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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. Using a difference-in-differences framework, we compare infant 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.

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The Clean Water Act is a landmark, yet controversial, policy. The CWA caused significant reductions in pollution, but improvements in surface water quality stemming from the CWA have come at a high cost; projects funded through grants to wastewater treatment facilities between 1960 and 2005 have cost about $870 billion over their lifetimes (in 2017 dollars) (Keiser and Shapiro, 2019b). In total, US government and industry have spent over $1.9 trillion to abate surface water pollution (Keiser et al., 2019). Existing analyses of the Clean Water Act estimate benefits that are lower than the Act's costs (e.g. Lyon and Farrow (1995); Freeman (2010); Keiser et al. (2019)), but these analyses have not generally included improvements in health caused by the Clean Water Act because there has not been a systematic ex-post measurement of the health benefits of the CWA. To our knowledge, this paper is the first to estimate the effect of CWA grants on infant health.

Estimating the health benefits of CWA grants may matter for several reasons. Historically, policies targeting improvements in child health generate high returns to public funds (Hendren and Sprung-Keyser, 2020), and previous economics literature shows that even small differences in child and infant health can lead to large impacts on later life outcomes (Behrman and Rosenzweig, 2004; Royer, 2009; Black et al., 2007; Figlio et al., 2014; Isen et al., 2017; Black et al., 2019). 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).

Existing economics research estimates the benefits of improved surface water by measuring the effect of CWA grants on nearby housing prices, but this hedonic analysis may not fully capture any health effects of CWA grants. Comparing waters up and downstream from wastewater treatment facilities, Keiser and Shapiro (2019a) find that CWA grants caused reductions in downstream pollution. These improvements in water quality were capitalized into housing prices, but increases in home values were substantially smaller than the CWA's costs. By quantifying how residents value water quality, Keiser and Shapiro (2019a) improve upon previous cost-benefit calculations, 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 any negative health effects of surface water contamination, especially the negative impacts on developing fetuses in utero. By directly estimating the health effects of the CWA, our results complement those in Keiser and Shapiro (2019a) by quantifying one of the largest benefits of the CWA that hedonic analysis is least likely to capture.

Using a difference-in-differences design, we compare infant health outcomes upstream and downstream from wastewater treatment facilities before and after the facility receives a CWA grant. Comparing up and downstream births addresses the endogenous distribution of grants as well as any economic shocks caused by grant receipt, but estimates may still be biased if individuals sort into downstream areas or if these areas experience differential trends relative to upstream areas after grant receipt. To address this concern, we show that CWA grants only caused improvements in surface water quality downstream from facilities that were required to upgrade their treatment technology to comply with new treatment technology standards imposed by the CWA. This finding motivates a triple difference design that uses counties up and downstream from facilities where these treatment technology requirements were not binding as an additional control group. By using already compliant facilities that receive grants as an additional control group, we can account for differential sorting into downstream areas after grant receipt, so the health benefits we capture with this design are likely caused by improvements in water quality.

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.

Our results contribute to a literature documenting the importance of effective sewerage and clean water in protecting health historically in the US (Troesken, 2001, 2002; Cutler and Miller, 2005; Ferrie and Troesken, 2008; Beach et al., 2016; Anderson et al., 2020), as well as a literature on the complementarity of sewerage and clean water interventions. Examining water policy in early 20th century Massachusetts, Alsan and Goldin (2019) show that mortality declines were driven by a combination of clean water initiatives and effective sewerage. Watson (2006) shows that federal sanitation policies explain much of the convergence in Native American and White infant mortality rates in the US since 1970. By improving sewerage systems and reducing pollution of surface water throughout the US at a time when most publicly provided drinking water had some treatment, the CWA provides a new context to examine the effect of improved water quality on health in the late 20th century, as well as the complementarity between sewerage infrastructure and clean water in protecting health nationwide.

