# A Watershed Moment: The Clean Water Act and Infant Health

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**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 the 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 Originally enacted in 1948 as the Federal Water Pollution Control Act, Congress significantly expanded the CWA in 1972 to prohibit the discharge of "point source" pollution (i.e.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, 2019b). In total, US government and industry

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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 exceeded the benefits (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.

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, 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).

To our knowledge, 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. 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

[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).

if these areas experience differential trends relative to upstream areas after grant receipt. To address this concern, we show that improvements to surface water quality associated with CWA grants were only driven by facilities that were required to comply with the CWA's new treatment technology standards. This finding 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. By using already compliant facilities that receive grants as an additional control group, we can account for differential sorting into downstream areas after grant receipt, ensuring that we only capture health benefits caused by improvements in water quality.

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 (2019a) 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 (2019a) 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 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 (2019a) by quantifying one of the largest benefits of the CWA that hedonic analysis is least likely to capture.

While it is unlikely that residents are well informed about where their water is sourced from, 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). At the time the CWA came into effect, surface waters were still very polluted; it is estimated that 35 percent of lakes were too polluted to safely swim in in 1975 (Smith and Wolloh, 2012). 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 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. Indeed, 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 look for heterogeneous health effects across these facilities, and leverage variation in treatment technology in a triple difference specification that uses births that occurred downstream from 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. 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, suggesting that these improvements in infant health were 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 complimentary 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 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. If grant funds were targeted only 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.

# 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; 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 average educational attainment by one month.

Examining water policy in early 20th century Massachusetts, Alsan and Goldin (2019) shows that 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. Watson (2006) shows that federal sanitation policies explain much convergence in Native American and White infant mortality rates in the US since 1970, demonstrating that, at least in 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 regulate these "non-point" pollution sources. The CWA did not directly regulate drinking water supplies either; drinking water is regulated by a separate policy, the Safe Drinking Water Act, which sets 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

[2]Regulation through the NPDES reduced both profits (Rassier and Earnhart, 2010) and the number of environmental employees (Raff and Earnhart, 2019) at newly regulated polluters.

for treatment and discharge into local waterways (USEPA, 2004). Municipal waste is almost entirely organic (Hines, 1966), and microorganisms from human sewage or animal waste 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 placement and timing of grants facilitate 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 then 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. 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 should have affected upstream and downstream areas in the same way.

## 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.[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. 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).

The potential benefits of upgrading to secondary treatment were well understood, but

[3]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).

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) reported only using primary treatment technology.

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. CWA grants provided the resources that non-compliant facilities needed to offset the costs of upgrading, and 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 (Flynn and Smith, 2020).

Federal guidelines did not instruct 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. While facilities already using secondary treatment in 1972 could still make capital improvements, such as increasing capacity, they had relatively little incentive to do so. Since these upgrades were not mandated by the CWA, 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). For this reason, 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 (Flynn and Smith, 2020).

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. Keiser and Shapiro (2019a) shows 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 states distributed grants to facilities based on the same unobservable characteristics regardless of treatment technology, and the same kind of sorting occurred downstream from 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 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 compliant 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 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 using primary or secondary treatment technology in 1972.[4]

### Spatial Data on Waterways

We define treatment in terms of flow direction. 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.[5] 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

[4]1930 facilities are missing data on pre-CWA treatment technology. We assume that these facilities were already in compliance with the CWA's treatment technology requirements. Throughout the paper, when we refer to the set of "compliant" facilities, this set 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.

[5]Table A1 shows that our results are robust to concentrating on areas 5 or 10 miles downstream from treatment facilities.

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 surface water quality 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 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.[6] Table 1 presents summary statistics for births

[6]Data 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

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.

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 or higher birth in each county year.[7]

### 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.[8] This could cause 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.[9] Figure 2 shows the distribution of this treatment measure.

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.

[7]We 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 A5, 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.

[8]We see similar but attenuated results if we define treatment with a binary variable. These results are presented and discussed in the Appendix.

[9]We use data from 1990, because it is the first census for which population density data is available at the census block level.

# 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.

$$Q_{pdy} = \alpha_0 + \sum_{t=-5}^{-2} \pi_t 1\{y - y_p^* = t\} * d_d + \sum_{t=0}^{9} \gamma_t 1\{y - y_p^* = t\} * d_d + \beta W_{pdy} + \alpha_{pd} + \alpha_y + \epsilon_{pdy} \tag{1}$$

In our pollution estimates, there are two observations for each treatment plant $p$ for each year $y$ which describe average dissolved oxygen deficit upstream ($d_d = 0$) and downstream ($d_d = 1$) from that plant. 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 its first CWA grant, and $Q_{pdy}$ is a measure of dissolved oxygen deficit. All standard errors in our pollution estimates are clustered at the facility level.

We include year and plant-by-downstream fixed effects, $\alpha_y$ and $\alpha_{pd}$, respectively. This allows 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 constant over time. Since dissolved oxygen deficit varies inversely with temperature, $W_{pdy}$ measures temperature at the time the pollution reading was taken.

The $\pi_t$ and $\gamma_t$ describe the relationship between dissolved oxygen deficit and CWA grants in downstream waterways for the years before and after grant receipt.[10] We omit the dummy for the year before treatment ($D_{-1}$), normalizing the $\pi_t$ and $\gamma_t$ to zero in that year. The $\pi_t$ show the trend in dissolved oxygen deficit before treatment, and the $\gamma_t$ describe how dissolved oxygen deficit evolved in downstream waterways after treatment.

We 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 $g_{py}$ equals one after a facility receives its first CWA grant.[11]

While Keiser and Shapiro (2019a) includes a much more thorough discussion of the effect of CWA grants on pollution, and Jerch (2018) examines the relationship between pre-CWA treatment technology and downstream pollution, 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.

[10]In all of our event studies, we report coefficients for four years before and 8 years after grant receipt. These specifications also includes bins for 5 or more years before the grant and 9 or more years after the grant, but our results are not sensitive to this binning.

[11]Our pollution specifications compare waterways downstream from facilities that received CWA grants to all other areas. 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 3.2. Our preferred specification does not include facility-by-year fixed effects due to limitations in the pollution data. While the sample of pollution monitor readings is large, we do not have observations both up and downstream from every facility, so adding facility-by-year fixed effects reduces our sample size substantially.

