A Watershed Moment: The Clean Water Act and Infant Health

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Abstract

The Clean Water Act (CWA) led to significant improvements in surface water quality, but at a cost exceeding the estimated benefits. This paper is the first to quantify the impact of the Clean Water Act on a direct measure of health and to consider whether incorporating health benefits alters the conclusion of a cost-benefit analysis. We use a difference-in-differences framework to compare infant health outcomes upstream and downstream from wastewater treatment facilities before and after the facility receives a CWA grant. We show that improvements in surface water quality were larger for facilities that were newly required under the CWA to upgrade their treatment technology. We leverage this information in a triple difference design, using counties up and downstream from facilities that were not bound by the CWA's treatment technology requirements as an additional control group. We find that reductions in surface water pollution from the CWA are associated with an 8 gram increase in average birth weight. These results are driven by counties whose public water supply systems draw from surface water rather than groundwater. A back-of-the-envelope calculation finds that the monetary benefits of the CWA's effects on infant health are below 29 billion dollars, or 19 percent of the amount necessary to consider the Clean Water Act grants program cost-effective.

The Clean Water Act is a landmark, yet controversial, policy. Originally enacted in 1948 as the Federal Water Pollution Control Act, Congress significantly expanded the CWA in 1972 to prohibit the discharge of "point source" pollution (i.e. pollution that can be traced back to a specific discharge point) into navigable waters. Improvements in water quality stemming from the CWA have come at a high cost; projects funded through grants to wastewater treatment facilities between 1960 and 2005 cost about $870 billion over their lifetimes (in 2017 dollars) (Keiser and Shapiro, 2019). In total, US government and industry have spent over $1.9 trillion to abate surface water pollution (Keiser et al., 2019). Existing cost-benefit analyses of the Clean Water Act do not estimate positive benefit/cost ratios (e.g. Lyon and Farrow (1995); Freeman (2010)), but none of these analyses account for improvements in health caused by the Clean Water Act, because the health benefits of the CWA have never been quantified.

Historically, policies targeting improvements in child health generate high returns to public funds (Hendren and Sprung-Keyser, 2019), and previous economics literature shows that even small increases in child and infant health can lead to large improvements in later life outcomes.[1] Health benefits often account for a large portion of the total benefits of environmental regulation, with health effects accounting for over 95 percent of all benefits of air pollution regulation (Keiser et al., 2019).

This paper is the first to incorporate direct health benefits into a cost-benefit analysis of the CWA and consider how health effects might alter the cost-benefit ratio of the policy. We quantify these effects using a difference-in-differences framework that compares infant health outcomes upstream and downstream from wastewater treatment facilities before and after the facility received a CWA grant. We also show that improvements to surface water quality associated with CWA grants were largely driven by facilities that were required to comply with the CWA's new treatment technology standards. This motivates a triple difference design that uses counties up and downstream from facilities where treatment technology requirements were not binding as an additional control group.

Existing research estimates the benefits of improved surface water using hedonic analysis that measures the effect of CWA grants on nearby housing prices. Comparing areas up and downstream from wastewater treatment facilities, Keiser and Shapiro (2018) finds that the CWA's grant program led to a reduction in downstream pollution and an increase in downstream housing prices, but these increases were substantially smaller than the CWA's costs. By quantifying how downstream residents value water quality, Keiser and Shapiro (2018) improves upon previous cost-benefit calculations that only accounted for changes in pollution. However, as noted in Keiser et al. (2019), hedonic analysis assumes housing values

[1]For example, Behrman and Rosenzweig (2004) documents the effect of intrauterine nutrient intake on adult health and earnings and Royer (2009) finds cross-generational effects of low birth weight. Comparing lighter and heavier twins, Black et al. (2007) shows that a 10 percent increase in birth weight reduces one year mortality by approximately five deaths per 1,000 births. It is also associated with a 1 percent increase in adult earnings. Also comparing twins, Figlio et al. (2014) finds that a ten percent increase in birth weight is associated with a one twentieth standard deviation increase in high school test scores. Additionally, hospital stays for regular weight births are, on average, $8319 cheaper than those for low birth weight births (Almond et al., 2005).

reflect the implicit value that households place on the quality of nearby surface water. If households are uninformed about nearby surface water quality or do not understand the benefits of reduced surface water pollution, housing values will not reflect the health benefits of the program. In this historic context, it is unlikely that households fully understood the range and extent of the negative health effects from surface water contamination, especially the negative impacts on developing fetuses in utero. By directly estimating the health effects of the CWA, our results compliment those in Keiser and Shapiro (2018) by quantifying one of the largest benefits of the CWA that hedonic analysis is least likely to capture.

Public water systems, including those that draw from a surface water source such as a lake or river, often violate health-based water quality standards, and there is evidence that these violations impact infant and child health (Currie et al., 2013; Grossman and Slusky, 2019; Marcus, 2019). A report by the US Geological Survey (USGS) found that more than one in five source-water samples from public water system source wells contained one or more contaminants at concentrations dangerous to human health. In an analysis of matched water samples from 94 public source wells and their associated public water systems, the same organic contaminants detected in source water consistently appeared at similar concentrations in drinking water after treatment (Toccalino and Hopple, 2010). With over 70 percent of community water system users receiving drinking water from a surface water source as of 1970 (Dieter, 2018), addressing surface water pollution reduces the likelihood of exposure to contaminated drinking water in utero. This can affect birth weight directly, by reducing fetal exposure to contaminants that affect development, and indirectly, by reducing the likelihood that a mother will become ill while pregnant.

We focus on infant health for several reasons. Infant health measures have important and long-lasting impacts on a wide range of outcomes, including one-year mortality, test scores, and adult earnings (Black et al., 2007; Figlio et al., 2014). In addition, infant health is sensitive to a wide range of environmental factors (see, for example, Chay and Greenstone (2003), Currie et al. (2011, 2013), and Knittel et al. (2016)). While adult health depends on both current and historical exposure to pollution and responds to changes in environmental factors slowly, changes to infant health can arise quickly after pollution declines, since infant health depends only on exposure during the in utero period. Finally, infant health is one of the only health measures with geographic information that can be consistently and widely tracked back to the 1970s.

This paper combines data on Clean Water Act grants to wastewater treatment facilitates with information on facility-level compliance with treatment technology requirements imposed by the CWA. This newly combined data allows us to study whether CWA grants had a larger impact on surface water quality and health downstream from facilities that were required to upgrade their wastewater treatment technology. Unlike previous research, which focused on the CWA grants program (Keiser and Shapiro, 2018) or treatment technology regulation (Jerch, 2018) in isolation, this allows us to look at the effect of multiple CWA policies working together, rather than the Act's constituent parts working independently.

We expect grants to lead to the largest surface water quality improvements in areas downstream from facilities that have not yet upgraded to new treatment technology required by the CWA. We show that this is the case using water pollution data from the EPA. CWA grants are only associated with a statistically significant decline in dissolved oxygen deficit, a common measure of surface water quality, for waters downstream from facilities for which the new treatment technology requirement was binding. These declines are statistically larger than changes to water quality downstream from all other facilities. We look for heterogeneous health effects across these facilities, and leverage variation in treatment technology in a triple difference specification that uses facilities where CWA treatment technology requirements were not binding as an additional control group.

Across specifications, we consistently find that CWA grants had a statistically significant impact on birth weight. Our results show that reductions in surface water pollution from the CWA are associated with an 8 gram increase in average birth weight. Using data on public water systems source wells, we show that these results are driven by counties whose public water systems draw from surface rather than groundwater. We also find suggestive evidence that reduced exposure to surface water pollution from water recreation contributed to these effects.

Our results, along with those in Alsan and Goldin (2019), demonstrate that treatment at drinking water plants is not the only way to improve health through water policy. Until now, evidence of the complimentary between drinking water initiatives and sewerage improvements, along with most of our understanding of the effect of water quality on human health came from studies of the late nineteenth and early twentieth century (Troesken, 2001, 2002; Cutler and Miller, 2005; Beach et al., 2016). By studying the CWA, which came into effect long after filtration and chlorination of drinking water became widespread, we show that the complementary between clean water and sewerage policies holds well into the twentieth century and is not limited to settings where drinking water is untreated.

While the monetary benefits of improvements to infant health are substantial, incorporating infant health alone would not alter the final conclusion of a cost-benefit analysis of the CWA. A back-of-the-envelope calculation bounds the monetary benefits of the CWA on infant health under 29 billion dollars, 19 percent of the amount necessary to consider the Clean Water Act grants program cost-effective. However, if grant funds were targeted only towards facilities requiring upgrades to treatment technology, where downstream water quality improvements were found, the health benefits alone account for as much as 29 percent of the amount necessary for grants to be considered cost effective.

1 Background

The transition to public provision of drinking water in the late nineteenth century led to large reductions in diarrheal diseases and typhoid fever, and occurred when urban mortality rates fell more rapidly than at any other time in US history (Ferrie and Troesken, 2008). Improvements in water filtration and chlorination were responsible for nearly half the total mortality reduction, three quarters of the infant mortality reduction, and two thirds of the child mortality reduction in major cities in the late nineteenth and early twentieth centuries (Cutler and Miller, 2005). Beyond reductions in mortality, reduced exposure to contaminated water in utero and childhood can have affects throughout life. Beach et al. (2016) finds that eradicating early-life exposure to typhoid fever would have increased earnings in later life by one percent and increased educational attainment by one month.

These historical reductions in mortality were driven by a combination of clean water initiatives, which removed contaminants at drinking water treatment plants before distributing water for consumption and washing, and effective sewerage, which reduced contamination of drinking water at the source (Alsan and Goldin, 2019). By the time the CWA came into effect, almost all publicly provided drinking water was filtered and chlorinated, but surface water, which most community water systems source from, was still severely polluted. By improving sewerage systems and reducing pollution of source water at a time when drinking water treatment was widespread, the CWA provides a new context to examine the complementarity between sewerage infrastructure and clean water.

The Clean Water Act aimed to slow the flow of contaminants from point sources, such as municipal waste treatment facilities and industrial pollution sources, into rivers and lakes. Changes to industrial pollution regulation did not vary cross-sectionally, requiring all polluters to obtain a permit from the National Pollutant Discharge Elimination System (NPDES) before discharging waste water. Although much of the contamination of US waterways comes from sources that cannot be traced back to a specific facility, such as agricultural runoff, the Clean Water Act placed little regulation on these "non-point" pollution sources.

This paper focuses on the part of the CWA regarding municipal waste treatment, where the policy had different effects across facilities and time. Most communities in the US employ a system of sewers and wastewater treatment plants where sewers collect municipal wastewater from homes, businesses and industries and deliver it to wastewater treatment facilities for treatment and discharge into local waterways (USEPA, 2004). The CWA addressed pollution from municipal waste treatment plants through two arms: grants to wastewater treatment facilities, and regulation of wastewater treatment technology. Newly combined data on which facilities were bound by new treatment technology requirements and the placement and timing of grants facilitates our research design.

1.1 Grants

From 1972 to 1988, the EPA distributed $153 billion (in 2014 dollars) worth of grants to wastewater treatment facilities for capital upgrades. The EPA allocated CWA grant money to states according to a formula based on total population, forecast population, and wastewater treatment needs (Rubin, 1985). States distributed grants to wastewater treatment facilities according to priority lists based on the severity of nearby surface water pollution, the size of the population affected, the need for conservation of the affected waterway, and that waterway's specific category of need (USEPA, 1980).

Since state governments wrote their own priority lists, they had some discretion about where they distributed funds, so it is unlikely that we can treat grant placement as random. This motivates our research design; instead of treating grant timing and location as exogenous, our main specification compares the difference in birth outcomes in areas up and downstream from a given wastewater treatment facility before and after grant receipt between facilities that were required to make treatment technology upgrades and all other facilities. We also explore whether earlier grants were associated with larger health effects due to their higher priority status.

1.2 Regulation

In 1972, over half of US municipal wastewater treatment facilities reported using relatively inexpensive, but less effective, primary treatment. Primary treatment, depicted in Figure 1a, forces wastewater through a series of screens to remove large debris, then allows organic material to settle out in sedimentation tanks. While this removes large detritus and heavy biosolids, it still discharges all but the heaviest organic material into waterways (USEPA, 1998).

The Clean Water Act required all municipal treatment plants to upgrade to secondary treatment by 1977.[2] Plants use secondary treatment technology (Figure 1b) in addition to primary treatment where, after screens filter out large debris, wastewater sits in an aeration tank where bacteria in the water consumes organic material. Secondary treatment removes about 85 percent of organic matter from wastewater, much more than primary treatment removes. Additionally, effluent from secondary treatment is usually disinfected with chlorine before it is discharged into receiving waters, which kills more than 99 percent of harmful bacteria (USEPA, 1998).

At the time the CWA came into effect, 53 percent of plants in the 1972 Clean Watershed Needs Survey reported only using primary treatment. Federal guidelines did not instruct

[2]This goal was not met by 1977, however almost all facilities used at least secondary treatment technology by the end of our study period. In 1988, only 48 of the over 17,000 wastewater treatment facilities in the US were using only primary treatment, and these 48 facilities served less than one percent of the US population (Daigger, 1998).

states to account for a facility's treatment technology when distributing funds (USEPA, 1980), and since grant receipt depended on the needs of a waterway rather than the needs of a specific facility, many facilities already using secondary treatment still received CWA grants.