1 Background

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.[1] This paper focuses on CWA grants distributed to municipal wastewater treatment facilities. Wastewater from homes, businesses, and industries, as well as surface runoff, is typically collected through a system of sewers and delivered to a wastewater treatment facility for treatment and discharge into local waterways (USEPA, 2004). To reduce surface water contamination, the CWA addressed pollution from municipal waste treatment plants with two complementary policies: grants to wastewater treatment facilities, and regulation of wastewater treatment technology.[2]

1.1 Grants

From 1972 to 1988, the EPA distributed an estimated $153 billion (in 2014 dollars) in grants to municipal governments for capital upgrades to wastewater treatment facilities. The EPA allocated CWA grant money to states according to a formula based on total population, forecast population, and wastewater treatment needs (Rubin, 1985). States then distributed grants to municipalities according to priority lists based on the severity of nearby surface water pollution, the size of the population affected, the need for conservation of the affected

[1] Although much of the contamination of US waterways comes from sources that cannot be traced back to a specific facility, such as agricultural runoff, the Clean Water Act did not directly regulate these "non-point" pollution sources. The CWA did not directly regulate drinking water supplies either. The Safe Drinking Water Act sets minimum standards for drinking water quality for all public water systems in the US.

[2] In addition to regulating municipal waste treatment facilities, the CWA required all industrial polluters to obtain a permit from the National Pollutant Discharge Elimination System (NPDES) before discharging wastewater. Regulation through the NPDES led to reductions in both profits (Rassier and Earnhart, 2010) and the number of environmental employees (Raff and Earnhart, 2019) at newly regulated polluters.

waterway, and that waterway's specific category of need (USEPA, 1980).

Since state governments wrote their own priority lists, grant placement may be correlated with trends in infant health. Moreover, grants could cause increases in birth weight that are unrelated to changes in pollution by improving economic conditions with an influx of federal dollars. Instead of treating grant timing and location as exogenous, we compare the difference in birth outcomes in areas up and downstream from a given wastewater treatment facility before and after grant receipt between facilities that were required to make treatment technology upgrades and all other facilities. To the extent that other policies were changing during this time period, and that grants improved local economic conditions, these changes were likely to affect upstream and downstream areas similarly.

1.2 Regulation

In 1972, about a quarter of all US municipal wastewater treatment facilities reported using relatively inexpensive, but less effective, primary treatment (USEPA, 2000). This process, depicted in Figure A1a, forces wastewater through a series of screens. While primary treatment 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. Plants use secondary treatment technology, shown in Figure A1b, 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, which ultimately reduces biochemical oxygen demand (BOD).[3]

[3]Additionally, some states required facilities to meet more stringent treatment technology requirements than

Municipal waste is almost entirely organic (Hines, 1966), and often contains both pathogenic and nonpathogenic microorganisms harmful to human health. Pathogens harmful to human health include enteric bacteria, viruses, protozoa, parastic worms, and their eggs. These microorganisms from human sewage can cause a range of gastrointestinal illnesses and infections (Reynolds et al., 2008; Chahal et al., 2016). Even today, estimates suggest that up to 19.5 million cases of waterborne illnesses are associated with contaminated drinking water each year in the US (Reynolds et al., 2008; Colford Jr et al., 2006). Table A1 reports pathogens capable of causing waterborne or water-based disease. The potential health effects from exposure to waterborne or water-based diseases include gastroenteric infections and diseases, with symptoms such as nausea, vomiting, diarrhea, and stomach cramps. Exposure to waterborne contaminants can result from recreational use of affected surface water or from ingestion of contaminated public or private drinking water sources. Pregnant women are considered a high-risk population, and infant health may be impacted either directly through impacts on fetal development or indirectly through maternal illness that may result in reduced nutritional intake, for example.