## 3.2 Pollution Results

We first examine the relationship between pre-CWA wastewater treatment technology and downstream pollution. Because facilities that had to upgrade to secondary treatment technology had the most to gain in terms of downstream pollution reductions, we expect that the dissolved oxygen deficit will decrease more for these pre-CWA non-compliant facilities relative to other facilities.

Figure 3 presents results from estimating equation 1 on sub-samples of non-compliant and compliant facilities. Figure 3a shows flat trends before treatment and a decrease in dissolved oxygen deficit downstream from non-compliant facilities after grant receipt. 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).

Looking at Figure 3b, we see no evidence of a change to pollution in waterways downstream from other 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 2 summarizes these figures by estimating equation 2 on the full sample, non-compliant facilities and compliant facilities in columns 1, 2 and 3, respectively, and presents 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 (2019a). Since dissolved oxygen deficit is defined as 100 minus dissolved oxygen saturation, this results show that waters downstream from non-compliant facilities had a 1.7 percentage point higher oxygen saturation after grant receipt relative to all other areas. This represents a 2 percent increase relative to a mean of 78 percent oxygen saturation in our sample. 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 compliant facilities, as shown by the significant negative triple difference coefficient in column 3. In the analysis of the impact of CWA grants on infant health that follows, we leverage this comparison between non-compliant and other 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

$$Y_{cy} = \alpha_0 + \sum_{t=-5}^{-2} \pi_t 1\{y - y_c^* = t\} + \sum_{t=0}^{9} \gamma_t 1\{y - y_c^* = t\} * pct_{cy} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy} \quad (3)$$

where $1\{y - y_c^* = t\}$ measures time relative to 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 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 4.

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

This compares birth weight between counties downstream from any facility that received a grant, and all other counties. To account for any changes that might coincide with grant timing and affect both up and downstream areas, we also estimate equation 4 with an additional binary variable that equals one for both up and downstream counties after the nearby facility receives a grant.

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 subtract the mean birth weight in all counties upstream from the same facility in each year, then estimate the following event study with this difference, $\Delta Y_{py}$, as the outcome variable

$$\Delta Y_{py} = \alpha_0 + \sum_{t=-5}^{-2} \pi_t 1\{y - y_p^* = t\} + \sum_{t=0}^{9} \gamma_t 1\{y - y_p^* = t\} * pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py} \quad (5)$$

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, $\alpha_y$ and $\alpha_p$, respectively.[12] Standard errors are clustered at the facility level.

We then estimate the associated difference-in-difference[13]

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

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

[12]Controls 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.

[13]This specification is similar to adding facility by year fixed effects to equation 4.

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. 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 first estimate an event study specification

$$\begin{aligned} \Delta Y_{py} =& \alpha_0 + \sum_{t=-5}^{-2} \theta_t 1\{y - y_p^* = t\} * t_p + \sum_{t=0}^{9} \eta_t 1\{y - y_p^* = t\} * pct_{py} * t_p \\ &+ \sum_{t=-5}^{-2} \pi_t 1\{y - y_p^* = t\} + \sum_{t=0}^{9} \gamma_t 1\{y - y_p^* = t\} * pct_{py} \\ &+ \beta X_{py} + \phi X_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py} \end{aligned} \tag{7}$$

where $t_p$ 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

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

To the extent that individuals were sorting into downstream areas or that downstream areas were experiencing different economic trends, it is unlikely that these patterns were differential across non-compliant facilities and compliant facilities.

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

$$\Delta x_{py} = \gamma pct_{py} + \alpha_p + \alpha_y + \epsilon_{py} \tag{9}$$

where $\Delta x_{py}$ is the difference between demographic characteristic in counties up and downstream from facility $p$ in year $y$. Column 1 of Table 3 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 compliant facilities. Column 3 presents results from the associated triple difference,

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

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. Nevertheless, 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 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 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 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 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 3 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 4 using a sample of births from every county in the contiguous US. The addition of demographic controls to this specification in column 2 reduces the magnitude of the estimate by about half.

We impose additional structure in column 3 by including a dummy variable that turns on for counties after they are up or downstream from a treated facility. This compares counties up and downstream from facilities before and after treatment. The estimate changes very little between columns 2 and 3.

Births occurring in counties that are not near wastewater treatment facilities might not make a good control group. In column 4, 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 5 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 5a shows the event study results for birth weight from estimating equation 5. 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.[14]

[14] These 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.

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 -.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 5b 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.

### 4.3 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 6 on sub-samples of pre-CWA 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 these 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.

We summarize the effect of changes in surface water quality downstream from non-compliant facilities by estimating equation 8 on the pooled sample, which leverages all of our variation in one regression. Since equation 8 includes a full set of interactions, our estimate of $\gamma^{DDD}$, 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 compliant facilities.

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 an 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 shown in Panel B 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.

Figure 6 presents the corresponding event studies from estimating equation 7. As before, there is no evidence of pre-trends. 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.

## 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.[15]

We show that our results are driven by counties that had some public water systems that drew from surface water sources in Tables 6 and 7. Column 1 of Table 6 re-estimates equation 8 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. 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, and our estimates for areas that drew exclusively from groundwater are statistically insignificant and wrong-signed. The birth weight effect is statistically greater than

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

the effect in areas that only drew from groundwater. In Panels C and D, we re-estimate these specifications on samples of compliant facilities, which 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 in which some public water systems draw from surface water that are downstream from non-compliant facilities.

While we cannot rule out additional mechanisms, such as reduced exposure through recreation activities, our results are driven by counties with some public water sourced from surface water.[16] We also show in the Appendix that health improvements are detectable only 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, and that drinking water contamination is a primary channel through which CWA grants affected infant health.

## 4.5 Heterogeneity

We examine the heterogeneity of our estimates across race in Table 8 by estimating equation 8 on sub-samples of white and non-white births from counties with sizable non-white populations.[17] 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

[16]We 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.

[17]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.

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 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, 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 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 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[18] and the census bureau's work-life earnings estimate of $2.4 million to calculate a back-of-the-envelope estimate of the infant

[18] Estimates 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 .24, which would not change the final conclusion of a cost-benefit analysis.