It would have been difficult for facilities already using secondary treatment in 1972 to make substantial improvements to downstream surface water quality using CWA grant money. This is reflected in data from the 1972 Clean Watershed Needs Survey (CWNS), which was conducted before the EPA distributed any CWA grants. Table 1 shows that, as compared to facilities where upgrades were required, facilities already using secondary treatment were more likely to indicate that they would use CWA grant money to increase staff or improve operations and management. Additionally, Flynn and Smith (2020) finds that CWA grants to facilities already using secondary treatment crowded out funds that municipalities were already spending on sewerage capital rather than causing an increase in sewerage capital spending.

Treatment plants using only primary treatment in 1972 had the most to gain from CWA grants in terms of reductions in downstream pollution. We refer to these facilities as pre-CWA "non-compliant" facilities. The potential benefits of upgrading to secondary treatment were well understood, but waste treatment capital upgrades were expensive. One study by the National Environmental Research Center estimated that upgrading to secondary treatment technology could increase a facility's operating costs by up to 60 percent, and require capital investments of as much as 30 percent of the initial cost of the facility (National Environmental Research Center, 1972). CWA grants provided the resources that non-compliant facilities needed to offset these costs.

Since non-compliant facilities had a clear channel through which to improve surface water quality and were more likely to spend CWA grant money on capital upgrades, we expect the reductions in downstream pollution associated with CWA grants to be largest for non-compliant facilities. This motivates a triple difference design that uses areas downstream of facilities that were not indicated as pre-CWA non-compliant in the 1972 CWNS as an additional control group. Even if grants are placed endogenously, or if individuals sort into downstream communities, so long as states distributed grants to facilities based on the same unobservable characteristics regardless of treatment technology, using compliance as a third difference will capture unobserved changes to up and downstream counties occurring contemporaneously with CWA grants. We find supporting evidence for this assumption by showing that there are no differential changes in demographic characteristics of births after grant receipt in downstream counties relative to upstream across non-compliant and all other facilities.

2 Data

CWA Grants and Municipal Wastewater Treatment Plants

We examine the effects of the Clean Water Act on infant health using data on all 33,429 grants that the EPA distributed to 14,285 wastewater treatment plants. This data comes from the EPA's Grant Information Control System (GICS), and contains detailed information on the project that each grant funded. Most facilities received multiple grants, so we define a facility as "treated" after it receives it's first CWA grant, and treatment is an absorbing state.

Using a unique facility code, we merge grant data with the Clean Watershed Needs Survey. The CWNS is an assessment of the capital investment needed nationwide for publicly-owned wastewater treatment facilities to meet the water quality goals of the Clean Water Act. This linked data provides information on a facility's geographic location, whether or not it received a grant and when, and whether the facility was using primary or secondary treatment technology in 1972.

Spatial Data on Waterways

We define treatment in terms of flow direction. Waterways downstream from a wastewater treatment facility that received a CWA grant are in our treated group, while waterways upstream from wastewater plants will be in our control group. We determine if an area is up or downstream from a facility with the National Hydrography Data Set (NHD), an electronic atlas that maps out the location and flow direction of all waterways in the contiguous United States.

We follow both the EPA and other researchers studying the Clean Water Act by focusing on areas 25 miles up and downstream from treatment facilities.[3] Keiser and Shapiro (2018) found that changes in pollution levels associated with CWA grants are concentrated within 25 miles downstream of wastewater treatment plants. Similarly, this is the distance used by an EPA engineering study on the spread of contaminants from point sources (USEPA, 2001).

Water Pollution

We examine how CWA grants affected trends in downstream pollution, and the relationship between pre-CWA wastewater treatment technology and downstream pollution with pollution data from STORET legacy, which includes over 200 million readings from pollution monitoring stations across the US. We include readings from pollution monitors on rivers and lakes located 25 miles up or downstream from any facility in the CWNS data.

We focus on changes in dissolved oxygen deficit, a continuous measure of water quality defined as 100 minus dissolved oxygen saturation (dissolved oxygen level divided by water's maximum oxygen level). Water loses dissolved oxygen when microorganisms consume oxygen to decompose pollution, and upgrading treatment technology reduces the amount of organic material that a facility releases, so we would expect treatment technology upgrades to correspond with a decrease in downstream dissolved oxygen deficit.

Infant Health

We use birth certificate data from NCHS to measure infant health. These data contain information on birth weight, as well as birth order and mother's age and race. NCHS data also contain county of residence for each birth, which allows us to link births to CWA treatment. We collapse birth weight data to county means, calculating the average birth weight, the probability of being born weighing less than 2500 grams, the percent of non-white births, and the probability of being a mother's first, second, third, or fourth birth in each county year.[4]

[3] Our results are robust to concentrating on areas 5 or 10 miles downstream from treatment facilities. See Appendix.

[4] Data in years prior to 1972 constitutes a 50 percent sample of all births in the US. Years after 1972 contain information on every birth in the US from some states, and a 50 percent sample from the remaining states. Six states had full sample data in 1972, and all states and the District of Columbia had full sample

Population Density

We expect the health effects of improved surface water quality to be concentrated near treated waterways. The exposed fraction of a county's population depends on the number of individuals living near a treated waterway, so defining treatment in a binary way at the county level would include many untreated births in our treatment group. This could cause our reduced form estimates to understate the CWA's true effect. Instead, we use census block level population density data from the US Census Bureau to scale our results by the percent of a county's population living within a mile of a treated waterway, which is shown in Figure 2.

3 Methods

3.1 Pollution

Before comparing birth outcomes up and downstream from wastewater treatment facilities, we examine the first stage relationship between grant receipt and downstream water quality with equation 1.

$$Q_{pdy} = \alpha_0 + \sum_{t=-5}^{-2} \pi_t 1\{y - y_p^* = t\} * d_d + \sum_{t=0}^{7} \gamma_t 1\{y - y_p^* = t\} * d_d + W_{pdy} + \alpha_{pd} + \alpha_y + \epsilon_{pdy} \tag{1}$$

In our pollution estimates, there are two observations for each treatment plant p for each year y. One observation describes mean water quality upstream ($d_d = 0$) and one observation describes mean water quality downstream ($d_d = 1$). Time relative to treatment is defined by $1\{y - y_p^* = t\}$ which is a dummy variable that equals 1 for pollution monitors t years before or after a nearby facility received a CWA grant, and Q_{pdy} is a measure of dissolved oxygen deficit.

data by 1985. Table A3 shows the year in which each state switched to a full sample. To ensure that our results are not driven by the changes in samples, we re-estimate our main specifications on a data set that takes a 50 percent sample of births from state-years that report full sample data. See Appendix for details.

We include year and plant-by-downstream fixed effects, α_y and α_{pd}, respectively. This allows waters both up and downstream from a given wastewater treatment plant to have different mean levels of dissolved oxygen deficit, which controls for time invariant pollution sources that are only up or downstream from a plant. Since dissolved oxygen deficit varies inversely with temperature, W_{pdy} measures temperature at the time the pollution reading was taken.

The π_t and γ_t describe the relationship between dissolved oxygen deficit and CWA grants in downstream waterways for the four years before and eight years after grant receipt. We omit the dummy for the year before treatment (D_{-1}), normalizing the π_t and γ_t to zero in that year. The π_t show the trend in dissolved oxygen deficit before treatment, and the γ_t describe how dissolved oxygen deficit evolved in downstream waterways after treatment.

While Keiser and Shapiro (2018) includes a much more thorough discussion of the effect of CWA grants on pollution, this event study gives us a sense of how pollution downstream from facilities that received CWA grants evolved during our study period. We can further explore whether downstream pollution evolved similarly between non-compliant facilities and all other facilities following grant receipt.

We can summarize this event study by estimating

$$Q_{pdy} = \alpha_0 + \gamma g_{py} * d_d + \beta W_{pdy} + \alpha_y + \alpha_{pd} + \epsilon_{pdy} \tag{2}$$

where g_y equals one after a facility receives it's first CWA grant.[5]

3.2 Infant Health

We check for the existence of parallel trends in birth weight prior to treatment and examine how birth weight evolved in counties downstream from treated facilities after grant

[5]Our pollution specifications compare waterways downstream from facilities that received CWA grants to waterways upstream from these facilities and areas up and downstream from facilities that did not receive CWA grants. Alternatively, we could compare waterways downstream from facilities to waterways upstream from *the same* facility by including a facility-by-year fixed effect in equations 1 and 2. Results from estimating these specifications, presented in the Appendix, are relatively similar to those in Section 4.

receipt with the following event study

$$Y_{cy} = \alpha_0 + \sum_{t=-4}^{-2} \pi_t 1\{y - y_c^* = t\} + \sum_{t=0}^{8} \gamma_t 1\{y - y_c^* = t\} * pct_{cy} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy} \quad (3)$$

where $1\{y - y_c^* = t\}$ measures time relative to a county c being downstream from a facility that received a grant, Y_{cy} is an average birth outcome in county c in year y, and pct_{cy} is the percent of county c's population living within a mile of a treated waterway in year y. Controls in X_{cy} include the percent of births that were a mother's first, second, third, or fourth, and county averages of mother's age and race. Observations are at the county-year level. Since we collapse birth weight data to county means, we weight all of our results by the total number of births that occurred in a county-year.

After presenting this flexible framework, we impose a difference-in-difference structure. We begin with the most general control group, comparing counties downstream from a wastewater treatment facility to all other counties by estimating

$$Y_{cy} = \alpha_0 + \gamma pct_{cy} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy} \quad (4)$$

The presence of local area trends specific to a facility's location could mean that an upstream county is only a good counterfactual for a county located downstream from the same facility. We address this concern in our next specification by collapsing our data to the facility rather than the county level. We take the mean birth weight in all counties downstream from a facility and subtracting the mean birth weight in all counties upstream from the same facility in each year, then estimate the following event study with this difference, ΔY_{py}, as the outcome variable

$$\Delta Y_{py} = \alpha_0 + \sum_{t=-4}^{-2} \pi_t 1\{y - y_p^* = t\} + \sum_{t=0}^{8} \gamma_t 1\{y - y_p^* = t\} * pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py} \quad (5)$$

where p indexes facilities, and pct_{py} measures the percent of downstream counties' populations living within a mile of a treated waterway. We include year and facility fixed effects, α_y and α_p, respectively.[6]

[6]Controls in facility-level specifications are averages from all births in up and downstream counties. Our

We then estimate the associated difference-in-difference[7]

$$\Delta Y_{py} = \alpha_0 + \gamma pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py} \tag{6}$$

This research design exploits a birth's location relative to a wastewater treatment facility by comparing average birth outcomes before and after a facility received a CWA grant between counties up and downstream from that facility. The primary identifying assumption of this design is that, in the absence of CWA grants, birth weight would have evolved similarly in up and downstream counties. We explore whether this assumption is likely to hold in our basic difference-in-difference framework, as well as a triple difference framework that uses facility compliance with new treatment technology standards as a third difference, by putting demographic characteristics on the left-hand side.

Even if individuals positively sorted into downstream communities after grant receipt, it is unlikely that this sorting is differential across facilities' treatment technology compliance. Table 2 tests for this directly by examining the effect of treatment on demographic characteristics that are correlated with birth weight by estimating

$$\Delta x_{py} = \gamma pct_{py} + \alpha_p + \alpha_y + \epsilon_{py} \tag{7}$$

where Δx_{py} is the difference between demographic characteristic in counties up and downstream from facility p in year y. Column 1 of Table 2 reports the result from estimating this equation on a sample of non-compliant facilities and column 2 reports the result from estimating the same equation on all other facilities. Column 3 presents results from the associated triple difference,

$$\Delta x_{py} = \alpha_0 + \gamma_0^{DD} pct_{py} + \gamma^{DDD} pct_{py} * t_p + \alpha_y t_p + \alpha_p + \alpha_y + \epsilon_{py} \tag{8}$$

Columns 1 and 2 show that areas downstream from facilities that received CWA grants had smaller non-white populations, slightly older mothers, and fewer higher order births.

results are robust to controlling for the difference between average demographic characteristics in up and downstream counties instead.

[7]This specification is equivalent to adding facility by year fixed effects to equation 4.

While we control for these demographic characteristics directly, there might have also been shifts in unobservable characteristics of individuals downstream relative to upstream following grants, which could bias specifications that rely only on comparisons between up and downstream communities. The triple difference coefficients presented in column 3 are small and statistically insignificant for all observed demographic outcomes, indicating that there was no observable differential sorting into downstream areas across non-compliant and all other facilities after grant receipt.

These results provide some evidence that our identification assumption for the following triple difference specification is likely to hold. In this specification, the first difference comes from where and when CWA grants were distributed, the second comes from if a birth occurred up or downstream from a wastewater treatment facility, and the third difference comes from the facility's pre-CWA wastewater treatment technology.

