

NBER WORKING PAPER SERIES

A WATERSHED MOMENT:
THE CLEAN WATER ACT AND INFANT HEALTH

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Working Paper 29152
<http://www.nber.org/papers/w29152>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2021

For their helpful comments, we thank Anna Aizer, Brian Beach, Lindsey Bullinger, Will Wheeler, Barton Willage, and participants at the NBER Health Economics meeting and seminar participants at Ball State, Singapore Management University, Tilburg University, and the Vanderbilt Empirical Applied Microeconomics seminar. The authors have no relevant or material financial interests that relate to the research described in this paper. All remaining errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 29152
August 2021
JEL No. H51,I1,Q51,Q53

ABSTRACT

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A Watershed Moment: The Clean Water Act and Infant Health

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August 6, 2021

Abstract

The Clean Water Act (CWA) significantly improved surface water quality, but at a cost exceeding the estimated benefits. We quantify the effect of the CWA on a direct measure of health and incorporate health benefits into a cost-benefit analysis. Using a difference-in-differences framework, we compare health upstream and downstream from wastewater treatment facilities before and after CWA grant receipt. Pollution only decreased downstream from facilities required to upgrade their treatment technology, and we leverage this additional variation with a triple difference. CWA grants increased average birth weight by 8 grams. A back-of-the-envelope calculation bounds infant health benefits below \$29 billion.

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 Originally enacted in 1948 as the Federal Water Pollution Control Act, Congress significantly expanded the CWA in 1972 to regulate the discharge of “point source” pollution (i.e.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, 2019b). 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 estimate that the costs of this policy exceed

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its benefits (e.g. Lyon and Farrow (1995); Freeman (2010); Keiser et al. (2019)), but these analyses have not generally included improvements in health caused by the Clean Water Act because there has not been a systematic ex-post measurement of the health benefits of the CWA.

Incorporating health benefits into a cost-benefit analysis may matter for a number of reasons. Historically, policies targeting improvements in child health generate high returns to public funds (Hendren and Sprung-Keyser, 2020), 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).

To our knowledge, this paper is the first to incorporate infant 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 receives a CWA grant. Comparing up and downstream births addresses the endogenous distribution of grants as well as any economic shocks caused by grant receipt, however, estimates may still be biased if individuals sort into downstream areas or if these areas experience differential trends relative to upstream areas after grant receipt. To address this concern, we show that improvements in surface water quality associated with CWA grants are only driven by facilities that were required to upgrade their treatment technology to comply with new treatment technology standards. This finding motivates a triple difference design that uses counties up and downstream from facilities where these treatment technology requirements were not binding as an additional control group. By using already compliant facilities that receive grants as an additional control group, we

¹For 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).

can account for differential sorting into downstream areas after grant receipt, so the health benefits we capture with this design are likely caused by improvements in water quality.

Existing economics 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 (2019a) find that the CWA’s grant program led to a reduction in downstream pollution. These improvements in water quality were capitalized into housing prices, but the increases in home values were substantially smaller than the CWA’s costs. By quantifying how downstream residents value water quality, Keiser and Shapiro (2019a) improve upon previous cost-benefit calculations that only account for changes in pollution, however, as noted in Keiser et al. (2019), hedonic analysis assumes housing values 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 complement those in Keiser and Shapiro (2019a) 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 systems contained one or more contaminants at concentrations dangerous to human health. In an analysis of matched water samples from 94 water sources 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), suggesting that policies targeting improvements in surface water quality may have important impacts on health. At the time the CWA came into effect, surface waters were still very polluted; Smith and Wolloh (2012) estimate

that 35 percent of lakes were too polluted to safely swim in in 1975. 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 was likely to reduce exposure to contaminated drinking water. For infants in utero, this could have affected 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 expect grants to lead to the largest surface water quality improvements in areas downstream from facilities that had not yet upgraded to new treatment technology required by the CWA. We find that 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 leverage this variation in treatment technology in a triple difference specification that uses births near 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 downstream 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. The magnitude of this effect is the same as the estimated effect of stress in utero due to nearby landmine explosions on birth weight (Camacho, 2008). Using data on public water systems sources, we show that these results are driven by counties whose public water systems draw from surface rather than groundwater, suggesting that these improvements in infant health are primarily driven by reductions in exposure to contaminated drinking water.

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 complementarity between drinking water initiatives and sewerage improvements, along with most of our understanding of the effect of water quality on human health, came primarily from studies of the late nineteenth and early twentieth century (Troesken, 2001, 2002; Cutler and Miller, 2005; Beach et al., 2016; Anderson et al., 2020). By studying the CWA, which came into effect long after filtration and chlorination of drinking water

became widespread, we show that the complementarity 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 does not alter the 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. For grant funds targeted towards facilities requiring upgrades to treatment technology, which experienced the largest improvements in downstream water quality, the infant health benefits alone account for as much as 29 percent of the amount necessary for grants to be considered cost effective. It is important to note that this analysis incorporates just one of potentially many dimensions of health impacted by the CWA. Including other health outcomes, such as reduced hospital admissions, reduced school absences, and health effects for adolescents and adults would likely improve this benefit/cost ratio further and should be the subject of future research.

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). Early drinking water interventions, such as water filtration, contributed in part to this reduction in mortality (Cutler and Miller, 2005; Anderson et al., 2020). The effects of reduced exposure to contaminated water in utero and childhood can persist throughout life; for example, Beach et al. (2016) find that eradicating early-life exposure to typhoid fever would have increased earnings in later life by one percent and increased average educational attainment by one month.

Examining water policy in early 20th century Massachusetts, Alsan and Goldin (2019) show that these historical reductions in mortality were driven by a combination of clean water initiatives, which removed contaminants at drinking water treatment plants before distribut-

ing water for consumption and washing, and effective sewerage, which reduced contamination of drinking water at the source. Watson (2006) shows that federal sanitation policies explain much of the convergence in Native American and White infant mortality rates in the US since 1970, demonstrating that, at least in certain contexts, this complementarity holds into the later 20th century. By improving sewerage systems and reducing pollution of source water throughout the US at a time when almost all publicly provided drinking water was treated, the CWA provides a new context to examine the complementarity between sewerage infrastructure and clean water nationwide.

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. The CWA required all industrial polluters to obtain a permit from the National Pollutant Discharge Elimination System (NPDES) before discharging waste water.² 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 did not directly regulate these “non-point” pollution sources. The CWA did not directly regulate drinking water supplies either; drinking water is regulated through the Safe Drinking Water Act, which sets minimum standards for drinking water quality that apply to every public water system in the United States.