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 dollars, about 19 percent of the amount needed to make the CWA cost effective.

The $153 billion figure includes grants to compliant facilities which 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 (2019a) estimates a benefit to cost ratio of 0.26. 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 0.55 once improvements to infant health are incorporated. Including additional measures of health are likely to increase this ratio even further.

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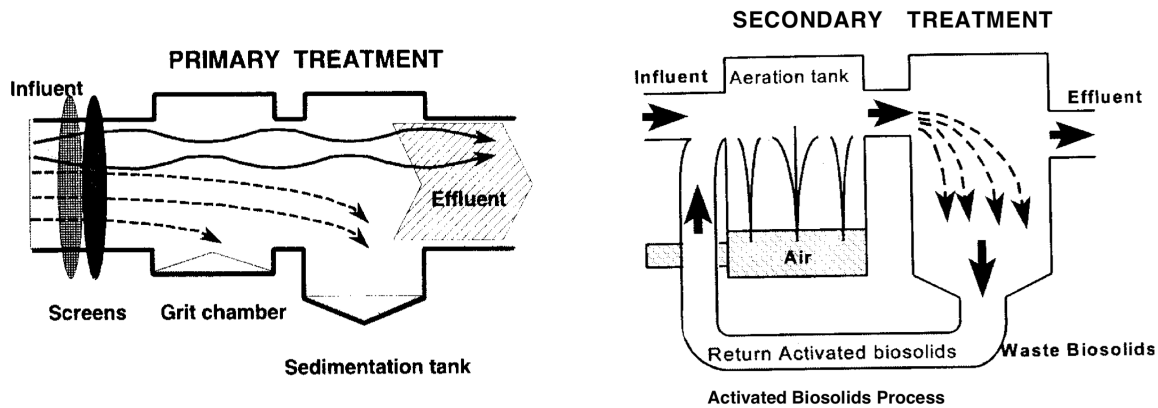
# Figures




(a)

(b)

Figure 1: Primary vs Secondary Treatment Technology

Source: USEPA (1998)

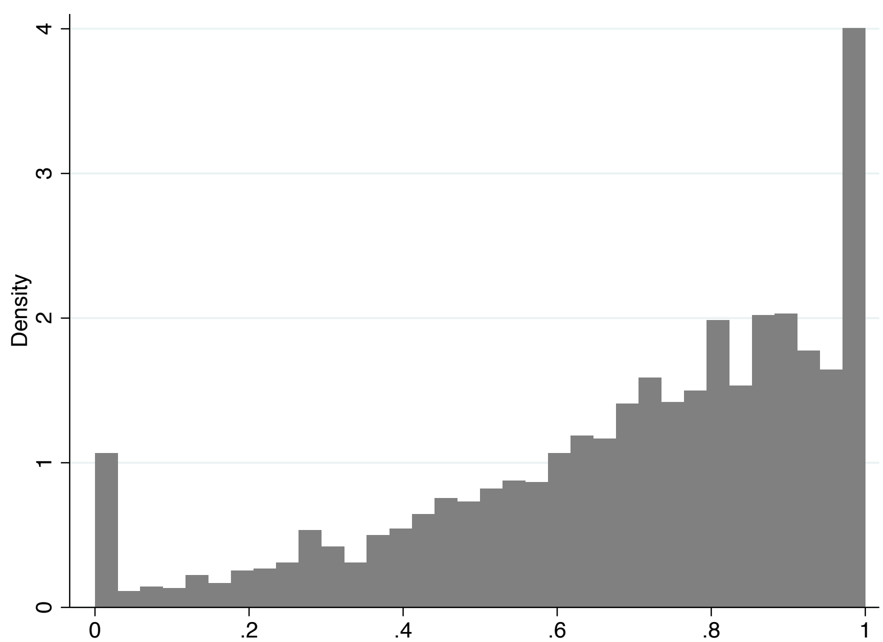
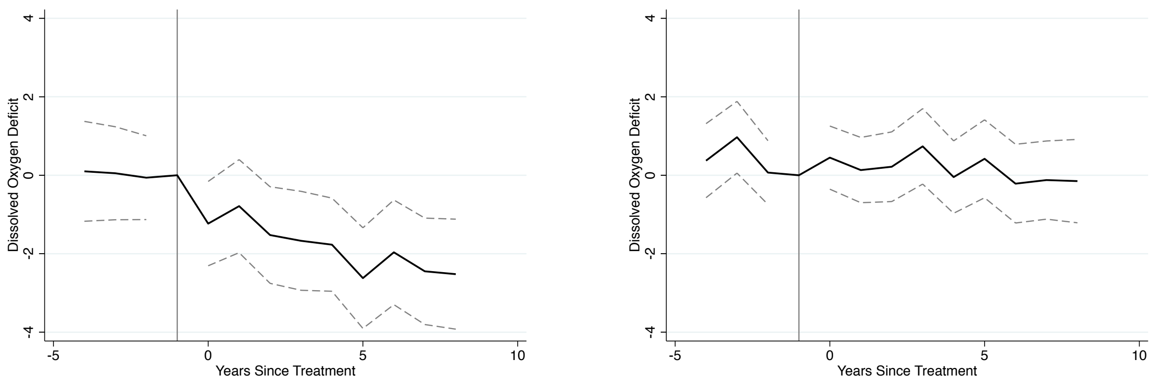



Figure 2: Percent of County Population Living Within a Mile of a Treated Waterway in 1988