We check for common trends in our triple difference specification with the following event study,

$$\begin{aligned}\Delta Y_{py} =& \alpha_0 + \sum_{t=-4}^{-2} \theta_t 1\{y - y_p^* = t\} * t_p + \sum_{t=0}^{8} \eta_t 1\{y - y_p^* = t\} * pct_{py} * t_p \\ &+ \sum_{t=-4}^{-2} \pi_t 1\{y - y_p^* = t\} + \sum_{t=0}^{8} \gamma_t 1\{y - y_p^* = t\} * pct_{py} \\ &+ \beta X_{py} + \phi X_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py}\end{aligned} \tag{9}$$

t_p is an indicator that equals one for non-compliant facilities, and the remaining variables are defined analogously to the previous specifications. We then summarize this event study by estimating

$$\Delta Y_{py} = \alpha_0 + \gamma_0^{DD} pct_{py} + \gamma^{DDD} pct_{py} * t_p + \beta X_{py} + \phi X_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py} \tag{10}$$

4 Results

Figure 3 shows how trends in downstream pollution changed after a facility received a CWA grant by presenting estimates of the π_t and γ_t from equation 1. After a facility received it's first grant, we see a gradual decrease in pollution downstream from that facility. Consistent with the gradual improvements in downstream pollution depicted in these event studies, the EPA estimates that upgrades paid for with CWA grants could take anywhere from 2 to 10 years from grant application to project completion, so some areas may experience longer lags between grant receipt and treatment (USEPA, 2002).

Figure 4 presents event study coefficients from estimates of equation 3 with county average birth weight as the dependent variable. The precisely estimated null effects in the four years before grant receipt strongly support a research design that leverages location on a waterway relative to wastewater treatment facilities by showing the existence of parallel trends in birth weight in up and downstream communities prior to treatment. This suggests that the parallel trends would have continued in the absence of treatment. The estimates begin to increase two years after the arrival of CWA grants, and continue to rise for six years after treatment. Importantly, this gradual improvement follows a similar shape to the trend in pollution shown in Figure 3.

The impact of the CWA on birth weight may not be uniform across the distribution of birth weight. Even though Figure 4 shows a modest increase in average birth weight, the overall health of the population may improve substantially if there are fewer low birth weight infants.

Figure 5 presents event study coefficients from re-estimating equation 3 with the probability of low birth weight as the dependent variable. There is no evidence of a pre-trend. Similar to the results in Figure 4, we see a small decrease in the probability of low birth weight after treatment.

Panel A of Table 3 shows that the effects on birth weight are robust across a variety of specifications. First, column 1 compares births in counties downstream from grant facilities to those in any other county by estimating equation 4 using a sample of births from every county in the contiguous US. Column 2 adds demographic controls to this specification.

Births occurring in counties that are not near wastewater treatment facilities might not make a good control group. In column 3, we drop counties that are not up or downstream from a wastewater treatment facility and re-estimate equation 4. This compares births in a downstream county to those in any upstream county. The results are similar to those from the full sample.

Counties upstream from the same facility are likely to make even better counterfactuals than counties upstream from any facility. Column 4 estimates equation 6, which compares birth weight in counties up and downstream from the same facility. The point estimate is slightly larger in magnitude with a smaller confidence interval. In addition, Figure 6 shows the event study results for birth weight from estimating equation 5. Again, there is no evidence of a pre-trend prior to grant receipt, and we see a small and significant increase in birth weight in downstream, relative to upstream, counties after the facility receives a grant.

Panel B of Table 3 presents results from re-estimating our difference-in-difference specifications with probability of low birth weight as the dependent variable. The point estimates are consistently negative, although not always significant, and range from -.09 to -.29 percentage points. About 7 percent of births in our sample were low birth weight, so this represents a change of 1 to 4 percent from the mean. Figure 7 shows the event study results for low birth weight from estimating equation 5. Similar to the birth weight results, the probability of low birth weight appears to decrease after grant receipt and this decline grows over time.

4.1 Triple Difference

Before introducing pre-CWA compliance as a third difference, we examine the relationship between pre-CWA wastewater treatment technology and downstream pollution.

Figure 8 presents results from re-estimating equation 1 on subsamples of non-compliant and all other facilities. Figure 8a shows flat trends before treatment and a decrease in dissolved oxygen deficit downstream from non-compliant facilities after grant receipt. Looking at Figure 8b, we see no evidence of a change to pollution in waterways downstream from compliant facilities after they received a CWA grant, as we expected. In addition, there does not appear to be any trend in pollution prior to grant receipt in waters downstream from compliant facilities, which might have arisen from early adoption of more advanced treatment technology.

Table 4 reports estimates of equation 2 for the full sample, non-compliant facilities and all other facilities in columns 1, 2 and 3, respectively, and coefficients from the associated triple difference in column 4. Dissolved oxygen deficit only decreased significantly for non-compliant facilities, and the effect size for non-compliant facilities is consistent with the decrease in dissolved oxygen deficit downstream from any facility that received a CWA grant found in Keiser and Shapiro (2018). Since dissolved oxygen deficit is defined as 100 minus dissolved oxygen saturation, this results show that waters downstream from non-compliant facilities had 1.7 percentage point higher oxygen saturation after grant receipt relative to areas upstream from non-compliant facilities that received grants and waters up and downstream from non-compliant facilities that did not receive grants. The coefficient for compliant facilities in column 2 is small and statistically insignificant, and the reduction in dissolved oxygen deficit downstream from non-compliant facilities is statistically larger than for all other facilities, as shown by the significant negative triple difference coefficient in column 3. This is consistent with the hypothesis that grants led to the largest improvement in downstream water quality for non-compliant facilities.

We then estimate our triple difference specification on birth outcomes. Columns 1 and 2 of Table 5 present results from estimating equation 6 on samples of pre-CWA non-compliant facilities and all other facilities, respectively. Consistent with our pollution results in Table 4, we see a large and statistically significant improvement in birth weight downstream from non-compliant facilities. The effect in areas downstream from all other facilities is also positive, but smaller. The improvements in infant health in areas downstream from these facilities may be driven by the demographic shifts shown in Table 2. Since there were similar demographic changes in areas downstream from non-compliant facilities, the difference between the effects downstream from non-complaint and all other facilities likely comes from the differences in surface water quality shown in Table 4.

We summarize the effect of changes in surface water quality downstream from non-compliant facilities by estimating equation 10 on the pooled sample, which leverages all of our variation in one regression. Our estimate of γ^{DDD}, reported in column 3 of Table 5, will be equivalent to the difference of the estimates of equation 6 from each sub-sample. As with the pollution estimate, the improvements in birth outcomes downstream from non-compliant facilities are statistically larger than improvements downstream from all other facilities.

The corresponding event studies from estimating equation 9 are shown in Figures 9 and 10. As before, there is no evidence of pre-trends prior to receiving a grant. For birth weight, there is a statistically significant increase in downstream (relative to upstream) counties after a non-compliant facility receives a grant (relative to other facilities). For low birth weight, the point estimates are similar in shape but are statistically insignificant.

The results from this triple difference show that going from having zero to 100 percent of the county's population living within a mile of a treated waterway is associated with a 8.21 gram increase in average birth weight in counties downstream from facilities that were required to make upgrades to their treatment technology. Estimates of the effect on the probability of low birth weight are not significant, but they do bound improvements above a 0.236 percentage point decrease, or about 3 percent from the mean of low birth weight.

4.2 Mechanisms

If reductions in contaminated public drinking water are driving health improvements, we would expect to find larger effects in areas that source public water from surface water rather than groundwater, as CWA grants directly affected surface water quality. We use USGS water use data from Solley et al. (1988) to divide our sample into counties that had any public water system that drew from surface water in 1985, and counties whose public water systems drew exclusively from ground water.[8]

Column 1 of Table 6 re-estimates equation 10 on counties that had some public water systems that drew from surface water sources, while column 2 estimates the same specification on counties whose public water systems drew from groundwater exclusively. The results for areas drawing public water from surface water sources are similar to those from the full sample, while results for areas using only groundwater are wrong-signed and insignificant, implying that our results are almost completely driven by counties in which some public water systems draw from surface water.

In addition to exposure through drinking water contamination, individuals may come into contact with surface water pollution through recreational activities. If recreational exposure

[8]We use data from 1985 because it is the earliest year for which information on county level water usage is available.

is a primary channel through which these health effects occur, we might expect to find larger health improvements in states with more water-related recreation. While we do not observe water-related recreation activities directly, we can proxy for it using state-level per capita water recreation spending from the US Bureau of Economic Analysis.[9]

We test this channel in Table 7 by separately estimating equation 4 on sub-samples defined by terciles of state-level per capita water recreation spending.[10] While we find the largest and most significant results in states in tercile 3, which had the highest water recreation spending, the confidence intervals for all three terciles overlap and estimates for each tercile are not statistically distinguishable in the pooled sample for average birth weight.

Since 95 percent of all water recreational trips occur within 25 miles of one's home (Keiser and Shapiro, 2018), we re-estimate the results for wider bandwidths around treated waterways. Increasing the definition of the exposed area to those within 10 or 25 miles of a treated waterway attenuates our results, as shown in Table 8. The wider bandwidth is likely to capture individuals at farther distances who recreate at the treated waterway, but it will also capture many additional individuals who do not recreate at the treated waterway, which may lead to this attenuation.[11]

While we cannot rule out exposure through a recreation channel, our results are driven by counties with some public water sourced from surface water, and we are only able to detect health improvements for narrow bandwidths from the treated waterway. This suggests that the effect of reduced surface water pollution on health is highly concentrated near treated waterways. Since community water systems tend to draw water from the nearest available source to reduce the cost of pumping water (Toccalino and Hopple, 2010), this provides suggestive evidence that drinking water contamination is the primary channel through which CWA grants affected infant health.

[9] We focus on total spending for "Boating/Fishing" from 2012 to 2016, which includes canoeing/kayaking, fishing, sailing, and other boating. While data from the 1970's is not available, it is unlikely that cross-sectional variation in per capita recreational spending is changing much over time.

[10] Because facilities near state borders may have downstream counties in neighboring states and the recreation data is at the state level, we focus on equation 4 rather than specifications at the facility level.

[11] Kuwayama et al. (2018) provide related evidence that hedonic property models relying on treatment areas defined by concentric circles may not accurately capture water's recreational benefits.

4.3 Heterogeneity

We examine the heterogeneity of our estimates across race in Table 9 by estimating equation 10 on sub-samples of white and non-white births from counties with sizable non-white populations.[12] The point estimates for both white and non-white births are similar to the estimates of effects on average birth weight for any race, and results by race are not statistically distinguishable.

Next, we look for heterogeneity by the timing of grant receipt. If states wrote their priority lists to address the most severe pollution problems first, we would expect grants from the first few years of the CWA to have the largest effect on infant health. This is especially true if we think there is a convex relationship between pollution and health.

We address this in columns 3 and 4 of Table 9. In column 3, we drop all observations from facilities that received a grant after 1976 and re-estimate equation 6, and in column 4 we drop all observations from facilities that received a grant in or before 1976. The results are similar, so there is little evidence of heterogeneous effects by grant timing.

5 Discussion & Conclusion

The preceding evidence suggests that the Clean Water Act led to small, but significant improvements in infant health, with reductions in pollution associated with CWA grants leading to an eight gram increase in average birth weight in counties downstream from facilities that were required to make treatment technology upgrades, relative to other facilities. Given that previous studies have found statistically significant relationships between water quality and infant health, how do our results line up with the current literature, and how do they affect our understanding of the relationship between water and health generally?

We know that reductions in the contamination of drinking water lead to improvements in infant health. Specifically, Currie et al. (2013) found that in utero exposure to drinking water from facilities where contaminants were detected is associated with a 0.32 percentage

[12]The sample is restricted to counties where both the white and non-white average birth weight is calculated from 5 or more births. This ensures that we are making comparisons that rely on the same set of counties, in which there are sufficient individuals in both racial groups, rather than making comparisons between majority white and majority non-white communities. Results are not sensitive to this sample restriction.

point increase in the the probability of low birth weight. We estimate somewhat smaller, but similar sized effects for low birth weight. Consistent with this channel, we only find effects in areas whose public water systems drew from surface water. These effects are largest for areas downstream from facilities that were required to upgrade their treatment technology, which saw the greatest improvements to surface water quality. This shows that, similar to contamination of municipal water and ground water, surface water contamination affects a direct measure of human health.

We can use this information on the relationship between surface water quality and infant health to incorporate health benefits into a cost benefit analysis of the Clean Water Act. In total, CWA grants to wastewater treatment facilities cost about \$153 billion (in 2014 dollars). About 46.4 million births occurred in treated counties that had some public water systems that drew from surface water sources between 1972 and 1988, and we estimate that about 29.7 million of those births occurred within a mile of a treated waterway. While our preferred specification does not show statistically significant changes to the probability of low birth weight in areas that draw from surface water sources, it does bound improvements below a 0.261 percentage point reduction in the probability of low birth weight (as shown in Panel B of Table 6).

