study). Overall, we find that plants with either no ambient monitoring, or only one out of four quarters annual monitoring (for a consecutive number of years) reported polluting roughly 30 percent higher BOD concentration in mg/L relative to its effluent limits as well as BOD quantity in lbs/day relative to its permitted levels. This effect is significant because past studies have found that since water pollution abatement technology requires bulky capital investments (McClelland and Horowitz 1999) and they're inflexible in operation, polluters cannot adjust their discharges in response to effluent limit changes (Earnhart 2007) without a sufficient lead time. The research also contributes to the puzzling overcompliance literature and corroborates findings in studies like Chakraborti (2016) that polluters are responsive to ambient water quality, no matter the incentives.

DATA

Pollution Data

The National Pollutant Discharge Elimination System (NPDES) of the Clean Water Act (CWA) is the main source of self-reported pollution data reported by major polluters that are subject to monthly quantity and/or concentration limits on discharges of biochemical oxygen demand (BOD) and/or Total Suspended Solids (TSS). For this paper, I focus on three states Pennsylvania, South Carolina and Virginia. The primary factor was availability of pollution data submitted to the EPAs through the point sources' discharge monitoring reports (DMRS). The EPA's historical Permit Compliance System (PCS) database was discontinued and states began reporting to the Integrated Compliance Information System (ICIS) at different schedules. However, even drawing

from the PCS Envirofacts search the most dated DMRs can be obtained from the year 1998. For example, I drew upon prior (Freedom of Information Act) FOIA requests to the Pennsylvania's Department of Environmental Protection (DEP) to complete the panel from earlier years 1990 to 1997. And beyond 2006, I used Pennsylvania EPA's online electronic DMR (EDMR) reporting system. Similarly, for Virginia, the earliest DMR data obtained from PCS was from 1998 up until 2012. So, I drew upon FOIA requests to Virginia's Department of Environmental Quality (VADEQ) to complete the panel for the years 1990 to 1997. Unfortunately, my personal FOIA requests were for the majors in the states of Region 3 (of the EPA) that were permitted under BOD and carbonaceous-BOD (a conventional pollutant as opposed to nitrogenous-BOD and often with limits of 25 mg/l per month in contrast to 30 mg/l for BOD (5 day) as the most frequently implemented technology based requirement). So, the 1990 to 2010 panel could not be completed for the other conventional pollutant of total suspended solids (TSS). For South Carolina, PCS data was available from 1998 to 2012 for both BOD5 and TSS. To complete the panel from 1990 to 2010, I utilized prior FOIA data requested under the Chakraborti and Shimshack (2012) research project.

For Pennsylvania, there were 221 major facilities between 1990 and 2010 that faced either BOD5 or CBOD quantity monthly limits and there were 238 major facilities that faced either BOD5 or CBOD concentration monthly limits. We needed a long panel for the natural experiment as ambient water quality is slowly evolving due to assimilative capacity but pollution from facilities also takes time to change as discussed in the previous section on past studies. The challenge in utilizing 21 years of data, is that PCS facilities witness changes in major status e.g. minor to major and vice versa. The sample then exhibits a lot of variability in the years for which each of the 200 something facilities are tracked. The panel was unbalanced with 50% of the plants had around 11 years of data for both quantity and concentration limits. In robustness checks, we focus on plants with at least 50% monthly data.

For Virginia, there were 109 major facilities that faced BOD5 and CBOD quantity limits and 101 facilities with concentration limits. The panel was unbalanced with 50% of the plants roughly 12 years of data for both quantity and concentration limits.

For South Carolina, there were 124 facilities with concentration limits and 158 facilities with quantity limits. The panel was much more balanced with 50% of the plants reporting around 18 years of data for both concentration and quantity limits.

For concentration limits, the distribution across states varied between 75%, 80% and 83% of the facilities that were sewage treatment plants for Pennsylvania, South Carolina and Virginia respectively. For quantity limits, the proportion of sewage treatment plants varied between 60%, 77% and 85% for South Carolina, Virginia and Pennsylvania respectively. Sewage treatment plants are publicly owned and more likely to face both concentration and quantity limits as a means to impose requirements on both abatement technology as well as effluent loads into water bodies, as opposed to manufacturing facilities that are more likely to face only quantity limits as effluent load permits. As robustness check, we focus on sewage treatment plants and manufacturing (and others) separately; when pooling across the three states the final distribution between sewage treatment plants and manufacturing evened out at 80% and 20% for concentration limits and 75% and 25% for quantity, respectively.