Through biological oxidation, secondary treatment can remove over 90 percent of harmful pathogenic bacteria and viruses from sewage (Abdel-Raouf et al., 2012).[4] While it is not practical to monitor pathogens directly, regulators and researchers often use indicator organisms, such as total or fecal coliforms, to monitor water quality. Keiser and Shapiro (2019a) show that grants to wastewater treatment facilities improved key indicators of water

the CWA's mandate, such as tertiary treatment, which is aimed at removing ammonium, nitrate, and phosphate (USEPA, 2000).

[4]Suspended (e.g. activated sludge) growth reactors remove about 90 percent of viruses, but removal can be more varied in film reactors, which provide less absorption (Abdel-Raouf et al., 2012).

quality, including dissolved oxygen deficit, BOD, and fecal coliforms. As dissolved oxygen deficit is the most consistently and widely monitored measure of water quality in our sample, we focus on this measure.

The potential benefits of upgrading a facility's treatment technology were well understood, but waste treatment capital upgrades were expensive. 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, many treatment plants had not yet installed secondary treatment technology at the time of CWA federal mandate. Only about 47 percent of plants were in already in compliance, because they had already installed secondary or more stringent treatment technology, typically due historical pressure from downstream communities to reduce the flow of harmful pollutants and stronger state regulation of surface water pollution (Stoddard et al., 2003).[5] The remaining 53 percent of plants, as measured in the 1972 Clean Watershed Needs Survey (CWNS), were not yet in compliance with the relevant treatment technology mandates.[6] Treatment plants that were not already in compliance with both state and federal capital mandates in 1972, which we refer to as "non-compliant" facilities, had a strong incentive to use CWA grants to offset the costs of upgrading their treatment technology.[7]

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

[5]We show that outcomes in these compliant and non-compliant cities trend similarly prior to grant receipt in our event study models.

[6]See Appendix Section C.3 for more discussion.

[7]Permits distributed to polluters through the NPDES required municipal treatment plants to satisfy the treatment technology mandate, and violators could be fined up to $25,000 per day (Copeland, 2016).

increasing capacity, they had less incentive to do so. Since the CWA did not mandate these upgrades, there was no binding constraint requiring these facilities to spend grant money on sewerage capital upgrades, and the municipalities that operated them faced pressure to use grant money to offset the operating costs of their water and sewerage utilities in an attempt to lower costs for consumers and become more competitive (Daigger, 1998).[8]

Since non-compliant facilities had a clear channel through which to improve surface water quality and were more likely to spend CWA grant money on capital upgrades, we expect the reductions in downstream pollution associated with CWA grants to be largest for non-compliant facilities. This motivates a triple difference design that uses areas near facilities that were not indicated as pre-CWA non-compliant in the 1972 CWNS as an additional control group.

2 Data

CWA Grants and Municipal Wastewater Treatment Plants

We obtain data on all 33,429 grants that the EPA distributed to 14,285 wastewater treatment plants from the EPA's Grant Information Control System.[9] Most facilities received multiple grants, so we define a facility as "treated" after it receives its first CWA grant and show the distribution of facility-level treatment timing in Figure A2.

[8]Flynn and Smith (2021) show that CWA grants to non-compliant municipalities led to a dollar for dollar increase in sewerage capital spending, while grants to facilities already in compliance with state and federal capital mandates crowded out funds that municipalities were already spending on sewerage capital rather than causing an increase in sewerage capital spending.

[9]The 33,429 grants in our sample exclude grants that do not include a specific facility code, as it is unclear to what extent these grants were precisely for wastewater treatment plants. Appendix Section C.3 provides further discussion.

Using a unique facility code, we merge this grant data with the Clean Watershed Needs Survey, an assessment of the capital investment needed to meet the water quality goals of the CWA. This linked data includes facility location, grant timing, and state and federal treatment technology compliance status as of 1972.[10]

Spatial Data on Waterways

We define treatment in terms of the flow direction of waterways. We determine if a waterway is up or downstream from a facility with the National Hydrography Data Set, an electronic atlas that maps the location and flow direction of all US waterways. 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 (Keiser and Shapiro, 2019a; USEPA, 2001). Table B1 shows that our results are robust to concentrating on areas 5 or 10 miles downstream from treatment facilities.