Almond et al. (2005) estimates that low birth weight increases hospital costs by \$8319, and increases 1 year mortality by 37 per 1000 births, and Oreopoulos et al. (2008) finds that low birth weight reduces lifetime earnings by 3.8 percent. We combine these estimates with the EPA's value of a statistical life of \$7.4 million and the census bureau's work-life earnings estimate of \$2.4 million to calculate a back-of-the-envelope estimate of the infant health benefits of the CWA. While a more comprehensive calculation of the health benefits of the CWA would include other potentially impacted health outcomes, such as reduced hospital admissions for gastrointestinal illness, reduced school absences, and other health effects for adolescents and adults, we estimate the infant health benefits of the CWA are bounded below 29 billion dollars, about 19 percent of the amount needed to make the CWA cost effective.

The \$153 billion dollar cost includes grants to compliant facilities that did not lead to improvements in downstream water quality. Since we only see health effects downstream from non-compliant facilities that received grants, a more accurate cost benefit ratio might come from comparing the health benefits of CWA grants to the costs of grants to non-complaint facilities, which totaled about $101 billion (in 2014 dollars). Health effects alone account for as much as 29 percent of the amount needed to make grants to non-compliant facilities cost effective. Using increased housing prices to value the benefits of the CWA, Keiser and Shapiro (2018) estimates a benefit to cost ratio of .26. If we assume that hedonic estimates do not capture any health benefits, grants to non-compliant facilities might have a benefit to cost ratio as high as .55 once improvements to infant health are incorporated. Including additional measures of health are likely to increase this ratio even further.

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Figures

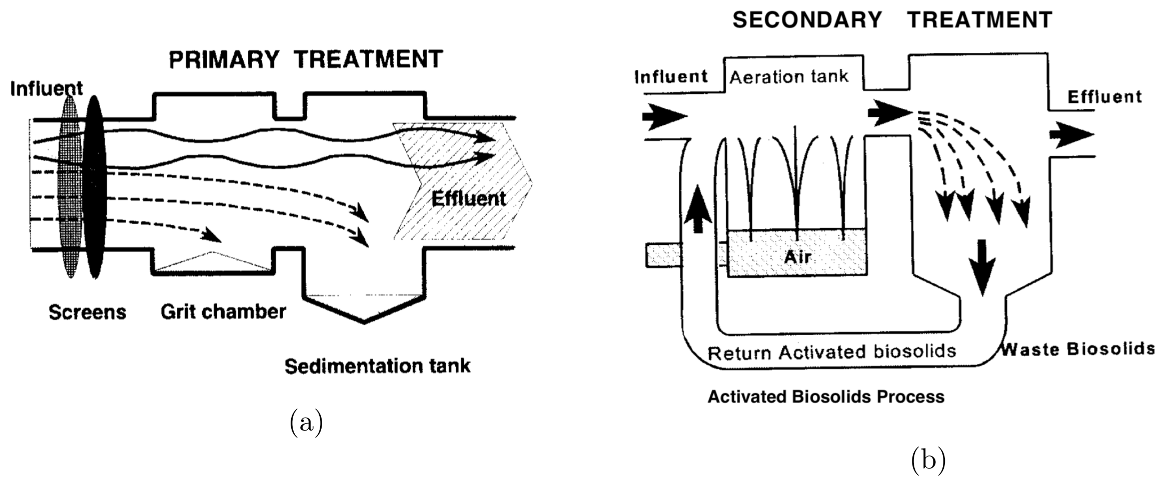


Figure 1: Primary vs Secondary Treatment Technology

Source: USEPA (1998)

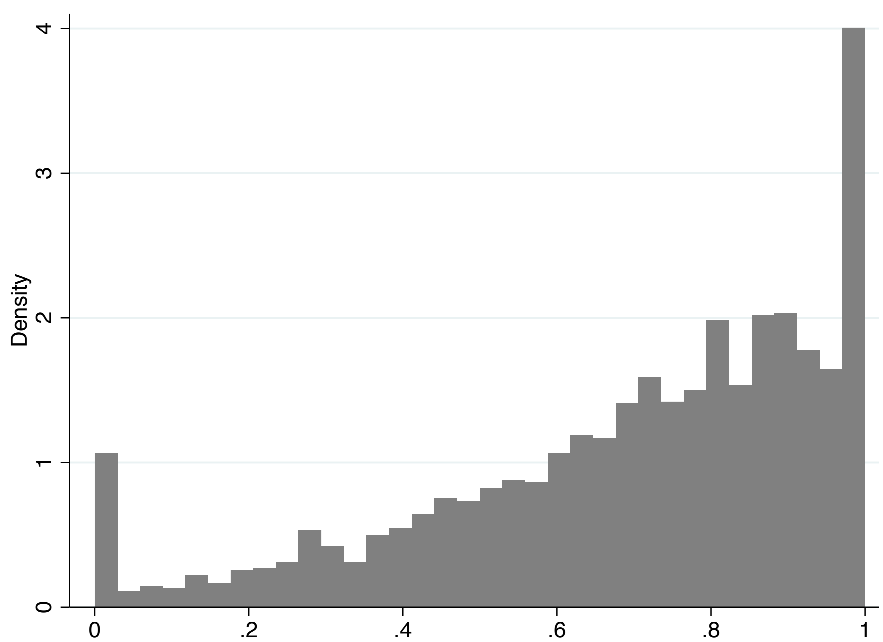


Figure 2: Percent of County Population Living Within a Mile of a Treated Waterway in 1988

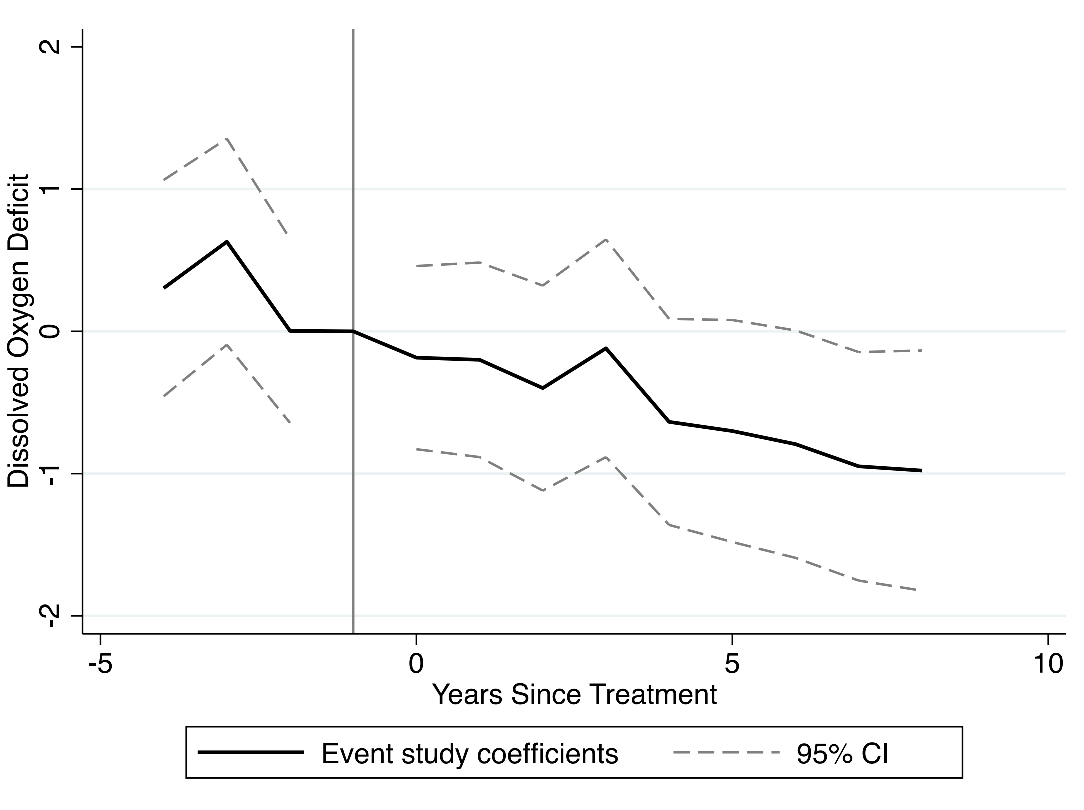


Figure 3: Downstream Pollution

Notes: The dependent variable is dissolved oxygen deficit. The figure plots the estimated coefficients on $1\{y - y_p^* = t\} * d_d$ from estimating $Q_{pdy} = \alpha_0 + \sum_{t=-4}^{-2} \pi_t 1\{y - y_p^* = t\} * d_d + \sum_{t=0}^{8} \gamma_t 1\{y - y_p^* = t\} * d_d + \beta W_{pdy} + \alpha_{pd} + \alpha_y + \epsilon_{pdy}$.

There are two observations for each treatment plant p for each year y. One observation describes mean water quality upstream ($d_d = 0$) and one observation describes mean water quality downstream ($d_d = 1$). Time relative to treatment is defined by $1\{y - y_p^* = t\}$ which is an indicator function that equals 1 for observations from pollution monitors t years before or after the facility the monitor is up or downstream from received a CWA grant, and Q_{pdy} is a measure of dissolved oxygen deficit. d_d is a dummy equaling one for observations downstream from a facility. The model includes facility by downstream fixed effects and year fixed effects, α_{pd} and α_y respectively, as well as controls for temperature. Panel A shows estimates from estimating this equation on a sample of pre-CWA non-compliant facilities (those that were required to make wastewater treatment capital upgrades) and Panel B shows estimates using all other facilities.

Source: (USEPA, 1967-1988)

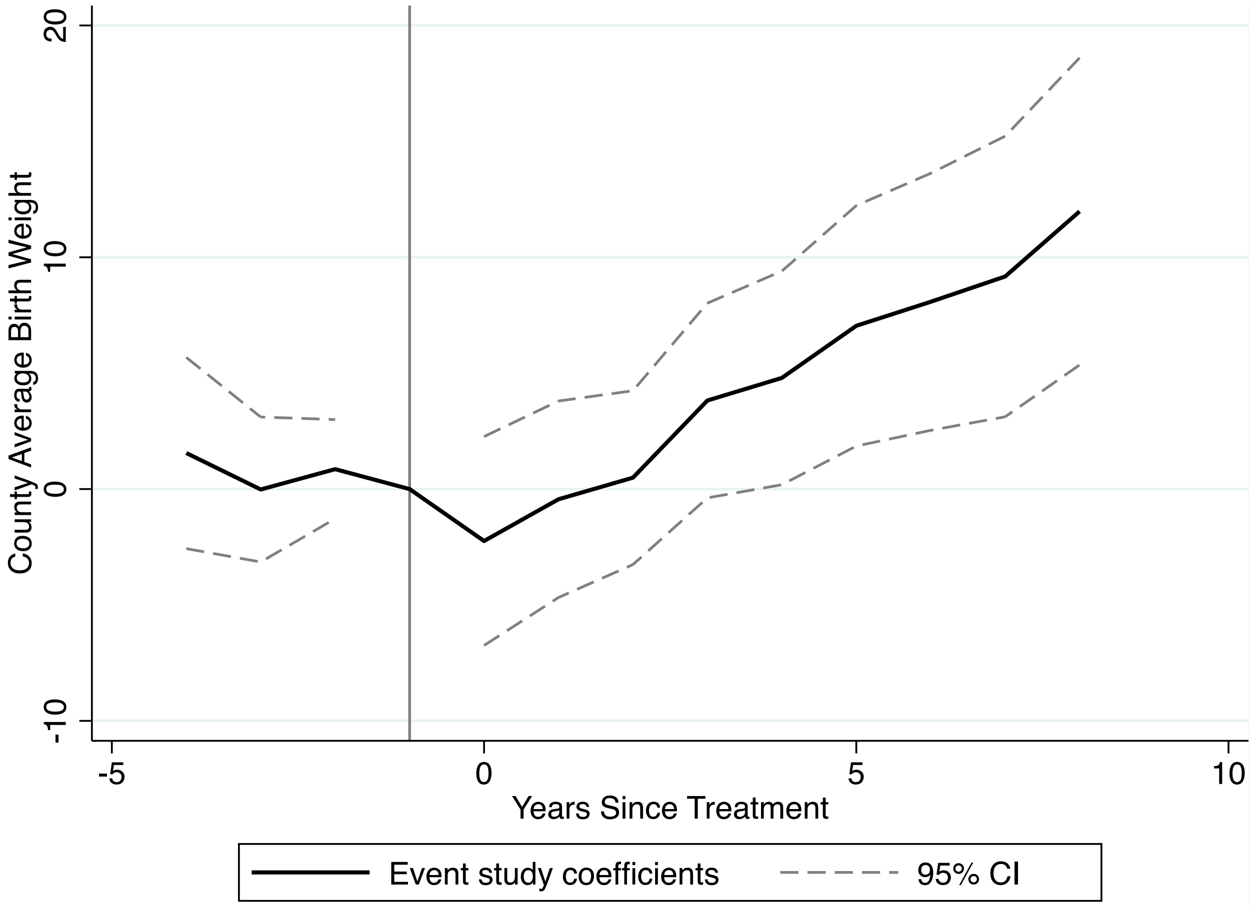


Figure 4: Birth Weight Downstream from Grant Facilities

Notes: The dependent variable is the the average birth weight in county c in year y. The figure plots the π_t and γ_t from estimating $bw_{cy} = \alpha_0 + \sum_{t=-4}^{-2} \pi_t 1\{y - y_c^* = t\} + \sum_{t=0}^{8} \gamma_t 1\{y - y_c^* = t\} * pct_{cy} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy}$. pct_{cy} is a continuous variable that takes values from zero to one, and indicates the percent of county c's population living within a mile of a treated waterway in year y. The model includes county and year fixed effects, α_c and α_y respectively, as well as controls for the percent of a county's births in a given birth order, and county averages of mother's age and race and child gender. The estimates are weighted by total number of births in a county-year.
Source: NCHS (1968-1988)