Ambient Water Quality Data

Parallel to the transition in pollution reporting system the EPA's centralized database on ambient water quality monitoring also underwent a process of historical data retained under the STORAGE and RETRIEVAL (STORET) Legacy Data Center up until 1998. And subsequently data is shared under the Water Quality eXchange (WQX) system from 1999 to current. Unfortunately, this transition was not smooth either from the perspective of a researcher. First, most agencies that were not state water quality monitoring departments were dropped for instance USGS monitoring. Second, and perhaps more relevant for the proposed experiment in this paper is that the network of monitoring stations changed substantially. From minor issues such as changes in station ids (same geographical reference) to not so minor issues such as monitoring locations dropped i.e. becoming inactive in operation while others introduced into the network for purposes of monitoring pollutants other than the conventional measures of dissolved oxygen, pH, turbidity and fecal coliform etc. Further research yielded that

some of these monitors were still in operation but failed to get consolidated with the modernized STORET-WQX system. Personal requests with the respective state officials were very successful in obtaining access to a rich panel data on dissolved oxygen monitoring data from Virginia e.g. Noteworthy, states in Region 3 of the EPA witnessed a rise in interest in monitoring and citizen complaints of illegal discharges under the Chesapeake Bay Program (CBP) initiative. In the end, we ended up with a reasonably (un)balanced panel of monthly DO and ambient TSS data for ten states in Regions 3 and 4 of the EPA. However, gathering data on ambient water quality from federal or state EPAs was more straightforward than completing the pollution panel for the 1990 to 2010 period. A stark example is the case of North Carolina with a rich panel of ambient water quality data from 1990 to 2010 but no pollution data on majors forthcoming from the year 2000 onwards.

Matching Pollution from Plants with Downstream Ambient Water Quality

We used EPA's Better Assessment Science Integrating point and Non-point Sources (BASINS) software to get the geographical location data on major polluters in the states and ambient water quality monitoring stations under the STORET data system. Availability of ambient water quality data at the nearest downstream monitoring station was a concern. So, we focused on the downstream water quality station at a reasonable distance (30 miles) downstream with a reasonably good panel on monthly ambient monitoring data.

For Pennsylvania, we could match roughly 85% of the major facilities with downstream monitoring stations with ambient water quality data (within 30 miles). For South Carolina, we could match roughly 83% of the facilities with downstream monitoring stations for both concentration and quantity limits. For Virginia, we could match almost 91% of the major facilities with downstream monitoring stations for both concentration and quantity limits.

Table 1 below shows that overall plants were overcomplying i.e. on average concentration discharges were only 34% of their limits in Pennsylvania and Virginia and 37% of their limits in South Carolina. As expected, the relative quantity discharges exhibit more variability both within and across states. Quantity loads are more

influenced by size and type of facility generating the waste in contrast to concentration which is more of an efficiency of abatement technology regulation.

Table 1. Summary Statistics of Pollution for the entire sample and frequency of monitoring

State	Ratio of BOD5 and CBOD concentration to limits	Ratio of BOD5 and CBOD quantity to limits	# of monthly ambient water quality, Pre-treatment	# of monthly ambient water quality, Post-treatment
Pennsylvania	.3439 (.9070808)	.4014729 (11.44917)	31,856	22,816
South Carolina	.3649942 (.2976651)	.2615168 (1.112078)	19,021	8,438
Virginia	.3429805 (1.19515)	.564787 (6.096937)	13,561	9,328

EMPIRICAL STRATEGY

In this section we present various models to establish that plants facing distinct frequencies of downstream ambient water quality monitoring behave different from those that were frequently monitored for the 21 years of CWA regulation. Studies like Chakraborti and McConnell (2012) have shown that the permitted level of effluents i.e. limits faced by major polluters were changed in response to downstream water quality monitoring results. Hence we speculate that the causal mechanism that might explain such responsiveness is the channel of changes in regulation i.e. changes in permits. Throughout, our identification strategy is the exogenous variation in ambient water quality monitoring faced by each polluter that is outside the polluters' control. We present both linear panel data and diff-in-diff models exploiting this exogenous variation in frequency of monitoring in particular changes such as reduced monitoring.

Analysis on Plants with and without Downstream Water Quality

Monitoring

In this section we exploit the exogenous (to the plants') variation in downstream water quality monitoring over the entire time period of 21 years. In other words, we investigate whether plants that were not monitored downstream for ambient water quality were different from plants that were monitored for water quality downstream to their effluent discharges.

3.1.1. Panel Data Model 1

$$\ln\left(\frac{BOD_{it}}{Limit_{it}}\right) = \alpha + \beta_i + \gamma_t year_t + \delta_i state_i + \vartheta nowat_i + \varepsilon_{it} \quad (1)$$

Equation (1) is a linear panel data model where the dependent variable is log of relative discharge i.e. the ratio of monthly concentration or quantity discharge to its corresponding limit. Quantity discharges are influenced more by the size of the plant or scale of operation as it is pollutant loadings while concentration of pollutant in effluents is more influenced by the efficiency of the abatement technology. β_i is the plant fixed effects included as plant specific dummy variables (size, age, type of facility), $nowat_i$ is the indicator/dummy variable that takes a value of 1 for plants that did not have any downstream ambient monitoring and 0 otherwise, $year_t$ capture year specific effects by including 20 annual year dummy variables and $state_i$ capture state specific effects such as differences in regulation or monitoring and enforcement stringency or environmental attitudes of citizens etc. The standard errors reported are clustered within plant as discharges from the same plant are expected to be correlated over time.