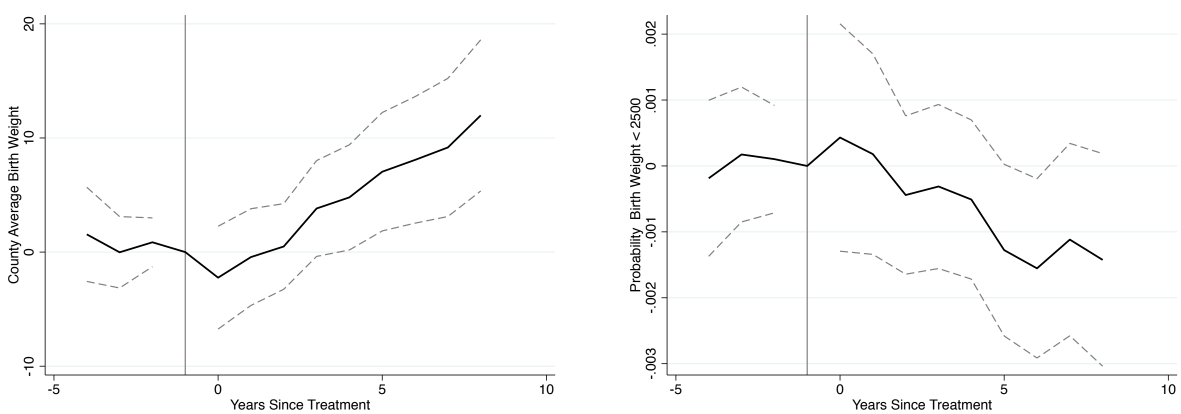



(a) Non-compliant

(b) Compliant

Figure 3: Downstream Pollution by Pre-CWA Compliance

Notes: The figure plots the estimated coefficients on $1\{y - y_p^* = t\} * d_d$ from estimating $Q_{pdy} = \alpha_0 + \sum_{t=-5}^{-2} \pi_t 1\{y - y_p^* = t\} * d_d + \sum_{t=0}^{9} \gamma_t 1\{y - y_p^* = t\} * d_d + \beta W_{pdy} + \alpha_{pd} + \alpha_y + \epsilon_{pdy}$. $Q_{pdy}$ 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, $\alpha_{pd}$ and $\alpha_y$ respectively, as well as controls for temperature. Sub-figure (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 sub-figure (b) shows estimates using compliant facilities.
Source: USEPA (1968-1988)

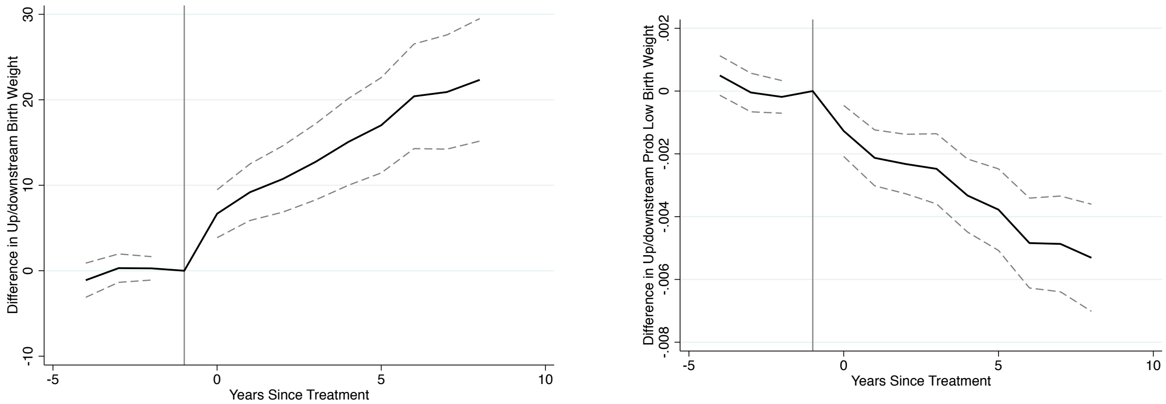



(a) Birth Weight

(b) Probability of Low Birth Weight

Figure 4: Birth Outcomes Downstream from Grant Facilities

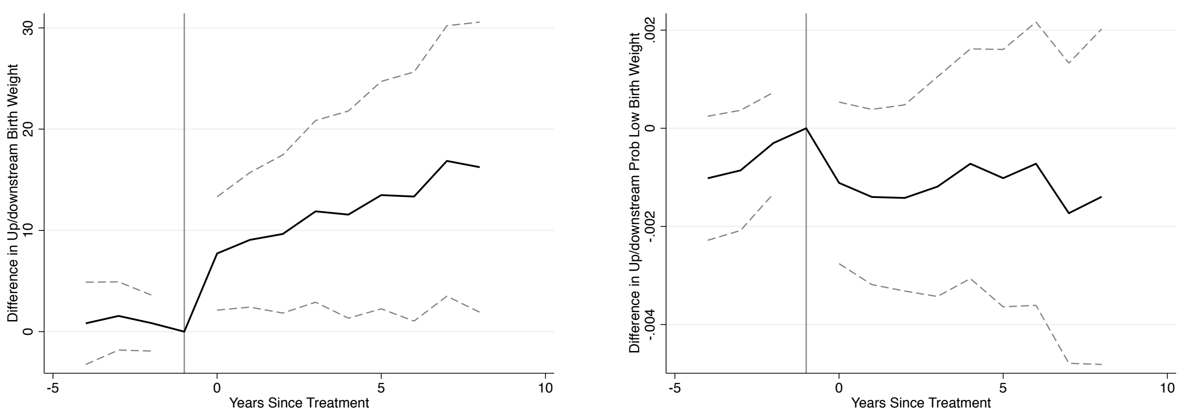
Notes: These figures plot the $\pi_t$ and $\gamma_t$ from estimating $Y_{cy} = \alpha_0 + \sum_{t=-5}^{-2} \pi_t 1\{y - y_c^* = t\} + \sum_{t=0}^{9} \gamma_t 1\{y - y_c^* = t\} * pct_{cy} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy}$. $pct_{cy}$ is a continuous variable that takes values from 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, $\alpha_c$ and $\alpha_y$ 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 $\pi_t$ and $\gamma_t$ from estimating $\Delta bw_{py} = \alpha_0 + \sum_{t=-5}^{-2} \pi_t 1\{y - y_p^* = t\} + \sum_{t=0}^{9} \gamma_t 1\{y - y_p^* = t\} * pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py}$. $pct_{py}$ 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, $\alpha_p$ and $\alpha_y$ 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 a facility 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 $\theta_t$ and $\eta_t$ from estimating $\Delta Y_{py} = \alpha_0 + \sum_{t=-5}^{-2} \theta_t 1\{y - y_p^* = t\} * t_p + \sum_{t=0}^{9} \eta_t 1\{y - y_p^* = t\} * pct_{py} * t_p + \sum_{t=-4}^{-2} \pi_t 1\{y - y_p^* = t\} + \sum_{t=0}^{8} \gamma_t 1\{y - y_p^* = t\} * pct_{py} + \beta X_{py} + \phi X_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py}$. $t_p$ 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) Full Sample | (2) Downstream | (3) Upstream | (4) Non-compliant | (5) Compliant | (6) Surface | (7) 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. Data is from births in 1970, two years before the CWA came into effect.
Source: National Center for Health Statistics (1968-1988a)