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). Municipal waste is almost entirely organic (Hines, 1966), and microorganisms from human sewage can cause a range of gastrointestinal illnesses and infections (Reynolds et al., 2008). 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

²Regulation through the NPDES led to reductions in both profits (Rassier and Earnhart, 2010) and the number of environmental employees (Raff and Earnhart, 2019) at newly regulated polluters.

placement and timing of grants facilitate our research design.

1.1 Grants

From 1972 to 1988, the EPA distributed an estimated \$153 billion (in 2014 dollars) worth of grants to municipal governments for capital upgrades to wastewater treatment facilities. 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 then distributed grants to municipalities 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. Grants themselves could also cause increases in birth weight that are unrelated to changes in pollution by improving economic conditions with an influx of federal dollars. Instead of treating grant timing and location as exogenous, we compare 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. To the extent that other policies were changing during this time period, and that grants improved local economic conditions, these changes were likely to affect upstream and downstream areas similarly.

1.2 Regulation

In 1972, about a quarter of all US municipal wastewater treatment facilities reported using relatively inexpensive, but less effective, primary treatment (USEPA, 2000). 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 1977.³ Plants use secondary treatment technology, shown in Figure 1b, in addition to primary treatment. After screens filter out large debris, wastewater sits in an aeration tank where bacteria in the water consume organic material. Secondary treatment removes about 85 percent of organic matter from wastewater, much more than primary treatment removes. Effluent from secondary treatment is also usually disinfected with chlorine before it is discharged into receiving waters, which kills more than 99 percent of harmful bacteria (USEPA, 1998). Additionally, many states required facilities to meet more stringent treatment technology requirements than the CWA’s mandate (USEPA, 2000).

The potential benefits of upgrading a facility’s treatment technology were well understood, but waste treatment capital upgrades were expensive. 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). Because of these costs, 53 percent of plants in the 1972 Clean Watershed Needs Survey (CWNS) were not in compliance with both state and federal treatment technology mandates.

Treatment plants that were not in compliance with both state and federal capital mandates in 1972, which we refer to as “non-compliant” facilities, had a strong incentive to use CWA grants to offset the costs of upgrading their treatment technology.⁴ Permits distributed to polluters through the NPDES required municipal treatment plants to satisfy the treatment technology mandate, and violating the terms of a permit resulted in a compliance order or civil suit by the EPA. Violators could be fined up to \$25,000 per day (Copeland, 2016).

Many facilities already in compliance with both state and federal mandates still received CWA grants. While these facilities could still make capital improvements, such as increasing

³This 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).

⁴In early work, Flynn and Smith (2021) show that grants to non-compliant municipalities led to a dollar for dollar increase in sewerage capital spending up to the point where facilities were in compliance with new treatment technology standards.

capacity, they had relatively little incentive to do so. Since the CWA did not mandate these upgrades, there was no binding constraint requiring these facilities to spend grant money on sewerage capital upgrades, and the municipalities that operated them faced pressure to use grant money to offset the operating costs of their water and sewerage utilities in an attempt to lower costs for consumers and become more competitive (Daigger, 1998).⁵

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 near facilities that were not indicated as pre-CWA non-compliant in the 1972 CWNS as an additional control group.

2 Data

CWA Grants and Municipal Wastewater Treatment Plants

We obtain data on all 33,429 grants that the EPA distributed to 14,285 wastewater treatment plants from the EPA’s Grant Information Control System. Most facilities received multiple grants, so we define a facility as “treated” after it receives its first CWA grant. 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 in compliance with state and federal capital mandates in 1972.⁶

⁵Flynn and Smith (2021) find evidence that CWA grants to facilities already in compliance with state and federal capital mandates crowded out funds that municipalities were already spending on sewerage capital rather than causing an increase in sewerage capital spending.

⁶There are 1,930 facilities in our analysis sample that are missing data on pre-CWA treatment technology. We assume that these facilities were already in compliance with state and federal treatment technology requirements. Throughout the paper, we refer to the set of “compliant” facilities, which includes all facilities that were not explicitly “non-compliant” in the 1972 CWNS. Our results are similar when we exclude facilities with missing information on treatment technology.

Spatial Data on Waterways

We define treatment in terms of the flow direction of waterways. We determine if an area is up or downstream from a facility with the National Hydrography Data Set, an electronic atlas that maps 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.⁷ Keiser and Shapiro (2019a) finds 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). We define a county as downstream if it contains any waterway that is within 25 miles downstream of a treated facility.

Water Pollution

We examine how CWA grants affected trends in downstream pollution and the relationship between pre-CWA wastewater treatment technology and downstream surface water quality with pollution data from STORET legacy, which includes over 200 million readings from pollution monitoring stations across the US.⁸ 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).⁹ Water loses dissolved oxygen when microorganisms consume oxygen to decompose pollution. Since upgrading treatment technology reduces the amount of organic material released by a facility, we expect treatment technology upgrades to decrease downstream dissolved oxygen deficit.

⁷Table A4 shows that our results are robust to concentrating on areas 5 or 10 miles downstream from treatment facilities.

⁸We follow the data cleaning steps laid out in the appendix of Keiser and Shapiro (2019a).

⁹Dissolved oxygen deficit is one of the most common measures of omnibus water pollution in research, and it responds to a wide variety of pollutants (Keiser and Shapiro, 2019a).

Infant Health

We use birth certificate data from the National Center for Health Statistics (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.¹⁰ Table 1 presents summary statistics for births in 1970, two years before the first CWA grants were distributed, from up and downstream counties, as well births in counties that drew at least some drinking water from a surface water source, and counties that drew exclusively from groundwater. These means are calculated from micro data on individual level births.

We collapse birth weight data to county means, calculating the average birth weight, the probability of low birth weight (less than 2500 grams), the percent of non-white births, average mother’s age, and the probability of being a mother’s first, second, third, or fourth or higher birth in each county year.¹¹

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.¹² This could cause

¹⁰Data in years prior to 1972 constitutes a 50 percent random 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 A10 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 in Figure A3 and Table A11.

While exact address of where children are born is available in some states, this information is not collected nationally and not all states record or allow researchers to access this information. Importantly for the CWA context, addresses are generally not available until the 1990s, after the adoption of the 1989 US Standard Birth Certificate revision and the use of electronic birth certificates. We were only able to find address data from the 1970s from Florida, but the field was missing for too many births to use these data reliably.