In our dataset, there are 50 major plants that faced concentration limits but without any downstream ambient monitoring—22 in Pennsylvania, 20 in South Carolina and 8 in Virginia. For quantity limits, there are 54 major plants without any ambient monitoring—19 in Pennsylvania, 26 in South Carolina and 9 in Virginia. The results presented in Table 2 shows that indeed plants without ambient water quality monitoring increase their relative concentration and quantity discharges, over the

entire 1990 to 2010 time period. This result leads us to infer that polluters might be strategic and be responsive to whether there are ambient water quality records downstream to its effluent discharges. The coefficient in the first column can be interpreted as plants without ambient monitoring double their relative concentration discharges compared to plants with downstream ambient monitoring. This suggests significant responsiveness of plants to ambient water quality other than effluent limits (regulations) and its stringency of implementation through monitoring and enforcement factors as has been shown in previous studies. It might also ‘identify’ a channel or a mechanism to explain costly overcompliance. The second column shows that plants without ambient monitoring increase their loads in lbs/day by 34% in contrast to plants with downstream monitoring. The magnitude is large given that pollutant loads are mostly determined by the scale of operation and type of facility.

Table 2. Fixed Effects Regression of Relative Discharges on Ambient Monitoring Indicator, 1990-2010

	log relative concentration discharge	log relative quantity discharge
nowat	1.120***	0.342***
	(0.074)	(0.018)
R²	0.46	0.46
N	40,111	46,746

Note: All regressions include plant dummy variables, state and year dummies; standard errors in parenthesis: * p<0.1; ** p<0.05; *** p<0.01.

Diff-in-Diff Model 1: The Effect of Reduction in Statewide Monitoring on Plants that were not monitored for downstream water quality

The exogenous policy change is a decline in frequency of ambient water quality monitoring post 1998 for Pennsylvania and post 2000 for Virginia, by 30% for both states. In South Carolina the frequency of ambient monitoring fell by almost 45% post 2000. See Table 1 for the frequency of reduced monitoring in monthly water quality records by state. So, for this experiment I test whether the treatment of decline in statewide ambient water quality monitoring had any differential impact on major

facilities without any downstream ambient water quality monitoring (treatment group) as opposed to facilities that had some downstream monitoring (control group). From our results of the linear models we hypothesize that the treatment effect would be captured by facilities without ambient monitoring increasing their pollution discharges in the post-treatment phase and the magnitude of this impact would be higher than facilities with ambient monitoring (as captured by the interaction term of no water quality indicator and post treatment period).

Table 3 (a, b, and c) below present summary statistics of the sample for the plants with and without ambient water quality but differentiated by the pre- and post-treatment of general decline in ambient water quality monitoring post 1998 for Pennsylvania, and post 2000 for South Carolina and Virginia. The data summary shows that as hypothesized plants without ambient monitoring increase their relative discharges in the post-treatment period more so than the plants with ambient monitoring (in the post-treatment period). Except for relative quantity discharges for majors in South Carolina (Table 3b).¹ In fact, plants with downstream monitoring seem to reduce their relative discharges on average (in contrast to the pre-treatment levels).

Table 3a. Summary Statistics on Pollution by Ambient Water Quality Groups, Pennsylvania

Variable	Pre-treatment		Post-treatment	
	With Ambient Water Quality, 1990-1998	Without Ambient Water Quality, 1990-1998	With Ambient Water Quality, 1999-2010	Without Ambient Water Quality, 1999-2010
Ratio of BOD5 and CBOD concentration to limits	.3979522 (1.100234)	.3286047 (.3896191)	.27183 (.2799216)	.4567794 (2.044829)
Ratio of BOD5	.5535479	.3400424	.2147769	.5576595

¹ As mentioned before quantity loadings are not only determined by efficiency of pollution abatement technology but also by effluent flow which captures size of the plant's operation.

and CBOD quantity to limits	(15.95879)	(.6447998)	(.2679585)	(3.369004)
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Table 3b. Summary Statistics on Pollution by Ambient Water Quality Groups, South Carolina

Variable	Pre-treatment		Post-treatment	
	With Ambient Water Quality, 1990-2000	Without Ambient Water Quality, 1990-2000	With Ambient Water Quality, 2001-2010	Without Ambient Water Quality, 2001-2010
Ratio of BOD5 and CBOD concentration to limits	.4158031 (.3389884)	.3495367 (.2202048)	.2934683 (.2268364)	.4561734 (.2864127)
Ratio of BOD5 and CBOD quantity to limits	.3258243 (1.495836)	.2912601 (.3615089)	.1593675 (.1600514)	.1766216 (.1603976)

Table 3c. Summary Statistics on Pollution by Ambient Water Quality Groups, Virginia

Variable	Pre-treatment		Post-treatment	
	With Ambient Water Quality, 1990-2000	Without Ambient Water Quality, 1990-2000	With Ambient Water Quality, 2001-2010	Without Ambient Water Quality, 2001-2010
Ratio of BOD5 and CBOD concentration to limits	.3624982 (1.454838)	.2646388 (.2752923)	.3171623 (.5970967)	.3203296 (.1682011)
Ratio of BOD5 and CBOD quantity to	.6949399 (7.364025)	.176212 (.1289854)	.4081222 (3.577165)	.2033309 (.1353012)

limits				
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Empirical Diff-in-Diff Model 1

$$\ln\left(\frac{BOD_{it}}{Limit_{it}}\right) = \alpha + \beta Post_t + \gamma nowat_i + \theta(Post_t * nowat_i) + \epsilon_{it} \quad (2)$$

Table 4 below shows that plants with downstream ambient water quality monitoring reduced their relative concentration and quantity discharges in the post-treatment period. The coefficient on *nowat* can be interpreted as plants without downstream water quality monitoring reduced their relative concentration and quantity discharges in the absence of the exogenous decline in water quality monitoring. The coefficient on the interaction term is the treatment effect i.e. indeed plants without ambient monitoring increase their relative concentration discharges by 34% and relative quantity discharges by 33% in contrast to plants with ambient monitoring, in the post-treatment period.