Table 2: Pollution Triple Difference

| | (1) full sample | (2) non-compliant | (3) compliant | (4) DDD |
|---|---|---|---|---|
| grant X downstream | -0.670*** | -1.672*** | -0.110 | -0.110 |
| | [-1.122,-0.219] | [-2.462,-0.881] | [-0.662,0.442] | [-0.662,0.442] |
| grant X downstream X non-compliant | | | | -1.562*** |
| | | | | [-2.525,-0.598] |
| 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, $\alpha_{pd}$ and $\alpha_y$.
Source: USEPA (1968-1988)

Table 3: 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 | .116 | .105 | .11 |
| 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 | 24.563 | 24.569 | 24.566 |
| 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 | .653 | .645 | .648 |
| 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 | .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 all other facilities. $\Delta x_{py}$ 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, $\alpha_p$ and $\alpha_y$ respectively. Column 3 presents estimates of the associated triple difference: $\Delta x_{py} = \alpha_0 + \gamma_0^{DD} pct_{py} + \gamma^{DDD} pct_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py}$ 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) | (5) |
| Panel A | county average birth weight | | | | |
| pct pop 1 mile | 12.80*** | 6.718*** | 7.741*** | 8.018*** | 13.33*** |
| | [6.709,18.89] | [2.034,11.40] | [2.823,12.66] | [3.075,12.96] | [10.11,16.55] |
| Panel B | probability birth weight < 2500 grams | | | | |
| pct pop 1 mile | -0.00288*** | -0.000874* | -0.000859 | -0.000927* | -0.00223*** |
| | [-0.00419,-0.00156] | [-0.00190,0.000152] | [-0.00191,0.000193] | [-0.00198,0.000125] | [-0.00299,-0.00147] |
| demographic controls | | X | X | X | X |
| unit and year fixed effects | X | X | X | X | X |
| collapsed to county level | X | X | X | X | |
| collapsed to facility level | | | | | X |
| N | 64239 | 64239 | 64239 | 64008 | 82320 |

This table presents (weighted) estimates from the following model

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

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 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 $y$. The model includes unit and year fixed effects, $\alpha_c$ and $\alpha_y$ respectively, and columns 2 through 5 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, 2 and 3 use data from every county in the US, while columns 4 and 5 restrict the sample to counties that are up or downstream from a wastewater treatment facility. Columns 3 and 4 include a dumy variable that turns on for observations after they are up or downstream from a treated facility.

In columns 1 through 4, data is collapsed to the county level. In column 5, data is collapsed to the facility level. This means that the results in columns 1, 2 and 3 come from comparisons between counties downstream from facilities that received grants and any other county, the results in column 4 come from comparisons between counties downstream from facilities that received grants and any county upstream from a facility, and the results in column 5 come from comparisons between counties downstream from facilities that received grants and counties upstream from the same facility.

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

Table 5: Triple Difference

| | non-compliant | compliant | DDD |
|---|---|---|---|
| | (1) | (2) | (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 depending on pre-CWA treatment technology. 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 compliant facilities (those that were not) 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, $\alpha_c$ and $\alpha_y$ 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 | Ground Water |
|---|---|---|
| | (1) | (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<br>(1) | Ground<br>(2) | DDD<br>(3) |
|---|---|---|---|
| Panel A. Non-compliant | county average birth weight | | |
| pct pop 1 mile | 10.15*** | -7.879 | -7.879 |
| | [5.927,14.38] | [-20.35,4.597] | [-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* | 0.00103 | 0.00103 |
| | [-0.00182,0.0000796] | [-0.00192,0.00399] | [-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 | 3.110 | 3.110 |
| | [-0.861,7.083] | [-4.426,10.65] | [-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 | -0.00183 | -0.00183 |
| | [-0.00138,0.000714] | [-0.00419,0.000522] | [-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 $\Delta Y_{py} = \alpha_0 + \gamma pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py}$ 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: $\Delta Y_{py} = \alpha_0 + \gamma_0^{DD} pct_{py} + \gamma^{DDD} pct_{py} * s_p + \beta X_{py} + \phi X_{py} * s_p + \alpha_y * s_p p + \alpha_p + \alpha_y + \epsilon_{py}$ 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) 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 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)

# A Appendix

## A.1 Additional Results

### A.1.1 Robustness to Distance Downstream

In the main text, we follow Keiser and Shapiro (2019a) 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 8 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.

Table A1: Other Distances Downstream

| | non-compliant (1) | compliant (2) | DDD (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: National Center for Health Statistics (1968-1988a)

### A.1.2 Recreation

While improved drinking water quality appears to be one channel through which grants improved infant health, improved surface water quality could also improve maternal health through water recreation either directly by reducing contact with contaminated water, or indirectly by making mothers more likely to exercise with a swim or a walk along a waterway. If recreational exposure 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 these activities using state-level per capita water recreation spending from the US Bureau of Economic Analysis.[19]

First, we test this channel in Table A2 by separately estimating equation 4 on sub-samples defined by terciles of state-level per capita water recreation spending. 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.

Next, in Table A3, we estimate the triple difference specification for each tercile of water recreation spending. Because the spending data is at the state level, we drop observations from the 889 facilities that have up or downstream counties in different states. In this specification, the middle tercile of states is driving our results. However, we still cannot statistically distinguish the point estimates across the three terciles.

Since 95 percent of all water recreational trips occur within 25 miles of one's home (Keiser and Shapiro, 2019a), 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 A4. 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.[20]

[19]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.

[20]Kuwayama et al. (2018) provide related evidence that hedonic property models relying on treatment

Due to data limitations in our measurement of water recreation, we are not able to draw strong conclusions as to whether recreational activities contribute to our main findings.