We define a county as downstream if it contains any waterway that is within 25 miles downstream of a treated facility. Therefore, we categorize counties with both up and downstream waterways as downstream. Figure 1 provides maps showing two examples of how counties are classified based on upstream and downstream waterways. Waterways within 25 miles downstream of a treated facility are dark blue and waterways 25 miles upstream are medium yellow. Figure 1a shows an example from a wastewater facility in Indiana, where Shelby and Johnson counties would be classified as downstream because they contain a waterway within 25 miles downstream of a treated facility. Hancock county, on the

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

other hand, would be classified as an upstream county, because it contains only upstream waterways. Figure 1b shows two wastewater treatment facilities in Georgia. One facility is located in Clarke county. For this facility, downstream counties include Clarke, Oconee, Oglethorpe, and Greene. In this case, Jackson is the only upstream county for this facility. Although Madison county contains upstream waterways for the facility located in Clarke county, it cannot be an upstream county because it contains downstream waterways for the other wastewater treatment facility and therefore, is classified as a downstream county.

Water Pollution

Data on dissolved oxygen deficit comes from STORET legacy, which includes readings from pollution monitoring stations across the US.[11] We include readings from pollution monitors on rivers and lakes located 25 miles up or downstream from any facility in the CWNS data. We also follow the data cleaning steps laid out in the appendix of Keiser and Shapiro (2019a).

Infant Health

We measure infant health with birth certificate data from the National Center for Health Statistics (NCHS) from 1968 to 1988. These data contain information on birth weight, birth order, mother's age and race, and county of residence for each birth.[12] Table A2 presents summary statistics for individual-level births in 1970, two years before the first CWA grants

[11]Dissolved oxygen deficit is a continuous measure defined as 100 minus dissolved oxygen saturation (dissolved oxygen level divided by water's maximum oxygen level). It is one of the most common measures of omnibus water pollution in research, and it responds to a wide variety of pollutants (Keiser and Shapiro, 2019a).

[12]Data before 1972 constitutes a 50 percent random sample of all births in the US. After 1972, some states report data on all births. Six states had full sample data in 1972, and all states and the District of Columbia had full sample data by 1985. Appendix C.1 provides additional information and shows our main results are not driven by sampling changes.

were distributed, from up and downstream counties.

While ideal data would contain exact addresses, these data are unavailable for most states, and even when collected, addresses are typically not available until the after the adoption of the 1989 US Standard Birth Certificate revision and the use of electronic birth certificates, which is after our study period.

We collapse birth data to county means, calculating the average birth weight, the probability of low birth weight, the percent of non-white births, average mother's age, and the probability of being a mother's first, second, third, or fourth or higher birth in each county year.[13] Although more recent birth records data contain far more variables of interest, such as gestation, maternal education, and maternal risk factors, these variables are either unavailable or not reliably and consistently recorded in data from 1968 to 1988.

Population Density

We expect the health effects of improved surface water quality to be concentrated near treated waterways. County-level exposure depends on the distribution of the population within a county relative to the location of treated waterways. We use 1990 census block population density data from the US Census Bureau to measure the percent of a county's population living within a mile of a treated waterway.[14] Assuming a uniform population distribution within census blocks, this provides a proxy for the probability that mothers

[13]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 A9, however our estimates are imprecise.

[14]We use data from 1990 because it is the first census for which population density data is available at the census block level. We also show similar but attenuated results if we define treatment with a binary variable in Appendix B.3. We also show in Table A6 that the results are robust to dropping the largest quartile of counties by geographic area, as these large counties may have more measurement error.

within the county are exposed to treated waterways. Figure A3 shows the distribution of this treatment measure. We discuss how this measure captures different exposure pathways in section 4.3.