Table 4. DID Estimates of the Effect of Reduction in Water Quality Monitoring on Plants without downstream monitoring

	log relative concentration discharge	log relative quantity discharge
Post	-0.280***	-0.453***
	(0.008)	(0.010)
nowat	-0.068***	-0.075***
	(0.017)	(0.020)
Post*nowat	0.337***	0.330***
	(0.030)	(0.038)
_cons	-1.260***	-1.653***
	(0.005)	(0.006)
R²	0.03	0.04
N	40,111	46,746

Note: Standard errors in parenthesis: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Panel Data Model 2: The Effect of 50% Drop in Monitoring on Plants that were monitored for Downstream Water Quality

In this section we investigate whether plants that witnessed a drop in annual ambient monitoring frequency by 50% in contrast to the pre-treatment period, increase their relative discharges in contrast to those plants that did not witness a corresponding decline in ambient monitoring. This is an empirical test of the validity of the exogenous change of decline in overall ambient water quality monitoring but focused on plants that had some water quality monitoring over the 21 years in our sample (unlike the previous section). The linear panel data results are presented focusing on the majors with some water quality monitoring over the entire period. The reduced monitoring frequency indicator itself was perfectly correlated with the treatment period in Experiment 1 and hence diff-in-diff analysis was not possible.

In our dataset, there were 120 majors facing concentration permits that witnessed a decline in frequency of monthly water quality monitoring by 50% in the post-treatment period. Of these 120, 51 plants were in South Carolina, 35 in Virginia and 34 in Pennsylvania. Among plants that faced quantity permits, 131 of them witnessed a decline in frequency of monthly water quality monitoring by 50% compared to the pre-treatment period. Of these 131, 63 plants were in South Carolina, 37 in Virginia and 31 in Pennsylvania. In Table 5 (a, b, and c) we present some summary statistics on the relative discharges of plants in the post-treatment period that witnessed a decline in 50% monitoring and plants in the post-treatment period that did not witness 50% decline in monitoring. We compare these two groups with average relative discharges in the pre-treatment period which we interpret as baseline levels of pollution. We observe that overall plants in both groups reduced their relative discharges in the post-treatment period; however, plants that did not witness a 50% decline in water quality monitoring reduced their pollution even more so that plants that did witness a 50% decline in monitoring (except for relative concentration and quantity discharges for Virginia, Table 5c).

Table 5a. Summary Statistics on Pollution by 50% drop in Ambient Monitoring Groups, Pennsylvania

Variable	Baseline (pre-treatment)	Post-treatment	
		Without 50% drop in Ambient Monitoring, 1999-2010	With 50% drop in Ambient Monitoring, 1999-2010
Relative Discharge	With Ambient Monitoring, 1990-1998	Without 50% drop in Ambient Monitoring, 1999-2010	With 50% drop in Ambient Monitoring, 1999-2010
Ratio of BOD5 and CBOD concentration to limits	.3941042 (1.073305)	.2771986 (.2901699)	.3400362 (1.451043)
Ratio of BOD5 and CBOD quantity to limits	.5473538 (15.72597)	.2235676 (.2781984)	.3127772 (2.189042)

Table 5b. Summary Statistics on Pollution by 50% drop in Ambient Monitoring Groups, South Carolina

Variable	Baseline (pre-treatment)	Post-treatment	
		Without 50% drop in Ambient Monitoring, 2001-2010	With 50% drop in Ambient Monitoring, 2001-2010
Relative Discharge	With Ambient Water Quality, 1990-2000	Without 50% drop in Ambient Monitoring, 2001-2010	With 50% drop in Ambient Monitoring, 2001-2010
Ratio of BOD5 and CBOD concentration to limits	.4065802 (.3258676)	.2770637 (.2231919)	.3124477 (.2339259)
Ratio of BOD5 and CBOD quantity to limits	.3208409 (1.390642)	.1465269 (.145875)	.169861 (.1692994)

Table 5c. Summary Statistics on Pollution by 50% drop in Ambient Monitoring Groups, Virginia

Variable	Baseline	Post-treatment	
	(pre-treatment)		
Relative Discharge	With Ambient Water Quality, 1990-2000	Without 50% drop in Ambient Monitoring, 2001-2010	With 50% drop in Ambient Monitoring, 2001-2010
Ratio of BOD5 and CBOD concentration to limits	.3532682 (1.410613)	.3204771 (.7180828)	.3069807 (.2227637)
Ratio of BOD5 and CBOD quantity to limits	.6552843 (7.092536)	.4828632 (4.333925)	.2435129 (.6378833)