Table A2: Split by Recreational Spending Per Capita

| | (1)<br>Tercile 1 | (2)<br>Tercile 2 | (3)<br>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 4 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: National Center for Health Statistics (1968-1988a); Bureau of Economic Analysis (2012-2017)

areas defined by concentric circles may not accurately capture water's recreational benefits.

Table A3: Triple Difference 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 X non-compliant | 1.231 | 14.76*** | 4.012 |
| | [-9.664,12.13] | [3.758,25.76] | [-7.433,15.46] |
| Panel B | | probability birth weight < 2500 grams | |
| pct pop 1 mile X non-compliant | 0.00183 | -0.00352** | 0.000262 |
| | [-0.000580,0.00423] | [-0.00687,-0.000171] | [-0.00251,0.00303] |
| demographic controls | X | X | X |
| unit and year fixed effects | X | X | X |
| collapsed to facility level | X | X | X |
| N | 20748 | 19656 | 23247 |

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 defined by terciles of state water-related recreational spending. Facilities in states with the lowest spending are in Tercile 1, while those in states with the highest spending are in Tercile 3.
Source: National Center for Health Statistics (1968-1988a); Bureau of Economic Analysis (2012-2017)

Table A4: Other Bandwidths

| | (1) 25 miles downstream 10 mile buffer | (2) 25 miles downstream 25 mile buffer |
|---|---|---|
| | county average birth weight | |
| pct pop 10 miles | 0.721 | |
| | [-1.727,3.169] | |
| pct pop 25 miles | | 0.775 |
| | | [-1.900,3.450] |
| 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.

### A.1.3 One Year Mortality

Using data from National Center for Health Statistics (1968-1988b), we re-estimate equation 8 with 1 year mortality as the dependent variable in Table A5. We consistently find no effect of being downstream from a facility that received a CWA grant.

Table A5: Mortality Triple Difference

| | (1) full sample | (2) surface | (3) ground |
|---|---|---|---|
| pct pop 1 mile X non-compliant | 0.389 | 0.619 | 0.510 |
| | [-19.65,20.43] | [-20.62,21.85] | [-14.28,15.30] |
| demographic controls | X | X | X |
| unit and year fixed effects | X | X | X |
| collapsed to facility level | X | X | X |
| N | 82320 | 67032 | 15288 |

95% confidence intervals in brackets

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

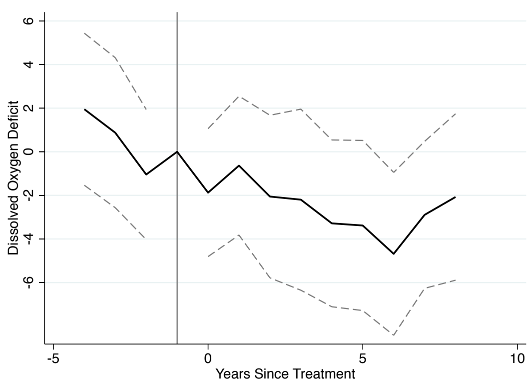
Notes: This table presents (weighted) estimates from the following model: $\Delta Y_{py} = \alpha_0 + \gamma pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py}$ . The dependent variable is the difference in one year mortality between counties up and downstream from facility $p$ in year $y$. Column 1 estiamtes this specification on the full sample, column 2 restricts the sample to facilities whose downstream counties draw at least some public water from surface water sources, and column 3 restricts the sample to facilities whose downstream counties source drinking water froum groundwater exclusively.
Source: National Center for Health Statistics (1968-1988b); Solley et al. (1988)

## A.2 Alternative Pollution Specifications

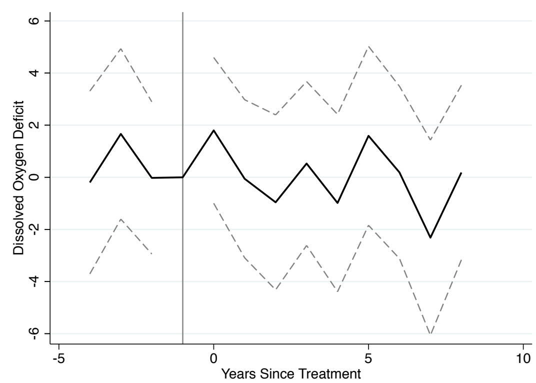
Our pollution results in the main text rely on comparisons of waterways downstream from facilities that received CWA grants to waterways upstream from these facilities, and areas up and downstream from facilities that did not receive CWA grants. Alternatively, we can compare waterways downstream from 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 Figure 3 and Table 2 with facility-by-year fixed effects in Figure A1 and Table A6.

As discussed in the main text, we prefer a specification without facility-by-year fixed effects due to limitations in the pollution data. While the sample of pollution monitor readings is large, we do not have observations both up and downstream from every facility, so adding facility-by-year fixed effects reduces our sample size substantially.




(a) Non-compliant




(b) Compliant Facilities

Figure A1: Downstream Pollution by Pre-CWA Compliance

Notes: The dependent variable is dissolved oxygen deficit. The figure plots the estimated coefficients on $1\{y - y_p^* = t\} * d_d$ from estimating $Q_{pdy} = \alpha_0 + \sum_{t=-4}^{-2} \pi_t 1\{y - y_p^* = t\} * d_d + \sum_{t=0}^{8} \gamma_t 1\{y - y_p^* = t\} * d_d + \beta W_{pdy} + \alpha_{pd} + \alpha_{py} + \epsilon_{pdy}$.. Sub-figure (a) shows estimates from estimating this equation on a sample of pre-CWA non-compliant facilities and sub-figure(b) shows estimates using compliant facilities.
Source: (USEPA, 1968-1988)

## A.3 Alternative Birth Weight Specifications

### A.3.1 Stacked Difference-in-Difference

Since we estimate two way fixed effects regressions, our results in the main text are an average of comparisons of (1) newly treated facilities relative to never-treated facilities, (2) newly treated facilities relative to facilities that have not yet been treated, and (3) newly treated facilities relative to already-treated facilities. When treatment effects are dynamic,

Table A6: Pollution Triple Difference with Facility-by-Year Fixed Effects

| | (1) full sample | (2) non-compliant | (3) compliant | (4) DDD |
|---|---|---|---|---|
| grant X downstream | -1.384** | -2.670** | -0.174 | -0.174 |
| | [-2.736,-0.0310] | [-4.766,-0.575] | [-1.958,1.610] | [-1.960,1.612] |
| grant X downstream X non-compliant | | | | -2.496* |
| | | | | [-5.249,0.256] |
| weather controls | X | X | X | X |
| facilty by downstream fixed effects | X | X | X | X |
| facilty by year 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 2 with facility-by-year fixed effects.
Source: (USEPA, 1968-1988)

the third type of comparison can be wrong signed (Goodman-Bacon, 2019). We can get estimates that do not include comparisons of newly treated facilities relative to already-treated facilities, and explore if our results are driven by comparisons of treated units to not-yet-treated units or never-treated units by re-organizing our data into "stacks".