3 First Stage: Water Pollution

3.1 Methods

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

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

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

We include plant-by-downstream and plant-by-year fixed effects, α_{pd} and α_{py}, respectively. Plant-by-downstream fixed effects allow waters up and downstream from a given wastewater treatment plant to have different mean levels of dissolved oxygen deficit, which controls for pollution sources located up or downstream from a plant that are constant over time. Plant-by-year fixed effects ensure that we are only comparing waters up and downstream from the same facility, which controls for any yearly shocks that affect waters both up and downstream from a facility. All standard errors in our pollution estimates are clustered at the facility level.

We estimate equation 1 for the full sample and subsamples of compliant and non-compliant facilites, as well as a fully interacted triple difference specification. These estimates give us a sense of how grants and regulations worked together by testing whether pollution evolved differently in waters downstream from non-compliant facilities and compliant facilities after grant receipt.

3.2 Pollution Results

Table 1 estimates the effect of CWA grant receipt on downstream water quality. Columns 1-3 present estimates of equation 1 on the full sample, non-compliant facilities, and compliant facilities, respectively. Column 4 presents coefficients from a triple difference specification. As shown in column 2, dissolved oxygen deficit only decreased significantly in water downstream from non-compliant facilities. Since dissolved oxygen deficit is defined as 100 minus dissolved oxygen saturation, this result show that, after grant receipt, dissolved oxygen saturation increased by 1.6 percentage point in waters downstream from non-compliant facilities relative to waters upstream from the same facility. The coefficient for waters downstream from compliant facilities in column 3 is small and statistically insignificant. The reduction in dissolved oxygen deficit downstream from non-compliant facilities is statistically larger than the change downstream from compliant facilities, as shown by the significant negative triple difference coefficient in column 4.

Figure 2a presents results from the event study corresponding to the triple difference in column 4. This figure shows that reductions in downstream pollution were significantly larger in waters downstream from non-compliant facilities relative to waters downstream from compliant facilities. In addition, there does not appear to be any trend in pollution prior to grant receipt, which might have arisen from compliant facilities early adoption of more advanced treatment technology. In the analysis of the impact of CWA grants on infant health that follows, we leverage this comparison between non-compliant and compliant facilities in a triple difference specification.

4 Infant Health

4.1 Methods

We begin our reduced-form analysis of the impact of CWA grants on infant health by comparing birth outcomes in counties downstream from treated facilities to all other areas with the following difference-in-differences specification

$$Y_{cy} = \gamma pct_{cy} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy} \tag{2}$$

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.[15] Controls in X_{cy} include

[15]By using the percent of a county's population living within a mile of a treated waterway as a proxy for the probability that mothers within the county are exposed to treated waterways, we employ a continuous measure of treatment. To identify the ATE we must assume that, for all doses, the average change in outcomes over time across all units if they had been assigned a particular dose is the same as the average changes in outcomes over time for all units that did experience that dose (Callaway et al., 2021). This assumption could be violated if treatment effects vary over time, or if there is selection into a given dose.

the percent of births that were a mother's first, second, third, or fourth, and county averages of mother's age and race. α_c and α_y are county and year fixed effects. Observations are at the county-year level and standard errors are clustered at the county level. Since we collapse birth weight data to county means, we weight our results by the total number of births that occurred in a county-year.

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. Our outcome variable is now ΔY_{py}, which is equal to the mean birth weight in all counties downstream from a facility minus the mean birth weight in all counties upstream from the same facility in each year. We then estimate the following specification

$$\Delta Y_{py} = \gamma pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py} \tag{3}$$

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

This specification requires us to assume that, in the absence of grant receipt, birth outcomes would have evolved similarly in areas up and downstream from the same facility after

We address the dynamic treatment effects in appendices B.2 and B.3. As the dose in this setting is simply a measure of what portion of births in a county are likely to be treated, we think the strong parallel trends assumption is reasonable.