Empirical Model

The linear panel data model that is estimated in presented in equation (3) below. The only difference from panel data model 1 is the *drophalfwat_{it}* indicator variable that takes on a value of 1 in the post-treatment period for plants that witnessed a drop in ambient monitoring frequency by 50% and a value of 0 for plants that did not experience a 50% drop in ambient monitoring in the post-treatment period. This indicator takes on the same value of 0 for the pre-treatment period. Hence we exploit the exogenous (to the plants’) variation in ambient monitoring frequency within the same plant(s) in the fixed effects models to identify the impact of 50% drop in monitoring frequency.

$$\ln\left(\frac{BOD_{it}}{Limit_{it}}\right) = \alpha + \beta_i + \gamma_t year_t + \delta_i state_i + \vartheta drophalfwat_{it} + \varepsilon_{it} \quad (3)$$

Where T refers to the two time periods of pre-treatment and post-treatment
T={0,1} for 1990-1998, 1999-2010 for Pennsylvania,
and 1990-2000, 2001-2010 for South Carolina and Virginia

The results shown in Table 6 below can be interpreted as plants experiencing a 50% drop in monthly ambient monitoring increase their relative concentration discharges by 13% while plants experiencing a 50% drop in ambient monitoring increase their relative quantity discharges by 7%.

Table 6: Fixed Effects Regression of Relative Discharges on 50% drop in Water Quality Monitoring Indicator, 1990-2010

	log relative concentration discharge	log relative quantity discharge
50% drop in	0.132***	0.072***
water monitoring	(0.014)	(0.017)
R²	0.46	0.46
N	39,906	46,571

Note: All regressions include plant dummy variables, state and year dummies; standard errors in parenthesis: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

The Effect of Annual Frequency of Monitoring on Plants that were monitored for Downstream Water Quality

Panel Data Model 3: Do plants respond to frequency of water quality monitoring on a yearly basis?

In this section, we exploit the panel nature of the data and investigate whether short run (annual) changes in frequency of ambient water quality monitoring results in plants' response by influencing their relative discharge levels. As mentioned before ambient water quality records are publicly accessible through the EPA and state environmental agencies so polluters can access and gain knowledge of the water quality as well as frequency of monitoring downstream to their effluent discharges. I hypothesize that reduced frequency of monitoring leads polluters to increase their relative discharges (given that they are significantly overcomplying with their limits). In particular, equation (3) below presents the empirical model where the log of relative discharges is regressed on an indicator of frequency of "low" water quality

monitoring on an annual basis. We define “low” as only a quarter i.e. three months’ data records in 12 months.

In our dataset, there were 168 facilities that faced concentration limits and witnessed reduced frequency of water quality monitoring at least once in the entire time period. The distribution was 55 in Pennsylvania, 65 in South Carolina and 48 in Virginia. There were 176 facilities with quantity limits that witnessed reduced monitoring frequency for at least one year—41 in Pennsylvania, 84 in South Carolina and 51 in Virginia. The results presented below in Table 7 show that indeed low frequency of ambient water quality monitoring results in polluters increasing their current relative concentration and quantity discharges by about 6.7% and 6% respectively. We interpret these coefficients as economically significant abatement technology and flexibility has been found to be bulky and expensive with considerable lags even to changes in regulation. At the same time, it might be worth mentioning about the data that on average each plant faced this phase of 3/4 decline in annual monitoring for a period of more than 6 years (of the maximum possible of 21 years). So, our results are consistent with prior evidence on “lag” in pollution adjustments.

$$\ln\left(\frac{BOD_{it}}{Limit_{it}}\right) = \alpha + \beta_i + \gamma_t year_t + \delta_i state_i + \rho lowwat_{it} + \varepsilon_{it} \quad (4)$$

Table 7. Fixed Effects Regression of Relative Discharges on ¾ drop in Annual Monitoring Frequency Indicator, 1990-2010

	log relative concentration discharge	log relative quantity discharge
¾ drop in annual monitoring	0.067*** (0.011)	0.060*** (0.014)
R²	0.47	0.45
N	36,607	42,716

Note: All regressions include plant dummy variables, state and year dummies; standard errors in parenthesis: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Diff-in-Diff Model 2: The Effect of Drop in Monthly Monitoring by 3/4 Annually

In this section, we exploit the panel data on monthly ambient water quality monitoring to identify the treatment group of major facilities that witnessed a decline in downstream ambient water quality monitoring in contrast to the control group of facilities that did not witness a decline in monitoring on an annual basis. The exogenous policy change is again the decline in statewide ambient monitoring post 1998 for Pennsylvania and post 2000 for South Carolina and Virginia respectively. In particular, we investigate whether plants that witnessed a decline in annual monitoring by 3/4 i.e. 9 out of the 12 months, responded differently from plants that did not witness decline in annual monitoring frequency by three quarters.