¹¹We also calculate county means of one year mortality using data from NCHS (National Center for Health Statistics, 1968-1988b). We find no significant effect of CWA grants on this outcome in Table A3, however our estimates are imprecise. Gestation is not consistently recorded in our sample, so we cannot repeat our analysis with gestation length or pre-term birth as the dependent variable.

¹²We see similar but attenuated results if we define treatment with a binary variable. We present these

our reduced form estimates to understate the CWA’s true effect. Instead, we use 1990 census block 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.¹³ Figure 2 shows the distribution of this treatment measure.

3 First Stage: Water Pollution

3.1 Methods

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.

$$Q_{pdy} = \gamma g_{py} * d_d + \beta W_{pdy} + \alpha_{py} + \alpha_{pd} + \epsilon_{pdy} \tag{1}$$

Q_{pdy} is a measure of dissolved oxygen deficit and g_{py} equals one after a facility receives its first CWA grant. There are two observations for each treatment plant p for each year y , which describe average dissolved oxygen deficit upstream ($d_d = 0$) and downstream ($d_d = 1$) from that plant. Since dissolved oxygen deficit varies inversely with temperature, W_{pdy} measures water temperature.

We include plant-by-downstream and plant-by-year fixed effects, α_{pd} and α_{py} , respectively. Plant-by-downstream fixed effects allow waters up and downstream from a given wastewater treatment plant to have different mean levels of dissolved oxygen deficit, which controls for pollution sources that are only up or downstream from a plant that are con-

results in the Appendix.

¹³We use data from 1990, because it is the first census for which population density data is available at the census block level. Table A5 shows that our results are robust to scaling by the percent of a county’s population living within other bandwidths around treated waterways. In the appendix, we also leverage information on the location of community water system service areas to define the treated population as the percent of the county’s population served by a public drinking water system that is near a treated waterway. Despite a large reduction in sample size due to missing data on water system service areas, our results are robust to this alternate definition.

start over time. Plant-by-year fixed effects ensure that we are only comparing waters up and downstream from the same facility, which controls for any time variant shocks that affect waters both up and downstream from a facility. All standard errors in our pollution estimates are clustered at the facility level.

These estimates give us a sense of how grants and regulations worked together by seeing whether pollution evolved differently in waters downstream from non-compliant facilities and compliant facilities following grant receipt.

3.2 Pollution Results

Table 2 estimates the effect of CWA grant receipt on downstream water quality. Columns 1-3 present estimates of equation 1 on the full sample, non-compliant facilities, and compliant facilities, respectively. Column 4 presents coefficients from the associated triple difference. Dissolved oxygen deficit only decreased significantly in water downstream from 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 (2019a). Since dissolved oxygen deficit is defined as 100 minus dissolved oxygen saturation, this result show that waters downstream from non-compliant facilities had a 1.6 percentage point higher dissolved oxygen saturation after grant receipt relative to waters upstream from the same facility. This represents a 2 percent increase relative to a mean of 79 percent oxygen saturation in our sample. The coefficient for waters downstream from 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 any change downstream from compliant facilities, as shown by the significant negative triple difference coefficient in column 4.

Figure 3 presents results from the event study corresponding to the triple difference in column 4.¹⁴ This figure shows that reductions to downstream pollution were significantly larger in waters downstream from non-compliant facilities relative to compliant facilities.

¹⁴In all of our event studies, we report coefficients for four years before and eight years after grant receipt, which allows us to only report balanced coefficients in our infant health specifications. These specifications also includes bins for five or more years before the grant and nine or more years after the grant, but our results are not sensitive to this choice of binning.

In addition, there does not appear to be any trend in pollution prior to grant receipt, which might have arisen from complaint facilities early adoption of more advanced treatment technology. In the analysis of the impact of CWA grants on infant health that follows, we leverage this comparison between non-compliant and compliant facilities in a triple difference specification.

4 Infant Health

4.1 Methods

We begin our reduced-form analysis of the impact of CWA grants on infant health with the most general specification by comparing birth outcomes in counties downstream from treated facilities to all other areas. We check for the existence of parallel trends in birth outcomes prior to treatment and examine how infant health evolved in counties downstream from treated facilities after grant receipt with the following event study

$$Y_{cy} = \sum_{t=-5}^{-2} \pi_t 1\{y - y_c^* = t\} + \sum_{t=0}^9 \gamma_t 1\{y - y_c^* = t\} * pct_{cy} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy} \quad (2)$$

where Y_{cy} is an average birth outcome in county c in year y , $1\{y - y_c^* = t\}$ measures time relative to county c being downstream from a facility that received a grant, 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. α_c and α_y are county and year fixed effects. Observations are at the county-year level and standard errors are clustered at the county 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 with equation 3.

$$Y_{cy} = \gamma pct_{cy} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy} \quad (3)$$

This compares birth weight between counties downstream from any facility that received a grant and all other counties.

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. The outcome variable of interest is now ΔY_{py} , the mean birth weight in all counties downstream from a facility minus the mean birth weight in all counties upstream from the same facility in each year. We estimate the following specification¹⁵

$$\Delta Y_{py} = \gamma pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py} \quad (4)$$

where p indexes facilities, and pct_{py} measures the percent of downstream counties’ populations living within a mile of a treated waterway. We include facility and year fixed effects, α_p and α_y , respectively.¹⁶ Standard errors are clustered at the facility level.

This specification assumes that, in the absence of grant receipt, birth outcomes would have evolved similarly in areas up and downstream from the same facility after grant receipt. This assumption would be violated if, for example, downstream areas were experiencing greater economic growth relative to upstream areas, even in the absence of CWA grants.

To address concerns regarding differential trends in downstream relative to upstream areas in terms of economic growth or positive sorting of households into downstream areas, we employ a triple difference design.

$$\Delta Y_{py} = \gamma_0^{DD} pct_{py} + \gamma^{DDD} pct_{py} * t_p + \beta X_{py} + \phi X_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py} \quad (5)$$

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

¹⁵This specification is similar to adding facility-by-year fixed effects to equation 3.

¹⁶Controls in facility-level specifications are averages from all births in up and downstream counties. Our results are robust to controlling for the difference between average demographic characteristics in up and downstream counties instead.

treatment facility, and the third difference comes from the facility’s compliance with the required treatment technology mandate.

Keiser and Shapiro (2019a) show that downstream housing prices increase after grant receipt, which may cause healthier mothers to sort into downstream communities. Our triple difference design addresses this concern; even if grants are placed endogenously, or if individuals sort into downstream communities, so long as the sorting pattern induced by grant receipt is similar for both compliant and non-compliant facilities, using compliance as a third difference will capture unobserved changes to up and downstream counties occurring contemporaneously with CWA grants.