[16]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.

grant receipt. This assumption would be violated if, for example, downstream areas were experiencing differential sorting patterns or greater economic growth relative to upstream areas, even in the absence of CWA grants. For example, Keiser and Shapiro (2019a) show that downstream housing prices increase after grant receipt, which may cause healthier mothers to sort into downstream communities.

To address concerns regarding differential trends in infant health in downstream relative to upstream areas caused by differences in economic growth or sorting of households into downstream areas, we employ a triple difference design. We estimate the following equation

$$\Delta Y_{py} = \gamma_0^{DD} pct_{py} + \gamma^{DDD} pct_{py} * t_p + \beta X_{py} + \phi X_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py} \tag{4}$$

where t_p is an indicator that equals one for non-compliant facilities. 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 comes from the facility's compliance with the treatment technology mandate.

Even if individuals sort into downstream communities, so long as the sorting pattern induced by grant receipt is similar for both compliant and non-compliant facilities, using compliance as a third difference will capture unobserved changes to up and downstream counties occurring contemporaneously with CWA grant receipt. We test this by exploring how maternal characteristics evolve after grant receipt in upstream and downstream areas across non-compliant and compliant facilities. Table 2 estimates equation 2 on demographic characteristics that are correlated with birth weight, such as race, age, and birth order. Column 1 of Table 2 shows results for the subsample of non-compliant facilities and column 2 shows results for compliant facilities. Column 3 presents results from the associated triple difference. Columns 1 and 2 show that areas downstream from facilities that received CWA grants had smaller non-white populations, slightly older mothers, and fewer higher order births, but changes in downstream demographic characteristics 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. While we also control for these observable demographic characteristics in all regressions, these results provide some evidence that the identification assumption for the triple difference specification is likely to hold for unobservable characteristics as well.

4.2 Infant Health Results

Panel A of Table 3 shows effects on birth weight that 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 2 using a sample of births from every county in the contiguous US. Column 2 adds demographic controls to this specification.[17] Since births occurring in counties that are not near wastewater treatment facilities might not make a good control group, column 3 excludes counties that are not up or downstream from any wastewater treatment facility. 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 better counterfactuals for

[17] Figure A4 in the appendix shows the event study figures that correspond to the estimate in column 2.

downstream counties than counties upstream from any facility. Column 4 estimates equation 3, 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.[18,19]

The impact of the CWA on birth weight may not be uniform across the distribution of birth weight, so we also show results for low birth weight in Panel B of Table 3.[20] The point estimates are consistently negative, although not always significant, and range from -0.09 to -0.29 percentage points. About 7 percent of births in our sample are low birth weight, so this represents a change of 1 to 4 percent from the mean.

Finally, we estimate our triple difference specification on birth outcomes. Columns 5 and 6 of Table 3 present results from estimating equation 3 on sub-samples of non-compliant and compliant facilities, respectively. Consistent with our water pollution results in Table 1, we see a relatively large and statistically significant improvement in birth weight downstream from non-compliant facilities. The effect in areas downstream from compliant facilities is also positive, but smaller; improvements in infant health in areas downstream from compliant facilities may be driven by demographic or economic changes that coincide with grant timing. Since, as shown in Table 2, demographic changes were similar in areas downstream from

[18] Figure A5 shows the associated event study figures for column 4.

[19] 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, 2021). The third type of comparison can be wrong signed. We show in the Appendix sections B.2 and B.3 that our results are robust to using a stacked difference-in-difference design and Callaway and Sant'Anna (2021), which only rely on the first two types of comparisons. Appendix B.2 also provides estimates that use only the never treated or not yet treated counterfactual comparisons, which highlights the different comparisons made in our main estimates.