Table 8 (a, b and c) show the summary statistics of the two groups of plants—the ones that did not experience any decline in annual monitoring frequency, by three quarters, and those that did experience a decline in annual monitoring by three quarters. We observe that overall plants that did not witness any decline in annual monitoring frequency by three quarters, reduced their relative concentration and quantity discharges in the post-treatment period by a higher magnitude than the plants that did witness a decline in frequency of annual monitoring (except for relative concentration discharges in Virginia as seen in Table 8c). In general, both groups of plants reduced their relative discharges in the post-treatment period in contrast to their pre-treatment period.

Table 8a. Summary Statistics on Pollution by drop in $\frac{3}{4}$ Annual Monitoring Groups, Pennsylvania

Variable	Pre-treatment		Post-treatment	
	No decline in Ambient Water Quality, 1990-1998	Decline in Ambient Water Quality by 3/4, 1990-1998	No decline in Ambient Water Quality, 1999-2010	Decline in Ambient Water Quality by 3/4, 1999-2010
Ratio of BOD5 and CBOD	.4048305 (1.138075)	.3095742 (.3380988)	.2741291 (.3005285)	.2641961 (.1964912)

concentration to limits				
Ratio of BOD5 and CBOD quantity to limits	.5642783 (16.2739)	.2845646 (.230081)	.2124629 (.2756901)	.2263347 (.2252058)

Table 8b. Summary Statistics on Pollution by drop in $\frac{3}{4}$ Annual Monitoring Groups, South Carolina

Variable	Pre-treatment		Post-treatment	
	No decline in Ambient Water Quality, 1990-2000	Decline in Ambient Water Quality by 3/4, 1990-2000	No decline in Ambient Water Quality, 2001-2010	Decline in Ambient Water Quality by 3/4, 2001-2010
Ratio of BOD5 and CBOD concentration to limits	.4210642 (.3427606)	.3067503 (.2219305)	.2800444 (.2213593)	.3048561 (.2307989)
Ratio of BOD5 and CBOD quantity to limits	.3298915 (1.520386)	.2052654 (.1668847)	.1516576 (.1519433)	.1666702 (.1670584)

Table 8c. Summary Statistics on Pollution by drop in $\frac{3}{4}$ Annual Monitoring Groups, Virginia

Variable	Pre-treatment		Post-treatment	
	No decline in Ambient Water Quality, 1990-2000	Decline in Ambient Water Quality by 3/4, 1990-2000	No decline in Ambient Water Quality, 2001-2010	Decline in Ambient Water Quality by 3/4, 2001-2010
Ratio of BOD5 and	.3593626	.4358592	.3173059	.3167371

CBOD concentration to limits	(1.483229)	(.4003638)	(.6710424)	(.281223)
Ratio of BOD5 and CBOD quantity to limits	.7081937 (7.492747)	.3223333 (.5747046)	.4649892 (4.094769)	.2274572 (.3773108)

Empirical Diff-in-Diff Model 2

The interaction term in the equation (4) below captures the treatment effect of a decline in water quality monitoring (the exogenous change) on plants that experienced a drop in 3 out of the 4 quarters of ambient monitoring, annually. The results in Table 9 show that indeed plants that experienced a $\frac{3}{4}$ drop in annual monitoring increased their relative concentration discharges in the post-treatment period by 30% in contrast to the control group, and they increased their relative quantity discharges by 23% in contrast to those plants that did not experience a $\frac{3}{4}$ decline in annual monitoring. The other two coefficients are very similar in sign to the DID models estimated using no water quality monitoring as the treatment group (Table 4). Plants that did not witness a decline in $\frac{3}{4}$ drop in annual monitoring reduced their relative concentration and quantity discharges (coefficient on Post in Table 9; as well can be seen in the Tables 8 a, b and c). Plants that experienced a drop in $\frac{3}{4}$ annual monitoring reduced their relative concentration and quantity discharges in the absence of the exogenous change in reduction in water quality monitoring (the un-interacted coefficient on lowwat).

$$\ln\left(\frac{BOD_{it}}{Limit_{it}}\right) = \alpha + \pi Post_t + \tau lowwat_{it} + \mu(Post_t * lowwat_{it}) + \epsilon_{it} \quad (4)$$

Table 9. DID Estimates of the Effect of Reduction in Water Quality Monitoring on Plants with a drop in $\frac{3}{4}$ Annual Monitoring

	log relative concentration discharge	log relative quantity discharge
Post	-0.341***	-0.461***

	(0.010)	(0.012)
lowwat	-0.165***	-0.223***
	(0.024)	(0.035)
Post*lowwat	0.300***	0.225***
	(0.028)	(0.039)
_cons	-1.252***	-1.646***
	(0.005)	(0.006)
R²	0.03	0.05
N	36,607	42,716

Note: Standard error in parenthesis: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

ROBUSTNESS CHECKS

Quantile Regressions

In this section we address the question whether plants respond differently depending on whether they are close to their permitted levels of effluent discharges. We estimate conditional quantile regressions for relative concentration and quantity discharges. We include the water quality monitoring indicator and year and state dummy variables. In addition, we focus our analysis on a balanced sample i.e. plants with at least 50% monthly relative discharge data, in order to draw meaningful conclusions when we compare relative magnitudes across different quantiles of the log of relative discharges distribution.