We test this assumption by exploring how maternal characteristics evolve relative to grant timing in upstream and downstream areas across non-compliant and compliant facilities. Table 3 estimates the effect of treatment on demographic characteristics that are correlated with birth weight, such as race, age, and birth order, by estimating

$$\Delta x_{py} = \gamma pct_{py} + \alpha_p + \alpha_y + \epsilon_{py} \tag{6}$$

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

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. 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. These changes in demographic characteristics downstream are very similar across non-compliant and compliant facilities. 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 compliant facilities after grant receipt. These results provide some

evidence that the identification assumption for the triple difference specification is likely to hold.

4.2 Infant Health Results

Figure 4a presents event study coefficients from estimating equation 2 with county average birth weight as the dependent variable. The precisely estimated null effects in the four years before grant receipt 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. The estimates begin to increase shortly after the arrival of CWA grants, and continue to rise after treatment.

The impact of the CWA on birth weight may not be uniform across the distribution of birth weight. Even though Figure 4a 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 4b presents event study coefficients from re-estimating equation 2 with the probability of low birth weight as the dependent variable. There is no evidence of a pre-trend and, similar to the results in Figure 4a, we see a small decrease in the probability of low birth weight after treatment.

Panel A of Table 4 shows that the effects on birth weight are robust across a variety of specifications. Column 1 compares births in counties downstream from grant facilities to those in any other county by estimating equation 3 using a sample of births from every county in the contiguous US. Column 2 adds demographic controls to this specification, which reduces the magnitude of the estimate by about half. Since births occurring in counties that are not near wastewater treatment facilities might not make a good control group, column 3 excludes counties that are not up or downstream from a wastewater treatment facility. This compares births in a downstream county to those in any upstream county, and the results are similar to those from the full sample.

Counties upstream from the same facility are likely to make even better counterfactuals for downstream counties than counties upstream from any facility. Column 4 estimates equation 4, 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.

Figure 5a shows the associated event study. Relative to Figure 4a, these estimates are similar in shape but are more precise. Again, there is no evidence of a 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.¹⁷

Panel B of Table 4 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 -0.09 to -0.29 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 5b shows the facility level event study results for low birth weight. Similar to the birth weight results, the probability of low birth weight decreases after grant receipt and this decline grows over time.

4.3 Triple Difference Results

We then estimate our triple difference specification on birth outcomes. Columns 1 and 2 of Table 5 present results from estimating equation 4 on sub-samples of non-compliant and compliant facilities, respectively. Consistent with our pollution results in Table 2, we see a relatively large and statistically significant improvement in birth weight downstream from non-compliant facilities. The effect in areas downstream from compliant facilities is also positive, but smaller; improvements in infant health in areas downstream from compliant facilities may be driven by demographic or economic changes that coincide with grant timing. Since there were similar demographic changes in areas downstream from non-compliant facilities, as shown in Table 3, the difference between the effects downstream from non-complaint and compliant facilities likely comes from the differences in surface water quality shown in Table 2, rather than shifting demographics.

Figure 6 presents the event studies for the corresponding triple difference. As before, there is no evidence of pre-treatment trends in infant health outcomes. For birth weight,

¹⁷These results are identified off of comparisons of newly treated facilities relative to never-treated facilities, newly treated facilities relative to facilities that have not yet been treated, and newly treated facilities relative to already-treated facilities (Goodman-Bacon, 2019). The third type of comparison can be wrong signed and render our results uninterpretable, but we show in the Appendix that our results are robust to using stacked difference-in-difference and aggregated group-time treatment effect designs (Callaway and Sant’Anna, 2019) which only rely on the first two types of comparisons.

there is a statistically significant increase in downstream (relative to upstream) counties after a non-compliant facility receives a grant (relative to other facilities).¹⁸ For low birth weight, the point estimates are similar in shape but are statistically insignificant. Of the infant health specifications, this is the closest analogue to our triple difference pollution specification. Importantly, the shapes of these event studies are similar to the patterns in pollution shown in Figure 3.

We summarize the effect of changes in surface water quality downstream from non-compliant facilities on infant health by estimating equation 5 on the pooled sample, which leverages all of our variation in one regression. Since equation 5 includes a full set of interactions, our estimate of γ^{DDD} , reported in column 3 of Table 5, will be equivalent to the difference of the estimates of equation 4 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 compliant facilities.¹⁹

The results from this triple difference show that going from having zero to 100 percent of a county’s population living within a mile of a treated waterway is associated with an 8.21 gram increase in average birth weight in counties downstream from facilities that were required to make upgrades to their treatment technology. In terms of magnitude, the effect on birth weight is about half of the estimated effect of any exposure to Ramadan during pregnancy (Almond and Mazumder, 2011), and about the same magnitude as the effect of stress in utero due to nearby landmine explosions on birth weight (Camacho, 2008). Estimates of the effect on the probability of low birth weight shown in Panel B of Table 5 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. This is slightly smaller than the estimated effect of drinking water contamination in utero on low birth weight estimated in a modern context

¹⁸As with all of our event studies, we report coefficients for four years before and 8 years after grant receipt. All of these coefficients are balanced. While unbalanced event study coefficients should be interpreted with caution, we present a version of Figure 6a with 16 years of post-treatment data in Figure A2. This Figure suggests that the effect of CWA grants on infant health flattens out by 10 years after treatment, consistent with grant projects taking up to 10 years to complete (USEPA, 2002).

¹⁹We show that this heterogeneity in effects is not driven by differences in facility size, population served or non-treatment technology upgrades in Table A8, which provides further evidence that improvements in downstream infant health are driven by upgrades to treatment technology.

(Currie et al., 2013).

4.4 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.²⁰

We show that our results are driven by counties that had some public water systems that drew from surface water sources in Table 6. Column 1 of Table 6 re-estimates equation 5 on facilities whose downstream counties had some public water systems that drew from surface water sources, while column 2 estimates the same specification on facilities whose downstream counties' public water systems drew from groundwater exclusively. CWA grants significantly increased birth weight for counties where some drinking water is sourced from surface water, but there is no significant effect among counties that provide drinking water exclusively from groundwater sources. In fact, the point estimate is negative for these counties.²¹

We disaggregate these results further in Table 7 by estimating a triple difference where the first difference comes from where and when CWA grants were distributed, the second difference comes from if a birth occurred up or downstream from a wastewater treatment facility, and the third difference comes from whether downstream public water systems drew from surface or groundwater. Panels A and B estimate this triple difference on a sample of non-compliant facilities. We see strongly significant increases in birth weight and marginally significant decreases in the probability of low birth weight in areas that drew from surface water sources. Our estimates for areas that drew exclusively from groundwater are statistically insignificant and wrong-signed, and the birth weight effect in areas that drew from surface

²⁰We use data from 1985 because it is the earliest year for which information on county level water usage is available. While water service areas and county borders do not always perfectly align, community water systems generally serve areas no larger than counties (USEPA, 1997).