A stack is defined by a treatment cohort, that is, a group of facilities that received their first grants in a given year (e.g. every facility that received its first grant in 1974). Each stack contains observations from every facility in a treatment cohort, which are labeled as treated in that stack, and a set of controls that consist of either units that were treated at least eight years in the future, or all never-treated facilities. We can then estimate the following stacked difference-in-difference:

$$Y_{py} = \alpha_0 + \gamma^{stacked} pct_{py} + \alpha_{ps} + \alpha_{sy} + \epsilon_{psy} \tag{11}$$

$p$ indexes facilities, $y$ indexes years, and $s$ indexes stacks. Facility-by-stack fixed effects,

$\alpha_{ps}$, are analogous to a unit fixed effect in our regressions in the main text. Year-by-stack fixed effects, $\alpha_{sy}$, ensure that we are only making comparisons within stacks, so our coefficient will not be identified off of comparisons of newly treated facilities relative to already-treated facilities.

We present estimates of equation 11 in Table A7. In column 1, the control group is not-yet-treated facilities. In column 2, it is never-treated facilities. In column 3, both never treated and not-yet-treated facilities are in the control group. We find significant effects on birth weight and the probability of low birth weight regardless of which control group we use. The effects are much larger when we compare treated units to never treated units, but since there are fewer never treated facilities than treated facilities, and since our two way fixed effect estimator averages these two effects together based on group size, our main results are closer to the results in column 1 than those in column 2.

Table A7: Stacked Difference in Difference

| | (1) not yet treated | (2) never treated | (3) both |
|---|---|---|---|
| Panel A | | county average birth weight | |
| pct pop 1 mile | 5.209** | 26.96*** | 5.458** |
| | [0.247,10.17] | [19.12,34.80] | [0.509,10.41] |
| Panel B | | probability bw < 2500 | |
| pct pop 1 mile | -0.00134** | -0.00541*** | -0.00139** |
| | [-0.00243,-0.000255] | [-0.00705,-0.00377] | [-0.00247,-0.000308] |
| demographic controls | X | X | X |
| unit and year fixed effects | X | X | X |
| collapsed to facility level | X | X | X |
| N | 83580 | 63041 | 86088 |

95% confidence intervals in brackets

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

Notes: This table presents results from estimating the following stacked difference in difference: $Y_{psy} = \alpha_0 + \gamma^{stacked} pct_{psy} + \alpha_{ps} + \alpha_{sy} + \epsilon_{psy}$. In column 1, the control group is facilities that will be treated at least 9 years in the future. In column 2, the control group is facilities that never receive a CWA grant. In column 3, both never treated and not-yet-treated units are in the control group. The dependent variable is the difference in birth weight between up and downstream counties in year $y$ in Panel A, and the difference in the probability of being born weighing less than 2500 grams between up and downstream counties in year $y$ in Panel B. Source: National Center for Health Statistics (1968-1988a)

### A.3.2 Binary Treatment

Our main results define treatment with a continuous measure, so our results are at least partially identified off of comparisons between counties where a large proportion of the population is treated relative to counties with a small proportion. Since we expect birth outcomes to improve homogeneously as more of the population becomes treated, there is nothing wrong with using this variation, however, we can also define treatment in a binary way with a dummy variable that turns on after a county is downstream from a treated facility.

We first estimate the following event study

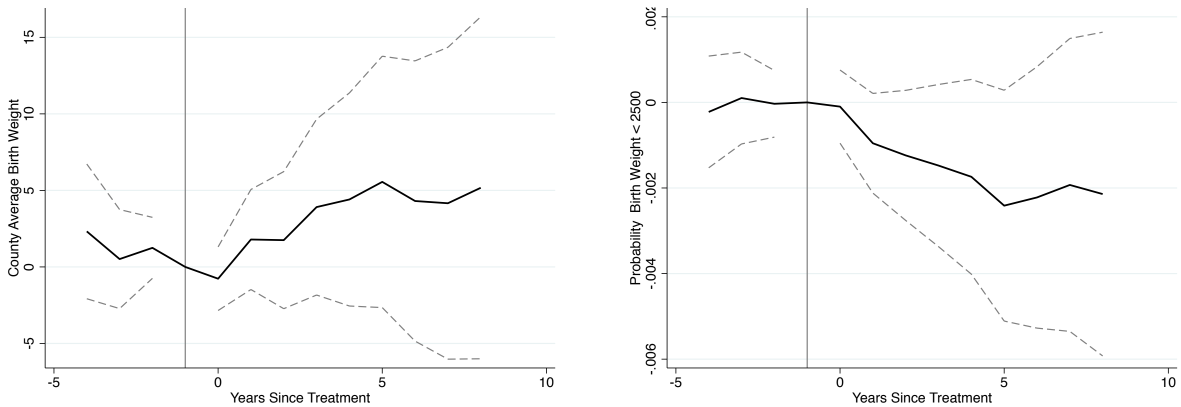
$$Y_{cy} = \alpha_0 + \sum_{t=-5}^{-2} \pi_t 1\{y - y_c^* = t\} + \sum_{t=0}^{9} \gamma_t 1\{y - y_c^* = t\} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy} \qquad (12)$$

which is identical to equation 3 except the timing dummies are not interacted with the percent of county population living within a mile of a treated waterway.