Table 10 below considers the no water quality monitoring indicator for the entire time period 1990 to 2010. Our hypothesis is that for plants that are close to their permitted levels of effluent discharges, we do not expect to see much responsiveness in terms of increased pollution when plants do not have ambient water quality monitoring. This is because major polluters face significant monitoring and enforcement actions if they are found in violation of their regulation. On the other hand, for plants that are in lower quantiles of the log relative discharge distribution are overcomplying substantially with their permitted levels of effluents and might be more responsive by increasing pollution when they do not have downstream ambient

water quality monitoring because they have reduced costs of expected non-compliance. Table 10 below shows that indeed plants that are at lower quantiles of the log of relative quantity distribution increase their pollution when they have no ambient water quality monitoring. At the 10th percentile of log relative quantity, plants increase their relative discharges by as much as 44%. This magnitude declines to 25% at the 25th percentile of log relative quantity discharges and 16% at the 50th percentile of log relative quantity discharges. For plants that are at higher quantiles of the log relative quantity distribution, we do not find that polluters exert any statistically significant influence by increasing pollution when there is no ambient water quality monitoring. For the log relative concentration discharge regressions, we do not find any difference in statistical significant results of increasing pollution when there is no ambient water quality monitoring data. We do notice a decline in magnitude for plants that are lower quantiles of the log relative concentration distribution as opposed to plants that are at higher quantiles which is economically meaningful. This result can be interpreted as polluters having more flexibility in adjusting their quantity loads as opposed to concentration of pollutants in their effluents as the latter puts restrictions on the efficiency of abatement technology of the polluters which is inflexible as previous studies find.

Table 10. Conditional Quantile Regressions of No Water Quality Indicator on Relative Discharges, Balanced Sample

	log relative concentration discharge	log relative quantity discharge
10% Quantile	0.268***	0.443***
	(0.027)	(0.039)
25% Quantile	0.112***	0.253***
	(0.026)	(0.027)
50% Quantile	0.074**	0.159***
	(0.032)	(0.018)
75% Quantile	0.065**	0.036

	(0.027)	(0.033)
90% Quantile	0.063**	-0.021
	(0.031)	(0.031)
N	26,410	31,657

Note: All regressions include state and year dummies; bootstrapped standard errors in parenthesis: * p<0.1; ** p<0.05; *** p<0.01.

Table 11 tests the measure of reduced frequency of ambient water quality monitoring on different quantiles of the log of relative quantity and concentration distribution. Our hypothesis is that plants at higher quantiles of log relative distribution do not have as much flexibility as plants at lower quantiles of the log relative distribution to increase their pollution when there is reduced monitoring of ambient water quality. Our results are for plants that reported at least 50% monthly pollution data for the 1990 to 2010 period. The conditional quantile regressions (with year and state dummy variables) show that indeed plants increase their relative quantity discharges by between 10% and 30% when they are at lower quantiles of the relative quantity discharges (10th to 50th percentiles). For relative concentration discharges, we find that the 50% drop in ambient monitoring indicator has a consistent effect at all log pollution percentiles.

Table 11: Conditional Quantile Regressions of drop in 50% Monitoring Indicator on Relative Discharges, Balanced Sample

	log relative concentration discharge	log relative quantity discharge
10% Quantile	0.182***	0.288***
	(0.021)	(0.028)
25% Quantile	0.158***	0.101***
	(0.020)	(0.017)
50% Quantile	0.121***	0.115***
	(0.017)	(0.015)

75% Quantile	0.170***	0.081***
	(0.021)	(0.024)
90% Quantile	0.188***	0.035
	(0.032)	(0.028)
N	26,275	31,522

Note: All regressions include state and year dummies; bootstrapped standard errors in parenthesis: * p<0.1; ** p<0.05; *** p<0.01.

The third set of quantile regressions utilize the drop in 3 out of 4 quarters monitoring on an annual basis for each plant and tests whether this indicator is consistent at different log pollution percentiles. Similar to the previous two water monitoring indicators, we find reduced annual monitoring to exert a positive effect i.e. higher relative quantity discharges at the lower quartiles. For relative concentration, reduced monitoring on an annual basis indicator has a consistent and statistically significant coefficient at all log pollution percentiles.

Table 12. Conditional Quantile Regressions drop in $\frac{3}{4}$ Annual Monitoring Indicator on Relative Discharges, Balanced Sample

	log relative concentration discharge	log relative quantity discharge
10% Quantile	0.069**	0.113***
	(0.028)	(0.034)
25% Quantile	0.080***	0.019
	(0.019)	(0.021)
50% Quantile	0.072***	0.032**
	(0.014)	(0.014)
75% Quantile	0.090***	0.013
	(0.018)	(0.017)
90% Quantile	0.086***	-0.011
	(0.022)	(0.022)

<i>N</i>	24,735	30,318
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Note: All regressions include state and year dummies; bootstrapped standard errors in parenthesis: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Public versus Private Ownership

Our last set of robustness checks divides up our sample of plants into publicly owned sewage treatment works (POTWS) and manufacturing and other facilities (that are privately owned). As mentioned before the distribution of public treatment works versus other manufacturing facilities was 80% and 20% for relative concentration discharges and 75% and 25% for relative quantity discharges. Despite discrepancies in sample size, we estimate our different models separately. Below we highlight some of the differences.