[20] Table A3 further explores the effect across the birth weight distribution. Replicating the specification from column 2, we find reductions in low birth weight are driven by decreases in both extremely low birth weight (ELBW is defined as below 1000 grams) and very low birth weight (VLBW is defined as below 1500 grams). We also observe an increase in births above 2,500 grams, which suggests that there is an upward shift in the birth weight.

non-compliant and complaint facilities, the difference between the effects downstream from non-compliant and compliant facilities likely comes from the differences in surface water quality shown in Table 1, rather than shifting demographics.

Figures 2b and 2c present the event studies that correspond to our triple difference specification for birth weight and low birth weight, respectively.[21] There is no evidence of pre-treatment trends in infant health outcomes. 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).[22] For low birth weight, the point estimates are similar in shape but are less precise.

We summarize the effect of changes in surface water quality downstream from non-compliant facilities on infant health by estimating equation 4 on the pooled sample, which leverages all of our variation in one regression. Since equation 4 includes a full set of interactions, our estimate of γ^{DDD}, reported in column 7 of Table 3, is equivalent to the difference in the estimates in columns 5 and 6. As in our water pollution estimates, the improvements in birth outcomes downstream from non-compliant facilities are statistically larger than improvements downstream from compliant facilities.[23] We show that this heterogene-

[21] Figure A6 shows the birth weight event study figures for compliant and non-compliant facilities separately. Across both types of facilities, pre-treatment trends are very similar and the effect of treatment is much larger for the non-compliant facilities in the post-treatment period, as expected.

[22] In all of our event studies, we report coefficients for four years before and eight years after grant receipt, so that we only report balanced coefficients in our infant health specifications. These specifications also includes bins for five or more years before the grant and nine or more years after the grant, but our results are not sensitive to this choice of binning. While unbalanced event study coefficients should be interpreted with caution, Figure B2 presents a version of Figure 2b with 16 years of post-treatment data. This figure suggests that the effect of CWA grants on infant health flattens out by 10 years after treatment, consistent with grant projects taking up to 10 years to complete (USEPA, 2002).

[23] It is important to note that the estimation equations for pollution and infant health are not identical due to data limitations for the geography available in the infant health data, which only records county. For completeness, we also provide estimates of our first stage impact on water quality using equation 4 in Table A4 of the appendix. We find these estimates are statistically indistinguishable and reassuringly

ity in effects is not driven by differences in facility size, population served or non-treatment technology upgrades in Table B4, which provides further evidence that improvements in downstream infant health are driven by upgrades to treatment technology. In appendix section A.3, we also explore heterogeneity of the main results by maternal race and grant timing, but find no significant differences along these dimensions.

The results from this triple difference show that increasing the probability of exposure to treated surface water from zero to 100 percent is associated with an 8.21 gram increase in average birth weight in counties downstream from facilities that were required to make upgrades to their treatment technology. In terms of magnitude, the effect on birth weight is about half of the estimated effect of any exposure to Ramadan during pregnancy (Almond and Mazumder, 2011), and about the same magnitude as the effect of stress in utero due to nearby landmine explosions on birth weight (Camacho, 2008). Estimates of the effect on the probability of low birth weight shown in Panel B of Table 3 are not significant, but they do bound improvements above a 0.236 percentage point decrease, or about 3 percent from the mean of low birth weight. This is slightly smaller than the estimated effect of drinking water contamination in utero on low birth weight estimated in a modern context (Currie et al., 2013).