²¹Columns 6 and 7 of Table 1 suggest that communities served by surface and groundwater systems serve similar populations.

water is statistically greater than the effect in areas that only drew from groundwater. In Panels C and D, we re-estimate these specifications on samples of compliant facilities. These estimates can be thought of as a placebo test since these facilities experienced no improvement in downstream water quality. We find no significant effects of treatment in areas whose community water systems drew from either surface or ground water sources, as we would have expected. This suggests that our results are almost completely driven by counties that are downstream from non-compliant facilities in which some public water systems draw from surface water.²²

4.5 Heterogeneity

We examine the heterogeneity of our estimates across race in Table 8 by estimating equation 5 on sub-samples of white and non-white births from counties with sizable non-white populations.²³ 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 8. In column 3, we drop all observations from facilities that received a grant after 1976 and re-estimate equation 4, and in column 4

²²We provide further evidence that the effect of CWA grants on birth weight is driven by reduced contamination of publicly provided water in the Appendix. Rather than defining the treated population as the percent of a county's population living within 1 mile of a treated waterway, we instead leverage information on the location of community water system service areas to define the treated population as the percent of the county's population served by a public drinking water system that is near a treated waterway. Despite a large reduction in sample size due to missing data on water system service areas, our results are robust to this alternate definition.

We also explore whether our results are driven by states with higher spending on water recreation activities in the Appendix, but our estimates lack power to detect these effects.

²³The 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.

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. Given that previous studies have found statistically significant relationships between water quality and infant health, how do our results relate to 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, in a modern context, Currie et al. (2013) found that in utero exposure to drinking water from drinking water facilities where contaminants were detected is associated with a 0.32 percentage point increase in the the probability of low birth weight. We estimate somewhat smaller, but similar effects for low birth weight. Consistent with this channel, we only detect 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. Even as recently as 2010, studies found that the organic contaminants detected in source water consistently appeared at similar concentrations in drinking water after treatment (Toccalino and Hopple, 2010), suggesting that the threats to health from surface water contamination are not limited to an historic context.

We use this information on the relationship between surface water quality and infant health to incorporate one measure of health benefits into a cost benefit analysis of the Clean Water Act. In total, CWA grants to wastewater treatment facilities cost an estimated \$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 triple difference 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 (VSL) 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 health effects for adolescents and adults, we estimate the infant health benefits of the CWA are bounded below \$29 billion, about 19 percent of the amount needed to make the CWA cost effective.²⁴

The \$153 billion figure includes grants to compliant facilities, which did not lead to improvements in downstream water quality. If CWA grants had been targeted only towards facilities requiring treatment technology upgrades, the cost-benefit ratio may have been more favorable, as health improvements were detected only downstream of these facilities. Health effects alone can account for as much as 29 percent of the \$101 billion (in 2014 dollars) in grants distributed to non-compliant facilities.

Using increased housing prices to value the benefits of the CWA, Keiser and Shapiro (2019a) estimate a benefit to cost ratio of 0.26. Assuming that hedonic estimates do not capture any health benefits, grants to non-compliant facilities might have a benefit to cost ratio as high as 0.55 after incorporating improvements to infant health. Considering that infant health is only one dimension of health potentially impacted by the Clean Water Act, this is a sizable improvement in the benefit-cost ratio and including additional measures of

²⁴Estimates of VSL vary. Kniesner and Viscusi (2019) finds that estimates of the VSL for the United States are around \$10 million. Using this figure instead of the EPA estimate bounds the infant health benefits of the CWA below \$36.4 billion and yields a benefit-cost ratio around 0.24.

health would likely increase this ratio even further. Moreover, this research establishes the importance of cleaner water at the source and that the complementarity between clean water and sewerage initiatives for improving human health holds well into the twentieth century.

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Figures

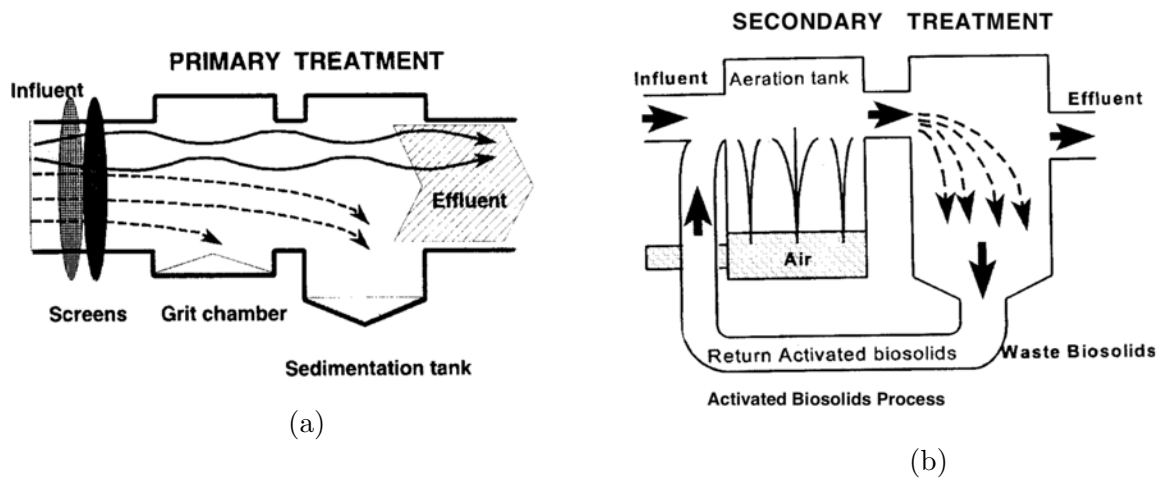


Figure 1: Primary vs Secondary Treatment Technology

Source: USEPA (1998)