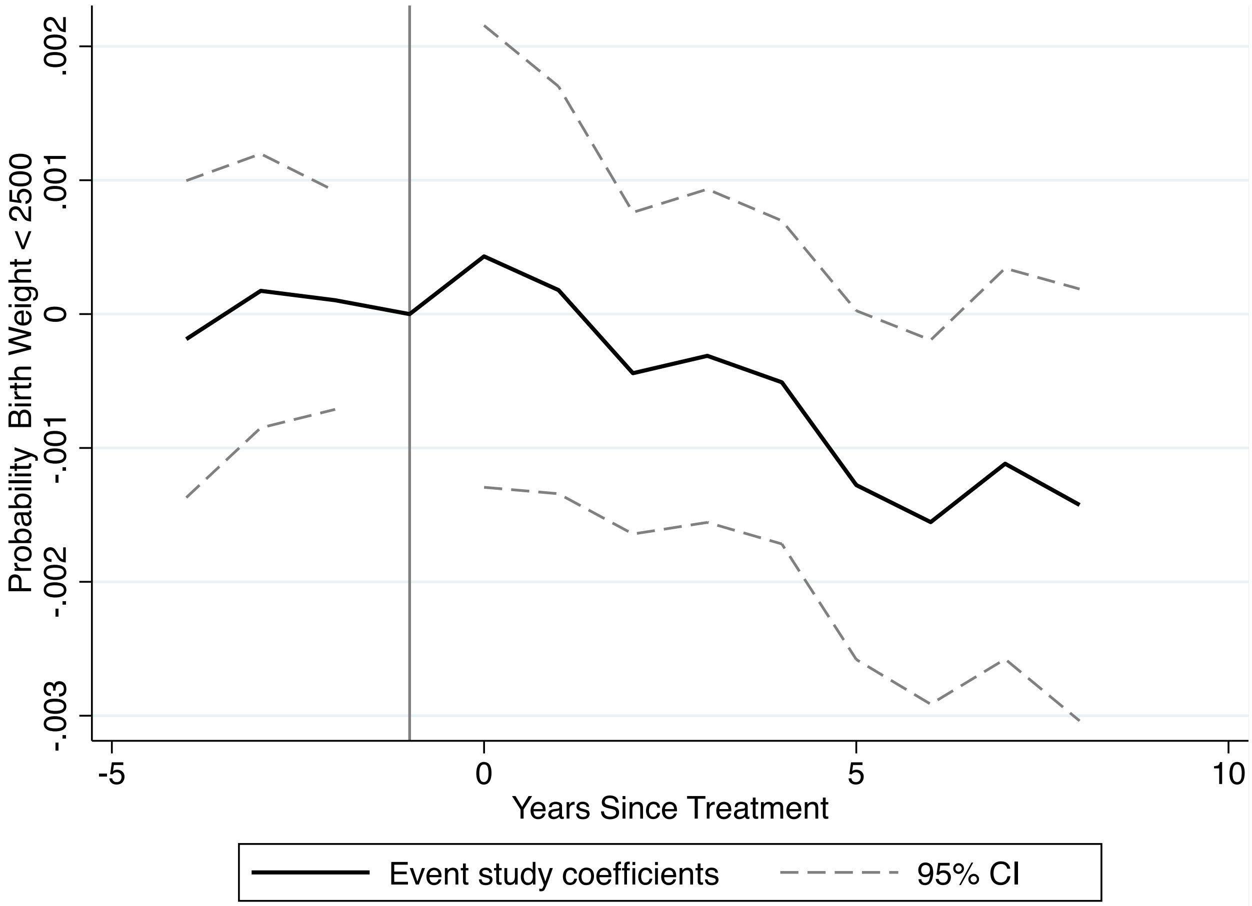


Figure 5: Probability of Low Birth Weight Downstream from Grant Facilities

Notes: This Figure re-estimates the results in Figure 4 with the probability of being born weighing less than 2500 grams as the dependent variable.
Source: NCHS (1968-1988)

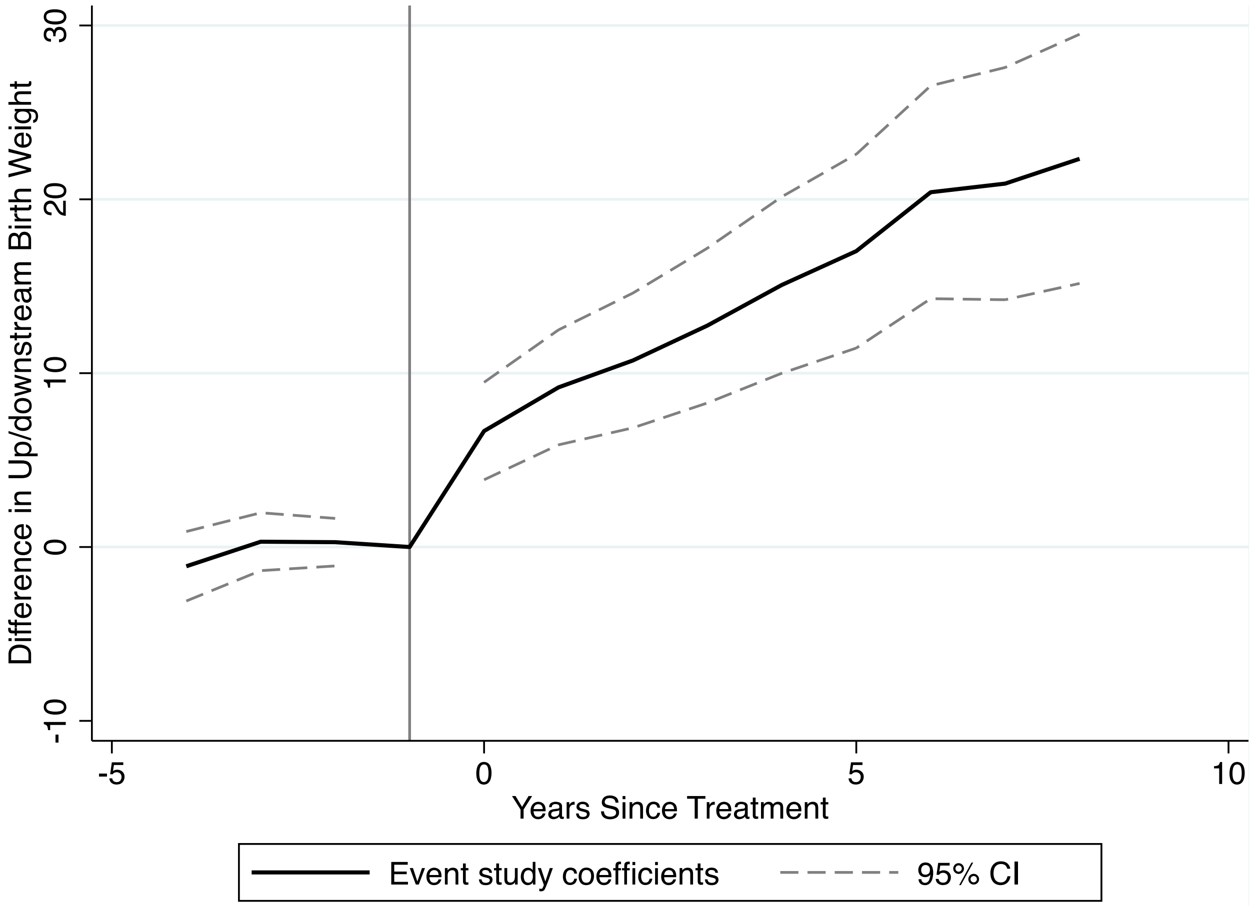


Figure 6: Difference in Birth Weight Up and Downstream from Grant Facilities

Notes: The dependent variable is the difference in birth weight between up and downstream counties in a given year. The figure plots the π_t and γ_t from estimating $\Delta bw_{py} = \alpha_0 + \sum_{t=-4}^{-2} \pi_t 1\{y - y_p^* = t\} + \sum_{t=0}^{8} \gamma_t 1\{y - y_p^* = t\} * pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py}$. pct_{py} is a continuous variable that takes values from zero to one, and indicates the percent of downstream counties' populations living within a mile of a treated waterway in year y. The model includes facility and year fixed effects, α_p and α_y respectively, as well as controls for the percent of up and downstream counties' births in a given birth order, and averages of up and downstream mother's age and race and child gender. The estimates are weighted by total number of births in counties up and downstream from a facility in year y.
Source: NCHS (1968-1988)

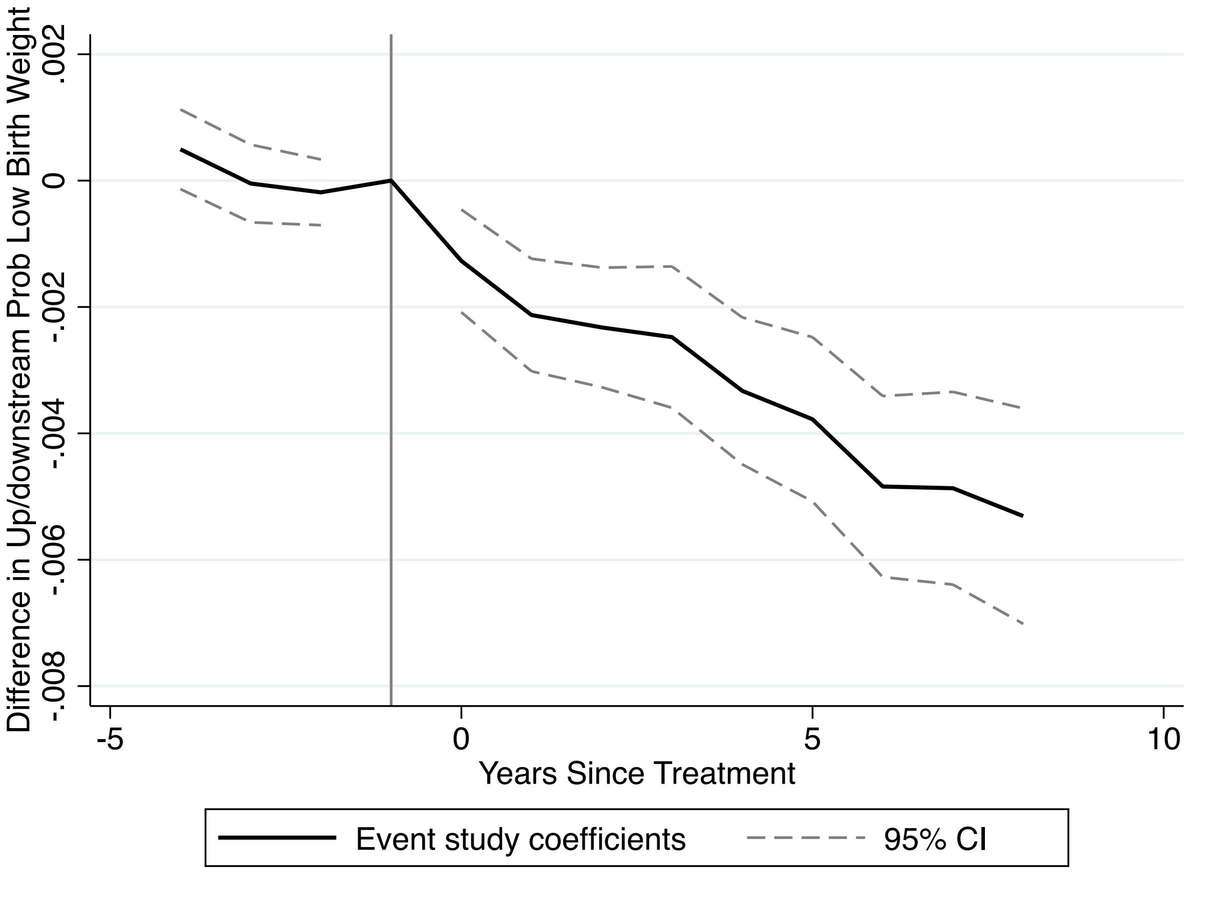
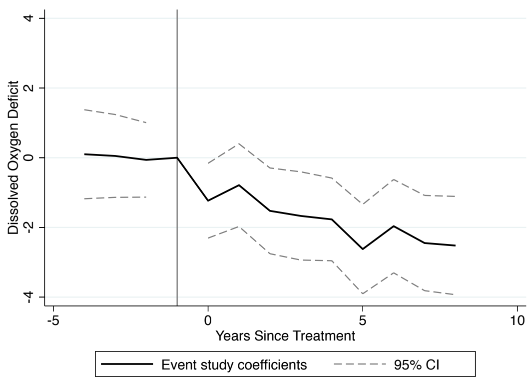
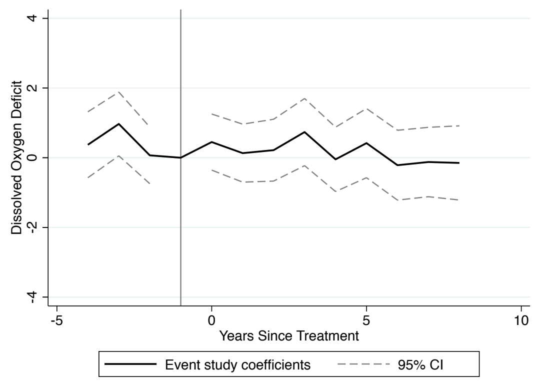