Table 13 shows that the no water quality monitoring indicator has a significant influence on increasing relative concentration and quantity discharges for POTWS and only for relative concentration discharges for privately owned plants.

Table 13. Fixed Effects Regression of No Water Monitoring Indicator on POTWS and others

	log relative concentration (POTWS)	log relative quantity (POTWS)	log relative concentration (others)	log relative quantity (others)
nowat	0.949***	1.279***	1.238***	0.044
	(0.000)	(0.042)	(0.189)	(0.128)
R²	0.49	0.49	0.40	0.40
N	30,823	30,597	9,288	16,149

Note: All regressions include plant dummy variables, state and year dummies; standard errors in parenthesis: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 14 below presents the difference in difference results of the treatment effect of reduction in overall water quality monitoring on plants without any water monitoring data, by POTWS and privately owned plants. The results are very similar in

sign to the entire sample estimation results; except for the un-interacted coefficient on ‘no water quality’ indicator which can be interpreted as POTWS reducing their relative concentration and quantity discharges in the absence of the exogenous change in ambient monitoring while privately owned plants increased their relative discharges in the absence of this exogenous event of reduction in monitoring.

Similar to fixed effects regressions in Table 13, the panel data estimations in Table 15, using the drop in 50% ambient monitoring frequency in the ‘post-treatment’ period, we see that the sign and significance on relative quantity discharges for privately owned plants is not similar to POTWS.

Tables 16 and 17 present the fixed effects and diff-in-diff estimations separately for POTWS and others privately owned plants. We do not observe any significant difference among the two types of plants.

Table 14: DID Estimates of the Effect of Reduction in Water Quality Monitoring on Plants with no Water Monitoring Indicator, POTWS and others

	log relative concentration (POTWS)	log relative quantity (POTWS)	log relative concentration (others)	log relative quantity (others)
Post	-0.288***	-0.490***	-0.276***	-0.343***
	(0.009)	(0.011)	(0.021)	(0.020)
nowat	-0.142***	-0.271***	0.134***	0.072**
	(0.019)	(0.025)	(0.033)	(0.031)
Post*nowat	0.345***	0.409***	0.338***	0.636***
	(0.034)	(0.043)	(0.060)	(0.081)
_cons	-1.215***	-1.710***	-1.410***	-1.550***
	(0.006)	(0.007)	(0.013)	(0.012)
R²	0.03	0.06	0.03	0.02
N	30,823	30,597	9,288	16,149

*Note: Standard errors in parenthesis: * p<0.1; ** p<0.05; *** p<0.01*

Table 15: Fixed Effects Regression of 50% drop in Water Quality Monitoring Indicator, POTWS and others

	log relative concentration (POTWS)	log relative quantity (POTWS)	log relative concentration (others)	log relative quantity (others)
50% drop in water monitoring	0.150***	0.133***	0.102***	-0.045
	(0.014)	(0.018)	(0.039)	(0.036)
R²	0.49	0.50	0.40	0.40
N	30,648	30,422	9,258	16,149

*Note: All regressions include plant dummy variables, state and year dummies; standard errors in parenthesis: * p<0.1; ** p<0.05; *** p<0.01.*

Table 16: Fixed Effects Regression of 3/4 drop in Water Quality Monitoring Indicator, POTWS and others

	log relative concentration (POTWS)	log relative quantity (POTWS)	log relative concentration (others)	log relative quantity (others)
3/4 drop in annual monitoring	0.067**	0.068**	0.079***	0.071***
	(0.030)	(0.031)	(0.012)	(0.015)
R²	0.40	0.39	0.49	0.49
N	8,059	14,384	28,548	28,332

Table 17: DID Estimates of the Effect of Reduction in Water Quality Monitoring on Plants with $\frac{3}{4}$ drop in Annual Monitoring, POTWs and others

	log relative concentration (POTWs)	log relative quantity (POTWs)	log relative concentration (others)	log relative quantity (others)
Post	-0.343***	-0.517***	-0.323***	-0.358***
	(0.011)	(0.013)	(0.024)	(0.022)
lowwat	-0.085***	-0.217***	-0.149***	-0.234***
	(0.031)	(0.040)	(0.041)	(0.066)
Post*lowwat	0.214***	0.265***	0.249***	0.259***
	(0.034)	(0.044)	(0.055)	(0.076)
_cons	-1.212***	-1.703***	-1.394***	-1.543***
	(0.006)	(0.007)	(0.014)	(0.012)
R²	0.04	0.06	0.02	0.02
N	28,548	28,332	8,059	14,384

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

FUTURE WORK

Get biennial impaired stream segments data and explore whether attainment status has a role to play as a channel of influence that explains why plants might be concerned about ambient water quality and its monitoring frequency per say.

Enduring task of expanding sample size to cover as many of the 10 states in Regions 3 and 4 of the EPA for which monthly ambient water quality data has already been gathered.

Estimating models for total suspended solids (TSS) the other conventional pollutant heavily studied in the CWA literature.

Including other interesting factors such as changes in local economic conditions.

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