Estimates of equation 12 with average birth weight and the probability of low birth weight are presented in Figure A2. The shapes of these event studies are similar to those in the main text.

When we define treatment with a dummy variable, we can deal with the problems caused by dynamic treatment effects discussed in Section A.3.1 in a more sophisticated way. To summarize these event studies, we use the estimation strategy proposed by Callaway and Sant'Anna (2019) to estimate treatment effects in Table A8.

Defining treatment in a binary way at the county level includes many untreated births, so these estimates are somewhat smaller and less significant than those in the main text, however, they are of the same sign as our main results, and the birth weight estimate is still marginally significant despite this attenuation.




(a) Birth Weight (b) Probability of Low Birth Weight

Figure A2: Birth Outcomes Downstream from Grant Facilities (Binary Treatment)

Notes: These figures plot the $\pi_t$ and $\gamma_t$ from estimating $Y_{cy} = \alpha_0 + \sum_{t=-5}^{-2} \pi_t 1\{y - y_c^* = t\} + \sum_{t=0}^{9} \gamma_t 1\{y - y_c^* = t\} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy}$. Regressions are weighted by the total number of births in county $c$ in year $y$. 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)

Table A8: Callaway and Sant'Anna (2019) Estimates

| | birth weight | prob bw < 2500 |
|---|---|---|
| | (1) | (2) |
| grant X downstream | 4.85* | -0.0018 |
| | (2.60) | (0.0032) |
| N | 64239 | 64239 |

standard errors in parenthesis

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

Notes: This table presents Callaway and Sant'Anna (2019) estimates of the effect of being downstream from a facility that recieved a CWA grant on birth outcomes.
Source: National Center for Health Statistics (1968-1988a)

## A.4 Birth Weight Data Details

### A.4.1 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 A9.

Table A9: 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 |

### A.4.2 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 A10 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.

Changes from half to full sample often occurred around the same time as treatment. To be certain that our results are not driven by this change, we take a 50 percent sample of births from state-years that reported full sample data and re-estimate equation 6 in Figure A3. We then re-estimate the results presented in Table 5 on this sample and report the results in Table A11. The results are similar to those reported in Section 4.

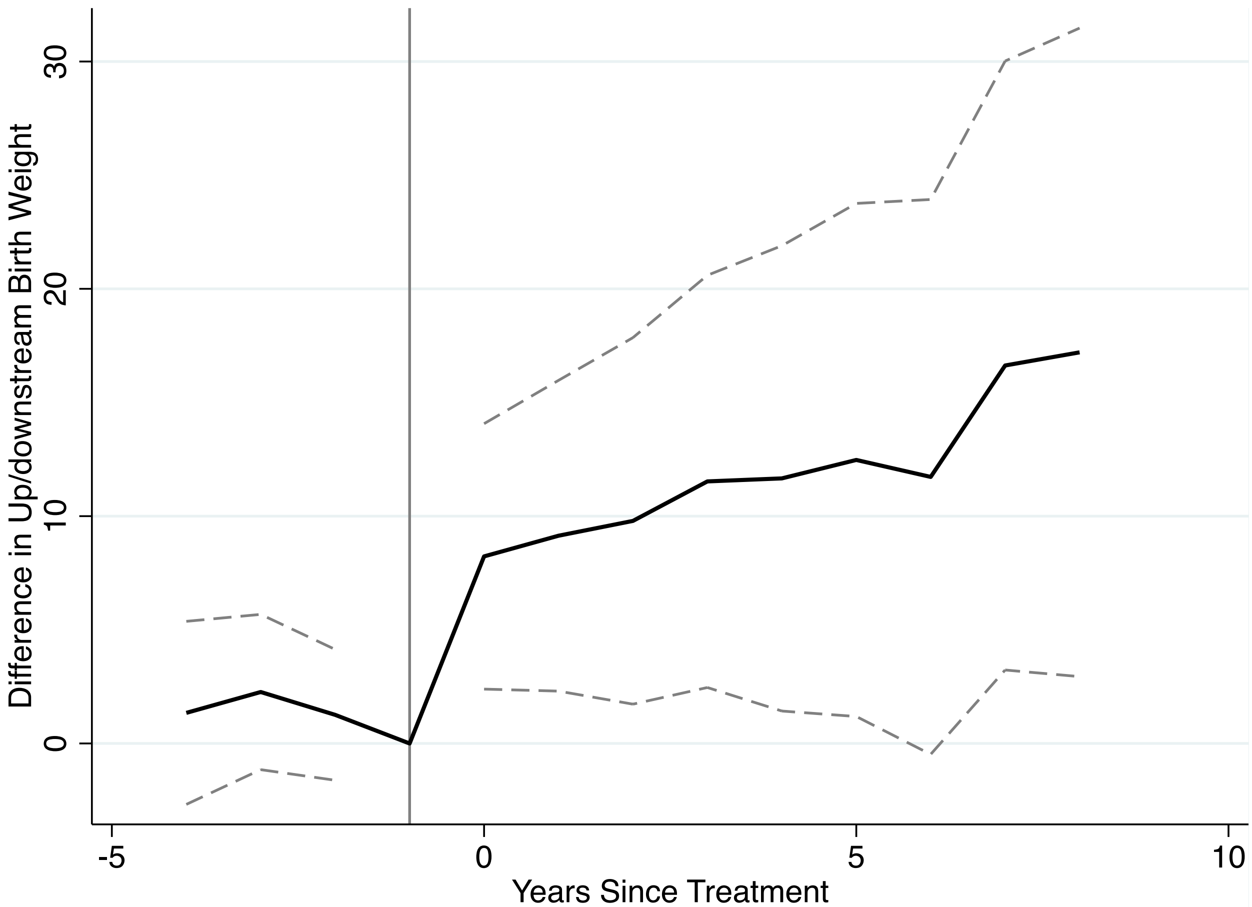



Figure A3: Birth Weight Triple Difference: Random Sample

Notes: This Figure re-estimates the results in Figure 6a 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 A10.
Soure: National Center for Health Statistics (1968-1988a)

Table A10: 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 A11: Triple Difference: Random Sample

| | (1)<br>non-compliant | (2)<br>compliant | (3)<br>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.
Source: National Center for Health Statistics (1968-1988a)