Figure 7: Difference in Probability of Low Birth Weight Up and Downstream from Grant Facilities

Notes: This Figure re-estimates the results in Figure 6 with the difference in the probability of being born weighing less than 2500 grams between up and downstream counties as the dependent variable.
Source: NCHS (1968-1988)



(a) Non-compliant



(b) All other Facilities

Figure 8: Downstream Pollution by Pre-CWA Compliance

Notes: This figure presents results from re-estimating the event study in Figure 3 on subsamples of facilities defined by pre-CWA compliance. Panel A shows estimates from estimating this equation on a sample of pre-CWA non-compliant facilities (those that were required to make wastewater treatment capital upgrades) and Panel B shows estimates using all other facilities.
Source: (USEPA, 1967-1988)

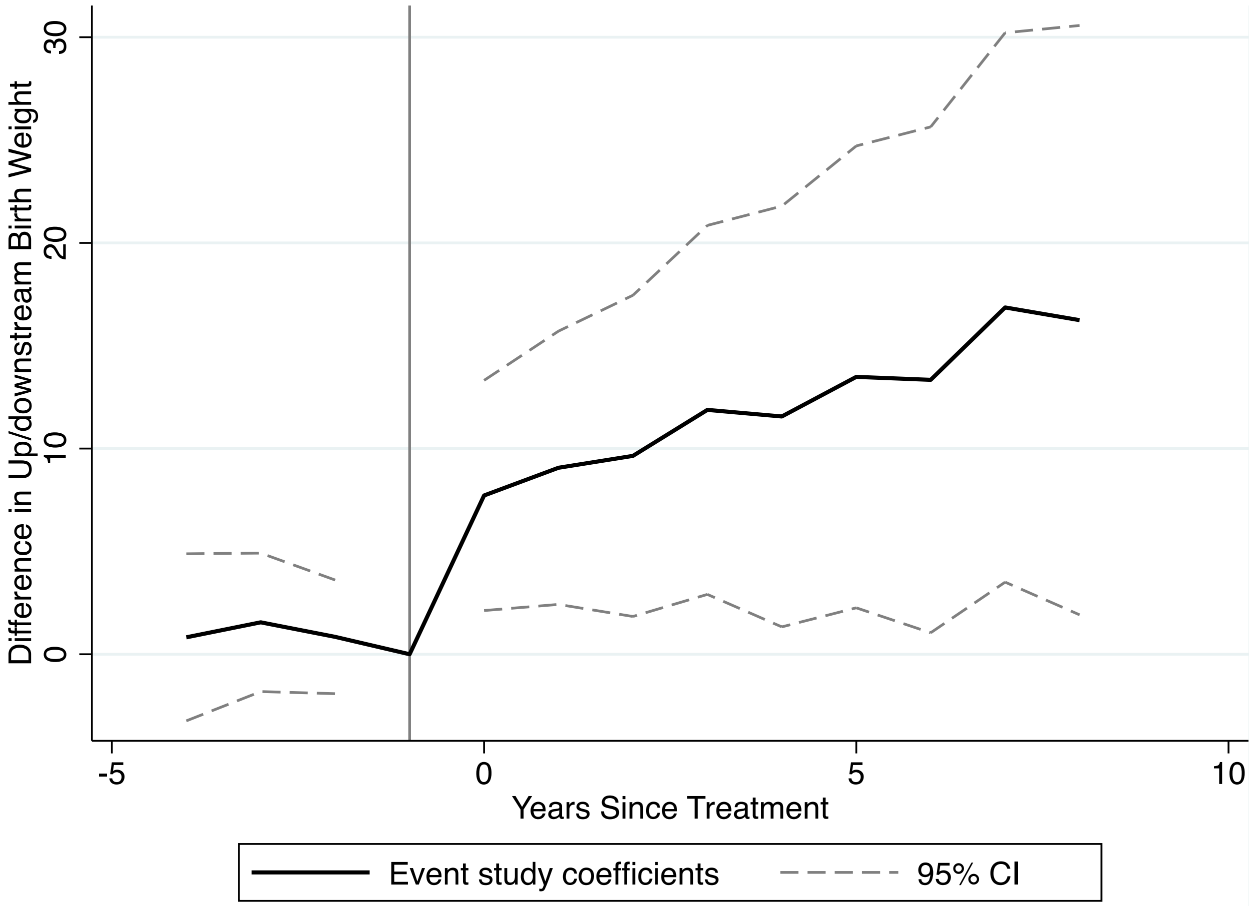


Figure 9: Birth Weight Triple Difference

Notes: The dependent variable is the difference in birth weight between up and downstream counties in a given year. The figure plots the θ_t and η_t from estimating $\Delta Y_{py} = \alpha_0 + \sum_{t=-4}^{-2} \theta_t 1\{y - y_p^* = t\} * t_p + \sum_{t=0}^{8} \eta_t 1\{y - y_p^* = t\} * pct_{py} * t_p + \sum_{t=-4}^{-2} \pi_t 1\{y - y_p^* = t\} + \sum_{t=0}^{8} \gamma_t 1\{y - y_p^* = t\} * pct_{py} + \beta X_{py} + \phi X_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py}$. pct_{py} is a continuous variable that takes values from zero to one, and indicates the percent of downstream counties' populations living within a mile of a treated waterway in year y. This model includes controls for the percent of up and downstream counties' births in a given birth order, and averages of up and downstream mother's age and race and child gender. The estimates are weighted by total number of births in counties up and downstream from a facility in year y.
Source: NCHS (1968-1988)

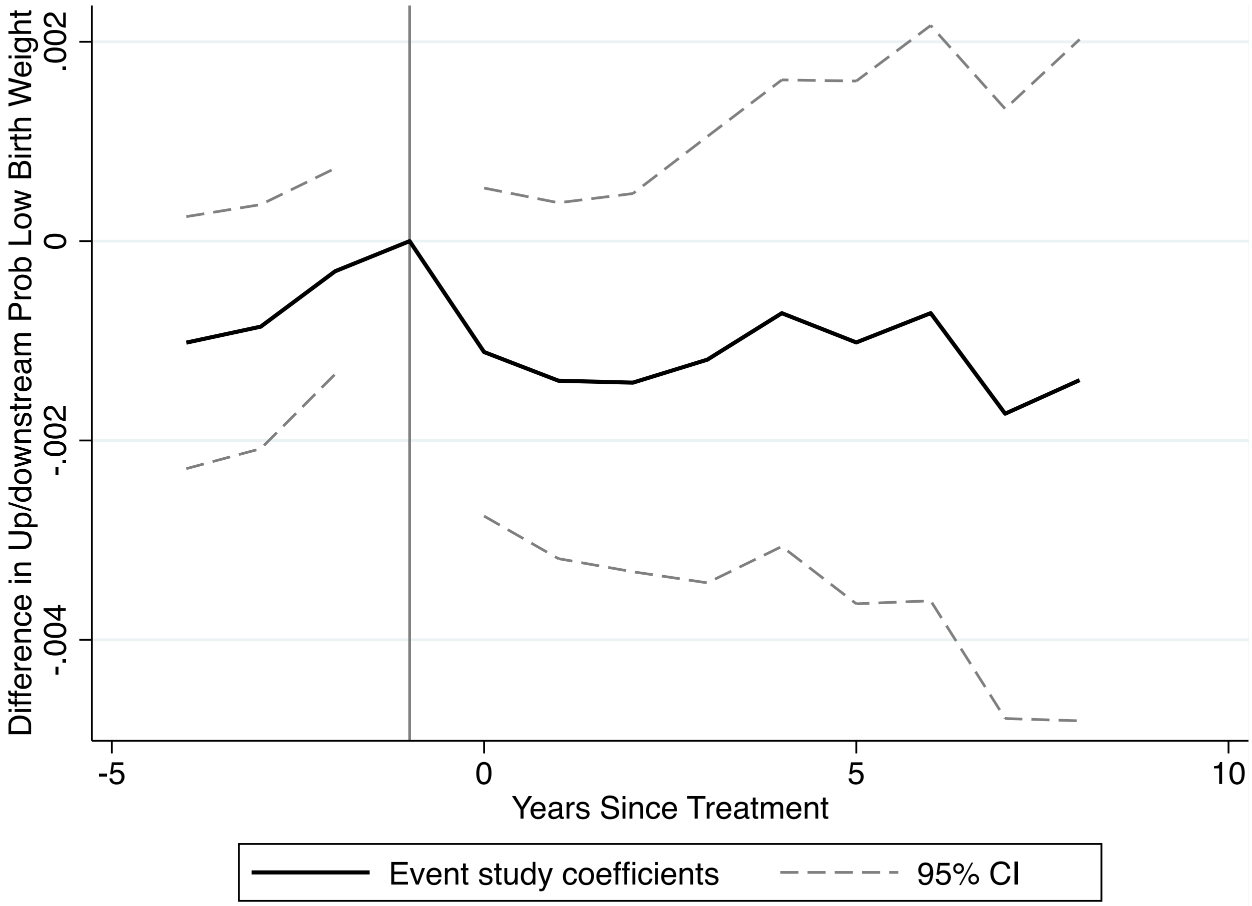


Figure 10: Probability of Low Birth Weight Triple Difference

Notes: This Figure re-estimates the results in Figure 9 with the difference in the probability of being born weighing less than 2500 grams between up and downstream counties as the dependent variable.
Source: NCHS (1968-1988)

Tables

Table 1: Clean Watershed Needs Survey

	non-compliant (1)	all other facilities (2)	difference (3)
new plant	.4	.222	-.178***
			[-.209,-.148]
replacement plant	.208	.119	-088***
			[-.114,-.064]
improve O&M/increase staff	.316	.396	.080***
			[.050,.110]
N	6908	1101	8009

95% confidence intervals in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Notes: This table compares the percent of non-compliant and all other facilities that indicated they would use CWA grant to pay for a new plant, a replacement plant, or improve plant operations.

Table 2: Controls as Dependant Variables

	non-compliant	compliant	DDD
	(1)	(2)	(3)
Panel A.	percent non-white		
pct pop 1 mile	-0.0223***	-0.0176***	-0.0176***
	[-0.0281,-0.0165]	[-0.0229,-0.0123]	[-0.0229,-0.0123]
pct pop 1 mile X non-compliant			-0.00471
			[-0.0126,0.00313]
mean	0.0922	0.0731	0.0828
standard deviation	0.136	0.136	0.136
Panel B.	mother's age		
pct pop 1 mile	0.126***	0.0784**	0.0784**
	[0.0557,0.197]	[0.0149,0.142]	[0.0150,0.142]
pct pop 1 mile X non-compliant			0.0479
			[-0.0470,0.143]
mean	-0.216	-0.160	-0.188
standard deviation	0.776	0.816	0.797
Panel C.	probability first or second birth		
pct pop 1 mile	-0.00210	0.00109	0.00109
	[-0.00916,0.00496]	[-0.00390,0.00608]	[-0.00390,0.00608]
pct pop 1 mile X non-compliant			-0.00319
			[-0.0118,0.00545]
mean	-0.00393	-0.00304	-0.00349
standard deviation	0.0392	0.0403	0.0398
Panel D.	probability third or higher birth		
pct pop 1 mile	-0.0105***	-0.00618***	-0.00618***
	[-0.0145,-0.00646]	[-0.00965,-0.00271]	[-0.00964,-0.00271]
pct pop 1 mile X non-compliant			-0.00429
			[-0.00958,0.00100]
mean	-0.000596	-0.0000211	-0.000311
standard deviation	0.0264	0.0277	0.0271
unit and year fixed effects	X	X	X
collapsed to facility level	X	X	X
N	34188	48132	82320

95% confidence intervals in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Notes: This table presents (weighted) estimates from the following model: $\Delta x_{py} = \alpha_0 + \gamma_0^{DD} pct_{py} + \gamma^{DDD} pct_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py}$. Δx_{py} is a measure of the difference between demographic characteristic in counties up and downstream from facility p in year y. Each panel represents a different demographic variable.
Source: NCHS (1968-1988)

Table 3: Difference in Difference

	full sample		up/downstream only	
	(1)	(2)	(3)	(4)
Panel A	county average birth weight			
pct pop 1 mile	12.80***	6.718**	7.134***	13.33***
	[6.709,18.89]	[2.444,11.82]	[2.034,11.40]	[10.11,16.55]
Panel B	probability birth weight < 2500 grams			
pct pop 1 mile	-0.00288***	-0.000874	-0.000963*	-0.00223***
	[-0.00419,-0.00156]	[-0.00198,0.0000584]	[-0.00190,0.000152]	[-0.00299,-0.00147]
controls		X	X	X
unit and year fixed effects	X	X	X	X
collapsed to county level	X	X	X	
collapsed to facility level				X
N	64239	64239	64008	82320

95% confidence intervals in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Notes: This table presents (weighted) estimates from the following model: $Y_{cy} = \alpha_0 + \gamma pct_{cy} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy}$. In Panel A, the dependent variable is the average birth weight in a county-year, and in Panel B, it's the probability of being born weighing less than 2500 grams. pct_{cy} is a continuous variable that takes values from zero to one, and indicates the proportion of county c's population that lived within a mile of a treated waterway in year y. The model includes unit and year fixed effects, α_c and α_y respectively, and columns 2 through 4 include controls for the percent of a county's births in a given birth order bin, and county averages of mother's age and race and child gender. Columns 1 and 2 use data from every county in the US, while columns 3 and 4 restrict the sample to counties that are up or downstream from a wastewater treatment facility.