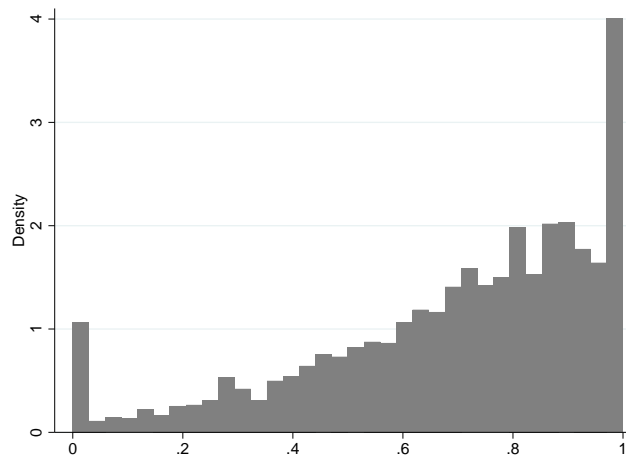


Figure 2: Percent of County Population Living Within a Mile of a Treated Waterway in 1988

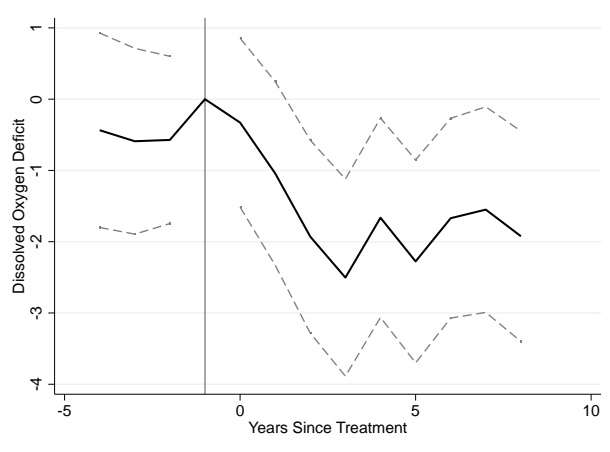
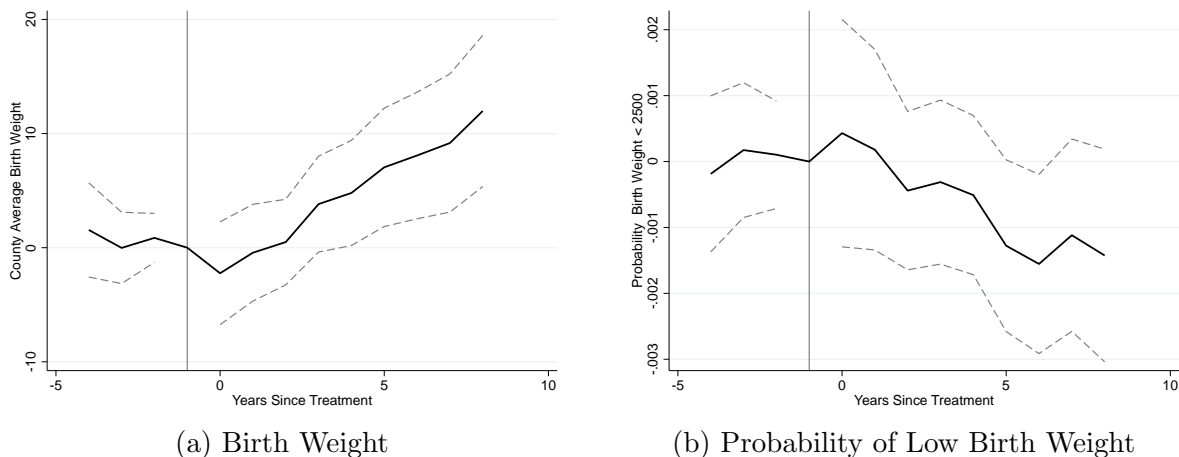


Figure 3: Pollution Triple Difference

Notes: The figure plots the estimated coefficients on $1\{y - y_p^* = t\} * d_d * t_p$ from $Q_{pdy} = \sum_{t=-5}^{-2} \theta_t 1\{y - y_p^* = t\} * d_d * t_p + \sum_{t=0}^9 \eta_t 1\{y - y_p^* = t\} * d_d * t_p + \sum_{t=-5}^{-2} \pi_t 1\{y - y_p^* = t\} * d_d + \sum_{t=0}^9 \gamma_t 1\{y - y_p^* = t\} * d_d + \beta W_{pdy} + \phi W_{pdy} * t_p + \alpha_{py} + \alpha_{pd} + \epsilon_{pdy}$. Q_{pdy} measures dissolved oxygen deficit, d_d is a dummy equaling one for observations downstream from a facility, and t_p is an indicator that equals one for non-compliant facilities. The model includes facility-by-downstream fixed effects and facility-by-year fixed effects, α_{pd} and α_{py} respectively, as well as controls for temperature.

Source: USEPA (1968-1988)



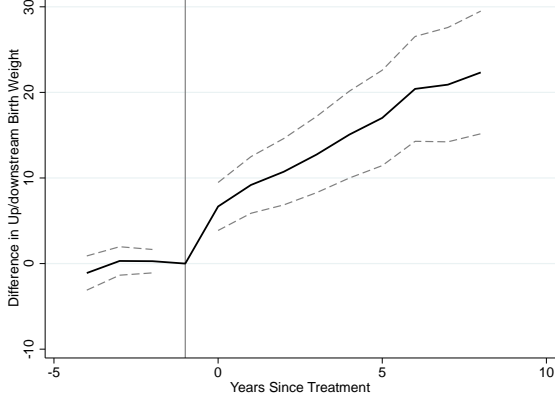
(a) Birth Weight

(b) Probability of Low Birth Weight

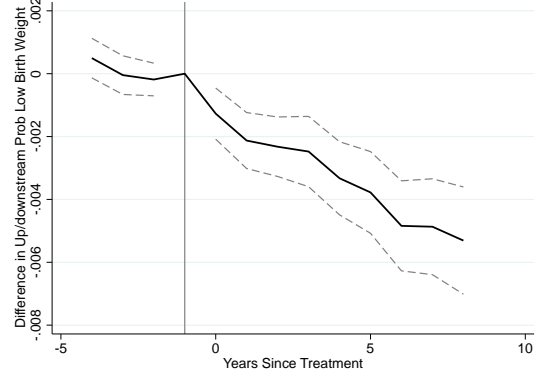
Figure 4: Birth Outcomes Downstream from Grant Facilities

Notes: These figures plot the π_t and γ_t from estimating $Y_{cy} = \sum_{t=-5}^{-2} \pi_t 1\{y - y_c^* = t\} + \sum_{t=0}^9 \gamma_t 1\{y - y_c^* = t\} * pct_{cy} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy}$. 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 of 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. The dependent variable is the the average birth weight in county c in year y in sub-figure (a), and the probability of being born weighing less than 2500 grams in county c in year y in sub-figure (b).

Source: National Center for Health Statistics (1968-1988a)



(a) Birth Weight

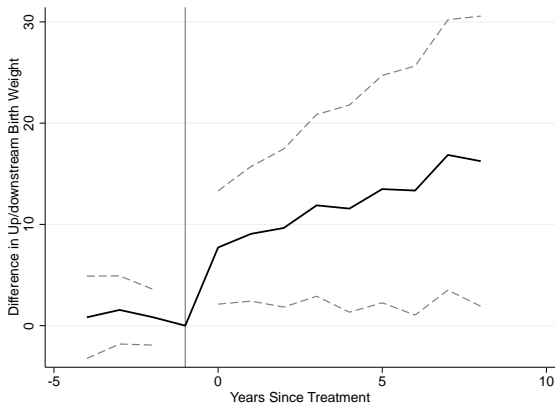


(b) Probability of Low Birth Weight

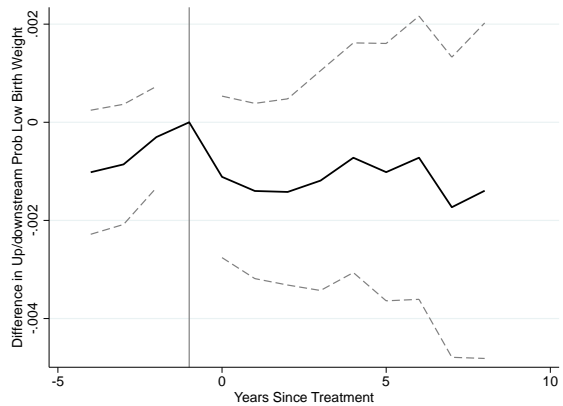
Figure 5: Difference in Birth Outcomes Up and Downstream from Grant Facilities

Notes: These figure plot the π_t and γ_t from estimating $\Delta Y_{py} = \sum_{t=-5}^{-2} \pi_t 1\{y - y_p^* = t\} + \sum_{t=0}^9 \gamma_t 1\{y - y_p^* = t\} * pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py}$. 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 of 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 facility p in year y . The dependent variable is the difference in birth weight between up and downstream counties in year y in sub-figure (a), and the difference in the probability of being born weighing less than 2500 grams between up and downstream counties in year y in sub-figure (b).

Source: National Center for Health Statistics (1968-1988a)



(a) Birth Weight



(b) Probability of Low Birth Weight

Figure 6: Birth Outcome Triple Difference

Notes: These figures plot the θ_t and η_t from estimating $\Delta Y_{py} = \sum_{t=-5}^{-2} \theta_t 1\{y - y_p^* = t\} * t_p + \sum_{t=0}^9 \eta_t 1\{y - y_p^* = t\} * pct_{py} * t_p + \sum_{t=-4}^{-2} \pi_t 1\{y - y_p^* = t\} + \sum_{t=0}^9 \gamma_t 1\{y - y_p^* = t\} * pct_{py} + \beta X_{py} + \phi X_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py}$. t_p is an indicator that equals one for non-compliant facilities and the remaining variables are defined analogously to those in Figure 5. The dependent variable is the difference in birth weight between up and downstream counties in year y in sub-figure (a), and the difference in the probability of being born weighing less than 2500 grams between up and downstream counties in year y in sub-figure (b).

Source: National Center for Health Statistics (1968-1988a)

Tables

Table 1: Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full Sample	Downstream	Upstream	Non-compliant	Compliant	Surface	Ground
birth weight	3279.61	3277.83	3297.25	3279.70	3279.37	3275.67	3296.68
probability bw < 2500	.078	.079	.074	.078	.077	.078	.077
nonwhite	.166	.170	.115	.155	.193	.161	.185
age of mother	24.58	24.58	24.62	24.66	24.39	24.63	24.40
education of mother	11.83	11.83	11.83	11.87	11.65	11.86	11.72
birth order	2.40	2.39	2.42	2.42	2.34	2.37	2.52
Observations	1788138	1571197	206017	1300614	487524	1452552	335586

Notes: This table presents the mean of birth weight, the probability of low birth weight, the percent of non-white births, average age and education of mothers, and average birth order for all counties, births in counties that were ever downstream from a facility that received a CWA grant, counties that were ever upstream from a facility that received a CWA grant, counties up or downstream from non-compliant facilities, counties up or downstream from compliant facilities, counties that had at least some public water systems that drew from surface water, and counties that used exclusively ground water. These means are calculated using individual birth data from 1970, two years before the CWA came into effect.

Source: National Center for Health Statistics (1968-1988a)

Table 2: Pollution Triple Difference

	(1)	(2)	(3)	(4)
	full sample	non-compliant	compliant	DDD
grant X downstream	-0.974***	-1.566***	-0.371	-0.371
	[-1.364,-0.584]	[-2.125,-1.008]	[-0.911,0.170]	[-0.911,0.170]
grant X downstream X non-compliant				-1.196***
				[-1.973,-0.419]
weather controls	X	X	X	X
facility by downstream fixed effects	X	X	X	X
facility by year fixed effects	X	X	X	X
N	114148	46968	67180	114148

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. Columns 1, 2 and 3 estimate $Q_{pdy} = \gamma g_y * d_d + \beta W_{pdy} + \alpha_{pd} + \alpha_{py} + \epsilon_{pdy}$ for areas up and downstream from all facilities in our sample, non-compliant facilities, and all other facilities respectively. 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: $Q_{pdy} = \gamma_0^{DD} g_y * d_d + \gamma^{DDD} g_y * d_d * t_p + \beta W_{pdy} + \phi W_{pdy} * t_p + \alpha_{py} + \alpha_{pd} + \epsilon_{pdy}$ where t_p is a dummy variable equaling one for observations from non-compliant facilities. All regressions include controls for water temperature, as well as facility-by-downstream and facility-by-year fixed effects, α_{pd} and α_{py} .