In columns 1 through 3, data is collapsed to the county level. In column 4, data is collapsed to the facility level. This means that the results in columns 1 and 2 come from comparisons between counties downstream from facilities that received grants and any other county, the results in column 3 come from comparisons between counties downstream from facilities that received grants and any county upstream from a facility, and the results in column 4 come from comparisons between counties downstream from facilities that received grants and counties upstream from the same facility.

Source: NCHS (1968-1988)

Table 4: Pollution Triple Difference

	(1) full sample	(2) non-compliant	(3) all other facilities	(4) DDD
grant X downstream	-0.670***	-1.672***	-0.110	-0.110
	[-1.124,-0.217]	[-2.467,-0.877]	[-0.663,0.443]	[-0.663,0.443]
grant X downstream X non-compliant				-1.562***
				[-2.530,-0.593]
weather controls	X	X	X	X
facility by downstream fixed effects	X	X	X	X
year fixed effects	X	X	X	X
N	90143	27073	63070	90143

95% confidence intervals in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Notes: This table describes the effects of Clean Water Act grants on downstream pollution for all facilities, non-compliant facilities (those that were required to make treatment technology upgrades) and all other facilities in our sample. Columns 1, 2 and 3 estimate $Q_{pdy} = \alpha_0 + \gamma g_y * d_d + \beta W_{pdy} + \alpha_{pd} + \alpha_y + \epsilon_{pdy}$ for areas up and downstream from non-compliant and all other facilities separately. Q_{pdy} is dissolved oxygen deficit, g_y is a dummy variable equaling one after a facility receives a CWA grant, and d_d is a dummy equaling one for observations downstream from a facility.

Column 4 presents estimates from the associated triple difference: $Q_{pdy} = \alpha_0 + \gamma_0^{DD} g_y * d_d + \gamma^{DDD} g_y * d_d * t_p + \beta W_{pdy} + \beta W_{pdy} * t_p + \alpha_y * t_p + \alpha_{pd} + \alpha_y + \epsilon_{pdy}$ where t_p is a dummy variable equaling one for observations from non-compliant facilities. All regressions include controls for water temperature, and facility by downstream fixed effects and year fixed effects, α_{pd} and α_y.

Source: (USEPA, 1967-1988)

Table 5: Triple Difference

	non-compliant (1)	all other facilities (2)	DDD (3)
Panel A.	county average birth weight		
pct pop 1 mile	13.36***	5.153**	5.153**
	[8.012,18.72]	[1.129,9.177]	[1.130,9.176]
pct pop 1 mile X non-compliant			8.211**
			[1.519,14.90]
Panel B.	probability birth weight < 2500 grams		
pct pop 1 mile	-0.00216***	-0.00138**	-0.00138**
	[-0.00334,-0.000979]	[-0.00244,-0.000325]	[-0.00244,-0.000325]
pct pop 1 mile X non-compliant			-0.000780
			[-0.00236,0.000803]
demographic controls	X	X	X
unit and year fixed effects	X	X	X
collapsed to facility level	X	X	X
N	34188	48132	82320

95% confidence intervals in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Notes: This table describes the effects of Clean Water Act grants on downstream birth weight. Columns 1 and 2 estimate $\Delta Y_{py} = \alpha_0 + \gamma pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py}$ for areas up and downstream from non-compliant facilities (those that were required to make treatment technology upgrades) and all other facilities separately. Column 3 estimates the associated triple difference: $\Delta Y_{py} = \alpha_0 + \gamma_0^{DD} pct_{py} + \gamma^{DDD} pct_{py} * t_p + \beta X_{py} + \phi X_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py}$. All regressions include demographic controls and unit and year fixed effects, α_c and α_y respectively. Average birth weight is the dependent variable in Panel A, and probability of low birth weight is the dependent variable in Panel B.
Source: NCHS (1968-1988)

Table 6: Effects by Public Water Source

	Surface Water (1)	Ground Water (2)
Panel A	county average birth weight	
pct pop 1 mile X non-compliant	8.893**	-5.137
	[1.874,15.91]	[-21.34,11.06]
Panel B	probability birth weight < 2500 grams	
pct pop 1 mile X non-compliant	-0.000952	0.000132
	[-0.00261,0.000705]	[-0.00375,0.00401]
demographic controls	X	X
unit and year fixed effects	X	X
collapsed to facility level	X	X
N	67032	15288

95% confidence intervals in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Notes: This table re-estimates the specification in column 3 of Table 5 on sub-samples of counties that had some public water systems that draw from surface water and counties whose public water systems only draw from groundwater.
Source: NCHS (1968-1988); Solley et al. (1988)

Table 7: Split by Recreational Spending Per Capita

	(1) Tercile 1	(2) Tercile 2	(3) Tercile 3
Panel A	county average birth weight		
pct pop 1 mile	0.163	4.701	15.19***
	[-7.608,7.934]	[-1.908,11.31]	[6.503,23.88]
Panel B	probability birth weight < 2500 grams		
pct pop 1 mile	-0.000429	-0.000453	-0.00220***
	[-0.00193,0.00107]	[-0.00234,0.00143]	[-0.00385,-0.000561]
demographic controls	X	X	X
unit and year fixed effects	X	X	X
collapsed to county level	X	X	X
N	21147	20160	22617

95% confidence intervals in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Notes: This table re-estimates the specification in column 2 of Table 3 on sub-samples defined by terciles of state water-related recreational spending. Counties in states with the lowest spending are in Tercile 1, while those in states with the highest spending are in Tercile 3.
Source: NCHS (1968-1988); BEA (2012-2017)

Table 8: Other Bandwidths

	(1) 25 miles downstream 10 mile buffer	(2) 25 miles downstream 25 mile buffer
	county average birth weight	
pct pop 10 miles	1.132	
	[-1.878,4.142]	
pct pop 25 miles		-0.620
		[-3.729,2.489]
demographic controls	X	X
unit and year fixed effects	X	X
collapsed to county level	X	X
N	64344	64344

95% confidence intervals in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Notes: This table presents (weighted) estimates from the following model: $bw_{cy} = \alpha_0 + \gamma pct_{cy} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy}$. pct_{cy} is a continuous variable that takes values from zero to one, and indicates the proportion of a county's population that lived within some bandwidth of a treated waterway in a given year. In column 1, this bandwidth is 10, and in column 2, it is 25.

Table 9: Heterogeneous Effects

	(1) white	(2) nonwhite	(3) early grants	(4) later grants
pct pop 1 mile X non-compliant	11.37***	14.32	14.04**	11.95**
	[3.778,18.97]	[-7.037,35.68]	[1.241,26.84]	[1.422,22.48]
demographic controls	X	X	X	X
unit and year fixed effects	X	X	X	X
collapsed to facility level	X	X	X	X
N	35406	35406	51639	31080

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Notes: This table re-estimates the specifications in Table 3 on sub-samples of the population. Columns 1 and 2 divide the sample by race and only include counties that had a sizeable nonwhite population, and columns 3 and 4 divide the sample by grant timing.
Source: NCHS (1968-1988)

A Appendix

A.1 Robustness to Distance Downstream

In the main text, we follow Keiser and Shapiro (2018) and the EPA (USEPA, 2001) by defining a waterway as treated if it is 25 miles downstream from a wastewater treatment facility. We show that our results are not sensitive to this choice by re-estimating equation 10 defining treated waterways as those either 5 or 10 miles downstream from a treated facility in Table A1. The results are similar to those presented in Section 4.

A.2 County Changes

Births records in NCHS data contain information on birth location at the county level. Several counties split or combined during our study period. Following Forstall (1995), we re-combine all counties that split or merge between 1968 and 1988. Changes are noted in Table A2.

A.3 Changes in Reported Sample

Data in years prior to 1972 constitutes a 50 percent sample of all births in the US. Years after 1972 contain information on every birth in the US from some states, and a 50 percent sample from the remaining States. Six states had full sample data in 1972, and all States and the District of Columbia had full sample data by 1985. Table A3 details the first year in which each state reported full sample data.

Our main results are weighted by total number of births in a county. Total births for observations from state-years reporting a 50 percent sample of births are defined as the number of observations from that county-year multiplied by two.

Since changes from half to full sample often occurred contemporaneously with treatment, we report results from re-estimating the results in Figure 9 using average birth outcomes calculated using a 50 percent sample of births from state-years that reported full sample data in Figure A1. We then re-estimate the results presented in Table 5 on this sample and report the results in Table A4. The results are similar to those reported in Section 4.

A.4 Alternative Pollution Specifications

Our pollution results in the main text rely on comparisons of waterways downstream from facilities that received CWA grants to waterways upstream from these facilities, and areas up and downstream from facilities that did not receive CWA grants. Alternatively, we can compare waterways downstream from facilities to waterways upstream from the same facility by adding a facility-by-year fixed effect to equations 1 and 2.

We present results from re-estimating the results in Figures 3 and 8 and Table 4 with facility-by-year fixed effects in Figures A2 and A3 and Table A5, respectively.

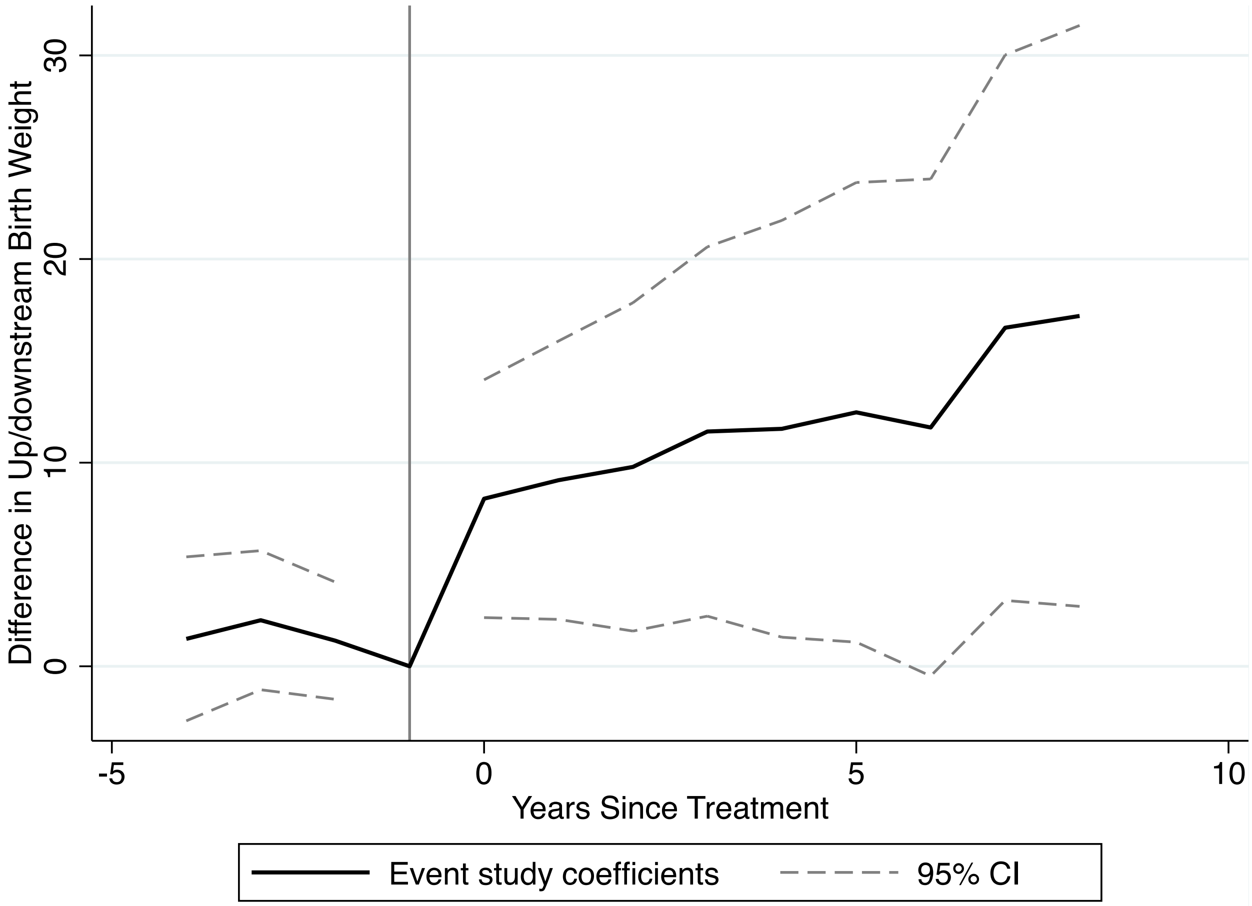


Figure A1: Birth Weight Triple Difference: Random Sample

Notes: This Figure re-estimates the results in Figure 9 after taking a fifty percent random sample of births that occurred in state-years that reported a full sample of births. The years that each state switched from a 50 percent sample to a full sample of births are detailed in Table A3.
Soure: NCHS (1968-1988)