Source: (USEPA, 1968-1988)

Table 3: Controls as Dependent Variables

	non-compliant (1)	compliant (2)	DDD (3)
Panel A.			
	percent non-white		
pct pop 1 mile	-0.0223*** [-0.0281,-0.0165]	-0.0176*** [-0.0229,-0.0123]	-0.0176*** [-0.0229,-0.0123]
pct pop 1 mile X non-compliant			-0.00471 [-0.0126,0.00313]
mean	.116	.105	.11
Panel B.			
	mother's age		
pct pop 1 mile	0.126*** [0.0557,0.197]	0.0784** [0.0149,0.142]	0.0784** [0.0150,0.142]
pct pop 1 mile X non-compliant			0.0479 [-0.0470,0.143]
mean	24.563	24.569	24.566
Panel C.			
	probability first or second birth		
pct pop 1 mile	-0.00210 [-0.00916,0.00496]	0.00109 [-0.00390,0.00608]	0.00109 [-0.00390,0.00608]
pct pop 1 mile X non-compliant			-0.00319 [-0.0118,0.00545]
mean	.653	.645	.648
Panel D.			
	probability third or higher birth		
pct pop 1 mile	-0.0105*** [-0.0145,-0.00646]	-0.00618*** [-0.00965,-0.00271]	-0.00618*** [-0.00964,-0.00271]
pct pop 1 mile X non-compliant			-0.00429 [-0.00958,0.00100]
mean	.338	.347	.343
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: Columns 1 and 2 present results from estimating $\Delta x_{py} = \gamma pct_{py} + \alpha_p + \alpha_y + \epsilon_{py}$ on subsamples of non-compliant and compliant facilities. Δx_{py} is a measure of the difference between demographic characteristic in counties up and downstream from facility p in year y , and 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 . Column 3 presents estimates of the associated triple difference, $\Delta x_{py} = \gamma_0^{DD} pct_{py} + \gamma^{DDD} pct_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py}$, where t_p is an indicator that equals one for non-compliant facilities. Each panel represents a different demographic variable. Means of each variable in 1970 from up and downstream counties are reported at the bottom of each panel.

Source: National Center for Health Statistics (1968-1988a)

Table 4: Difference in Difference

	full sample		up/downstream only	
	(1)	(2)	(3)	(4)
Panel A	county average birth weight			
pct pop 1 mile	12.80*** [6.709,18.89]	6.718*** [2.034,11.40]	7.134*** [2.444,11.82]	8.999*** [5.721,12.28]
Panel B	probability birth weight < 2500 grams			
pct pop 1 mile	-0.00288*** [-0.00419,-0.00156]	-0.000874* [-0.00190,0.000152]	-0.000963* [-0.00198,0.0000584]	-0.00177*** [-0.00256,-0.000985]
demographic 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

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

Notes: This table presents (weighted) estimates of the effect of CWA grants on downstream infant health. Columns 1-3 present estimates from the following model: $Y_{cy} = \gamma pct_{cy} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy}$. In Panel A, the dependent variable is the average birth weight in a county-year, and in Panel B, it is 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 . All estimates include unit and year fixed effects, 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, and we estimate $\Delta Y_{py} = \gamma pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py}$, where ΔY_{py} is the difference between birth outcomes in counties up and downstream from facility p in year y , and pct_{py} measures the percent of downstream counties' populations living within a mile of a treated waterway. 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 up and downstream from the same facility. Source: National Center for Health Statistics (1968-1988a)

Table 5: Triple Difference

	non-compliant (1)	compliant (2)	DDD (3)
Panel A.	county average birth weight		
pct pop 1 mile	13.36*** [8.012,18.72]	5.153** [1.129,9.177]	5.153** [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*** [-0.00334,-0.000979]	-0.00138** [-0.00244,-0.000325]	-0.00138** [-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 depending on pre-CWA treatment technology. Columns 1 and 2 estimate $\Delta Y_{py} = \gamma pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py}$ for areas up and downstream from non-compliant facilities (those that were required to make treatment technology upgrades) and compliant facilities (those that were not) separately. Column 3 estimates the associated triple difference: $\Delta Y_{py} = \gamma_0^{DD} pct_{py} + \gamma^{DDD} pct_{py} * t_p + \beta X_{py} + \phi X_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py}$. All regressions include demographic controls and unit and year fixed effects, α_p 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: National Center for Health Statistics (1968-1988a)

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: National Center for Health Statistics (1968-1988a); Solley et al. (1988)

Table 7: Public Water Source Triple Difference

	Surface (1)	Ground (2)	DDD (3)
Panel A. Non-compliant	county average birth weight		
pct pop 1 mile	10.15*** [5.927,14.38]	-7.879 [-20.35,4.597]	-7.879 [-20.23,4.473]
pct pop 1 mile X surface			18.03*** [4.976,31.09]
N	30009	4200	34209
Panel B. Non-compliant	probability birth weight < 2500 grams		
pct pop 1 mile	-0.000872* [-0.00182,0.0000796]	0.00103 [-0.00192,0.00399]	0.00103 [-0.00189,0.00396]
pct pop 1 mile X surface			-0.00190 [-0.00498,0.00117]
N	30009	4200	34209
Panel C. Compliant	county average birth weight		
pct pop 1 mile	3.111 [-0.861,7.083]	3.110 [-4.426,10.65]	3.110 [-4.402,10.62]
pct pop 1 mile X surface			0.000404 [-8.497,8.498]
N	37023	11088	48111
Panel D. Compliant	probability birth weight < 2500 grams		
pct pop 1 mile	-0.000333 [-0.00138,0.000714]	-0.00183 [-0.00419,0.000522]	-0.00183 [-0.00418,0.000515]
pct pop 1 mile X surface			0.00150 [-0.00107,0.00407]
N	37023	11088	48111
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 describes the effects of Clean Water Act grants on birth outcomes depending on public water source. Column 1 estimates $\Delta Y_{py} = \gamma pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py}$ for facilities whose downstream counties had some public water systems that drew from surface water, and column 2 re-estimates this specification for counties whose public water systems only drew from groundwater. Column 3 estimates the associated triple difference: $\Delta Y_{py} = \gamma_0^{DD} pct_{py} + \gamma^{DDD} pct_{py} * s_p + \beta X_{py} + \phi X_{py} * s_p + \alpha_y * s_p + \alpha_p + \alpha_y + \epsilon_{py}$ where s_p is a dummy variable that equals one for facilities with downstream counties that drew at least some drinking water from surface water sources. All regressions include demographic controls and unit and year fixed effects. Panels A and B run this analysis for non-compliant facilities, and Panels C and D repeat this analysis for compliant facilities as a robustness check. Average birth weight is the dependent variable in Panels A and C, and probability of low birth weight is the dependent variable in Panels B and D.

Source: National Center for Health Statistics (1968-1988a); Solley et al. (1988)

Table 8: Heterogeneous Effects

	(1)	(2)	(3)	(4)
	white	nonwhite	early grants	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 column 3 of Table 4 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: National Center for Health Statistics (1968-1988a)