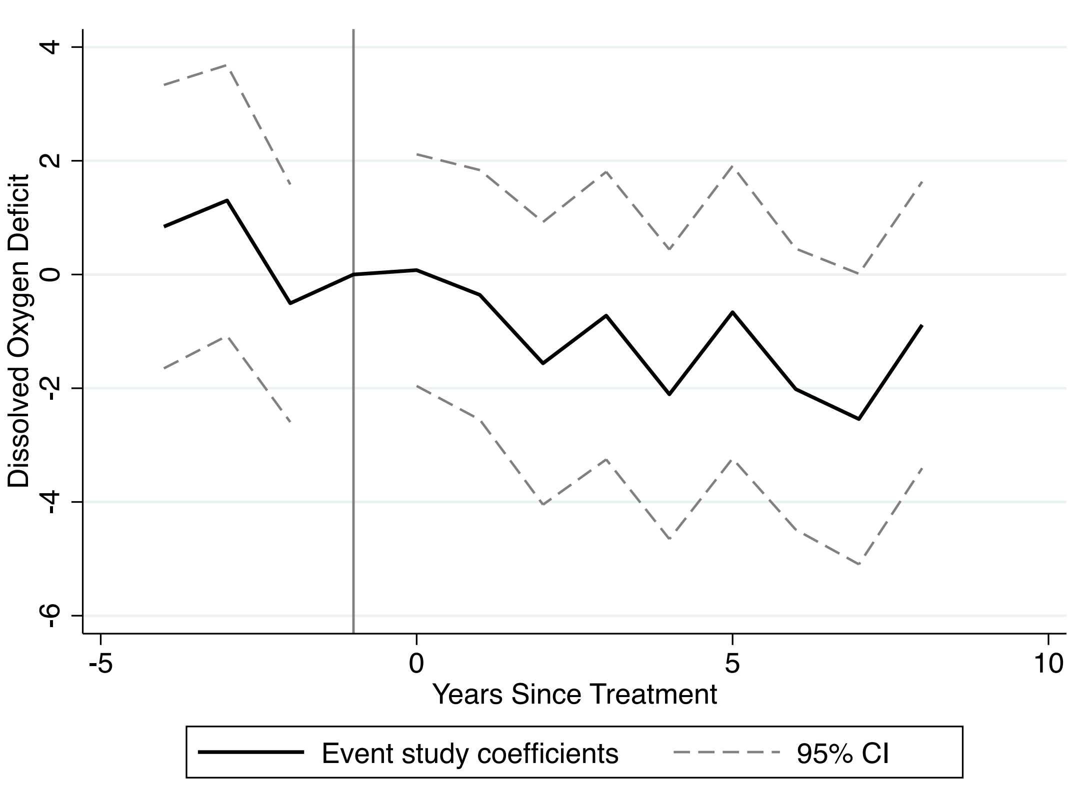
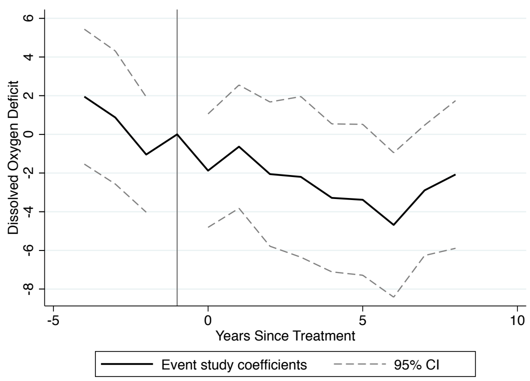
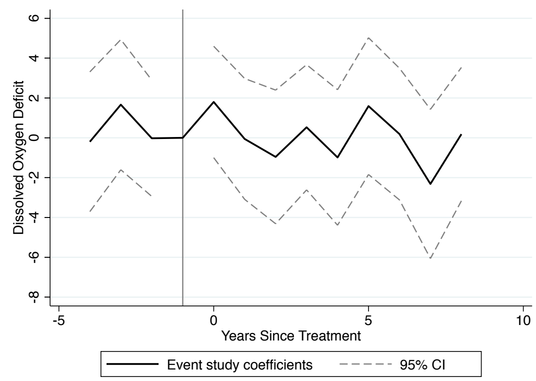


Figure A2: Downstream Pollution

Notes: The dependent variable is dissolved oxygen deficit. The figure plots the estimated coefficients on $1\{y - y_p^* = t\} * d_d$ from estimating $Q_{pdy} = \alpha_0 + \sum_{t=-4}^{-2} \pi_t 1\{y - y_p^* = t\} * d_d + \sum_{t=0}^{8} \gamma_t 1\{y - y_p^* = t\} * d_d + \beta W_{pdy} + \alpha_{pd} + \alpha_{py} + \epsilon_{pdy}$.
Source: (USEPA, 1967-1988)



(a) Non-compliant



(b) All other Facilities

Figure A3: Downstream Pollution by Pre-CWA Compliance

Notes: This figure presents results from re-estimating the event study in Figure A2 on subsamples of facilities defined by pre-CWA compliance. Panel A shows estimates from estimating this equation on a sample of pre-CWA non-compliant facilities (those that were required to make wastewater treatment capital upgrades) and Panel B shows estimates using all other facilities.
Source: (USEPA, 1967-1988)

Table A1: Other Distances Downstream

	non-compliant	all other facilities	DDD
	(1)	(2)	(3)
Panel A. 5 miles downstream	county average birth weight		
pct pop 1 mile	14.68***	6.358***	6.358***
	[9.192,20.18]	[2.190,10.53]	[2.191,10.52]
pct pop 1 mile X non-compliant			8.326**
			[1.435,15.22]
N	35973	50379	86352
Panel B. 10 miles downstream	county average birth weight		
pct pop 1 mile	14.44***	6.167***	6.167***
	[8.986,19.90]	[2.023,10.31]	[2.024,10.31]
pct pop 1 mile X non-compliant			8.278**
			[1.429,15.13]
N	35154	49413	84567
demographic controls	X	X	X
unit and year fixed effects	X	X	X
collapsed to facility level	X	X	X

95% confidence intervals in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Notes: This table presents (weighted) estimates from the following model: $bw_{py} = \alpha_0 + \gamma_0^{DD} pct_{py} + \gamma^{DDD} pct_{py} * t_p + \beta X_{py} + \phi X_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py}$. pct_{cy} is a continuous variable that takes values from zero to one, and indicates the proportion of downstream counties' populations that lived within a mile of a treated waterway in a given year. In Panel A, a waterway is considered treated if it is within 5 miles downstream from a facility that received a Clean Water Act Grant. In Panel B, a waterway is considered treated if it is within 10 miles downstream from a facility that received a Clean Water Act Grant. Source: NCHS (1968-1988)

Table A2: County Code Changes

State fips	New County fips	Old County fips	Year	Note
4	12	27	1983	La Paz County, AZ split off from Yuma county
13	510	215	1971	The city of Columbus, GA became a consolidated city-county
29	186	193	N/A	Ste. Genevieve county, MO changed codes
32	510	25	1968	Ormsby County became Carson City
35	6	61	1981	Cibola County, NM split off from Valencia County
46	71	131	1979	Washabaugh County was annexed to Jackson County
51	83	780	1995	South Boston City rejoins Halifax County
51	510	13	N/A	Alexandria City/Arlington County
51	515	19	1968	Bedford City splits from Bedford County
51	520	191	N/A	Bristol City/Washington County
51	530	163	N/A	Buena Vista City/Rockbridge County
51	540	3	N/A	Charlottesville City/Albemarle County
51	560	75	N/A	Clifton Forge City/Alleghany County
51	590	143	N/A	Danville City/Pittsylvania County
51	630	177	N/A	Fredericksburg City/Spotsylvania County
51	660	165	N/A	Harrisonburg City/Rockingham County
51	670	149	N/A	Hopewell City/Prince George County
51	680	31	N/A	Lynchburg City/Campbell County
51	683	153	1975	Manassas City splits from Prince William County
51	685	153	1975	Manassas Park City splits from Prince William County
51	690	89	N/A	Martinsville City/Henry County
51	710		N/A	Norfolk City came from Norfolk County, which was ultimately combined into Chesapeake City
51	730	53	N/A	Petersburg City/Dinwiddie County
51	735	199	1975	Poquoson City splits from York County
51	740		N/A	Portsmouth City came from Norfolk County before it was Chesapeake City
51	750	121	N/A	Radford City/Montgomery County
51	770	161	N/A	Roanoke City/Roanoke County
51	775	161	1968	Salem City splits from Roanoke County
51	790	15	N/A	Staunton City//Augusta County
51	800	123	1974	Nansemond County merges into Suffolk City
51	840	69	N/A	Winchester City//Frederick County

Table A3: Sample Changes

State Name	State NCHS Code	State fips Code	First Full Sample Year
Alabama	1	1	1976
Arizona	3	4	1985
Arkansas	4	5	1980
California	5	6	1985
Colorado	6	8	1973
Connecticut	7	9	1979
Delaware	8	10	1985
Washington DC	9	11	1984
Florida	10	12	1972
Georgia	11	13	1985
Idaho	13	16	1977
Illinois	14	17	1974

Indiana	15	18	1978
Iowa	16	19	1974
Kansas	17	20	1974
Kentucky	18	21	1976
Louisiana	19	22	1975
Maine	20	23	1972
Maryland	21	24	1975
Massachusetts	22	25	1977
Michigan	23	26	1973
Minnesota	24	27	1976
Mississippi	25	28	1979
Missouri	26	29	1972
Montana	27	30	1974
Nebraska	28	31	1974
Nevada	29	32	1976
New Hampshire	30	33	1972
New Jersey	31	34	1979
New Mexico	32	35	1982
New York	33	36	1977
North Carolina	34	37	1975
North Dakota	35	38	1983
Ohio	36	39	1977
Oklahoma	37	40	1975
Oregon	38	41	1974
Pennsylvania	39	42	1979
Rhode Island	40	44	1972
South Carolina	41	45	1974
South Dakota	42	46	1980
Tennessee	43	47	1975
Texas	44	48	1976

Utah	45	49	1978
Vermont	46	50	1972
Virginia	47	51	1975
Washington	48	52	1978
West Virginia	49	53	1976
Wisconsin	50	55	1975
Wyoming	51	56	1979

Table A4: Triple Difference: Random Sample

	(1) non-compliant	(2) all other facilities	(3) DDD
pct pop 1 mile	12.38***	4.448**	4.448**
	[7.015,17.74]	[0.303,8.593]	[0.304,8.592]
pct pop 1 mile X non-compliant			7.933**
			[1.157,14.71]
demographic controls	X	X	X
unit and year fixed effects	X	X	X
collapsed to facility level	X	X	X
N	34188	48132	82320

95% confidence intervals in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Notes: This table re-estimates the specifications in Panel A of Table 5 after taking a fifty percent random sample of births that occurred in state-years that reported a full sample of births. The years that each state switched from a 50 percent sample to a full sample of births are detailed in Table A3.
Source: NCHS (1968-1988)

Table A5: Pollution Triple Difference with Facility-by-Year Fixed Effects

	(1) full sample	(2) non-compliant	(3) all other facilities	(4) DDD
grant X downstream	-1.384**	-2.670**	-0.174	-0.174
	[-2.736,-0.0310]	[-4.763,-0.578]	[-1.957,1.609]	[-1.956,1.609]
grant X downstream X non-compliant				-2.496*
				[-5.243,0.250]
weather controls	X	X	X	X
facilty by downstream fixed effects	X	X	X	X
year fixed effects	X	X	X	X
N	18530	6418	12112	18530

95% confidence intervals in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Notes: This re-estimates the results from Table 4 with facility-by-year fixed effects.
Source: (USEPA, 1967-1988)