4.3 Potential Mechanisms

There are several potential pathways through which surface water pollution could affect health, including contamination of public drinking water sources, contamination of private

similar to our main specification. Figure A7 also shows that the associated event study reveals very similar dynamics to the health event studies.

groundwater sources, and exposure through recreation. First, improvements in surface water quality from the CWA may affect infant health through a reduction in pollution in the source water that public water systems draw 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 these violations impact infant and child health (Currie et al., 2013; Grossman and Slusky, 2019; Marcus, 2021). A report by the US Geological Survey (USGS) found that more than one in five source-water samples from public water systems contained one or more contaminants at concentrations dangerous to human health. In an analysis of matched water samples from 94 water sources and their associated public water systems, the same organic contaminants detected in source water consistently appeared at similar concentrations in drinking water after treatment (Toccalino and Hopple, 2010). In 1970, over 70 percent of community water system users received drinking water from a surface water source (Dieter, 2018), so improvements in surface water quality from CWA grants may have reduced exposure to harmful pollutants by improving public drinking water quality. Second, reductions in surface water pollution could affect populations who get their drinking water from private wells. Surface water quality can impact nearby groundwater quality through seepage and runoff, so private groundwater well users may also benefit from reduced pollution from wastewater treatment facilities. Since private wells are unregulated and untreated, these households may be at greater risk for direct exposure through their drinking water. Third, individuals could be exposed to surface water through recreation. This channel could impact health directly through physical contact with, or ingestion of, contaminated water, or indirectly through changes in activity and exercise, such as swimming or walking along a waterway.

Our measure of treatment, the percent of a county's population that lives within one mile of a treated waterway, is likely to capture all three of these potential mechanisms to a certain extent. Impacts through private well contamination and through recreational exposure are likely to be largest for households nearest to the treated waterway. While our main results focus on the population within one mile of a treated waterway, it is not clear how far people will travel for water recreation, or how far private wells may be impacted.[24] With this in mind, Table A5 shows that our results are robust to using other bandwidths around treated waterways. We find a larger point estimate for a narrower bandwidth and a smaller yet still significant estimate for a wider bandwidth.

If public water is a primary channel of exposure, distance is not the ideal measure. Instead, a better measure of treatment would be the percent of the population served by a public water system drawing water from a treated waterway. Unfortunately, data limitations prevent us from creating this measure. Data on public and private water supply is very limited, especially in this historic context. Spatial data on public water system's service supply areas are only available for more recent time periods in a handful of states, and modern supply areas may not accurately reflect service areas in the 1970s and 1980s. In addition, we have no information on the exact location from which public water systems draw their water supply. There is also no historic data on private well locations. While not ideal, we still take advantage of the available spatial data on modern public water system's service areas from eight states for which this data is available (see Section C.2 for details on these data). For these states, we calculate the percent of a county's population living

[24] While distance is a factor in recreational use, accurately measuring recreational benefits is especially difficult (Kuwayama et al., 2018). Unfortunately, we lack direct measures of water-related recreation activities from this time period.

within a public water system's service area.[25] Table A7 shows that this measure, which is based on public water supply areas, is highly correlated with our primary treatment measure, which is based on distance. This suggests that our main results likely capture the public water channel. We also note that, to the extent there is measurement error in our measure of exposure, our estimates will be attenuated towards zero and could be interpreted as an underestimate.

These three mechanisms are difficult to measure and disentangle with available data. While these data limitations prevent us from definitively determining the main pathway of exposure, we explore potential mechanisms in Appendix Section A.5. We take advantage of country-wide data on the percent of a county's population receiving public water from groundwater or surface water sources in 1985. We find that our results are driven by counties with water systems drawing from surface water sources, which provides suggestive evidence that public drinking water sourced from surface waters is one channel through which reductions in surface water pollution can improve infant health.

5 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 8 gram increase in average birth weight in counties downstream from facilities that were required to make treatment technology upgrades. These results are consistent

[25]If populations are receiving publicly provided drinking water sourced upstream from other counties, our measure of treatment may not accurately describe the treated population. However, community water systems generally serve areas smaller than counties (USEPA, 1997).

with the significantly larger improvements in water quality we find downstream from these facilities.

We note that our study has a number of important limitations. Data availability in this historic period restricts our ability to determine precise residential locations and the location of all drinking water sources and supply areas, as described in more detail in section 4.3. To the extent that these data limitations generate measurement error in our estimates, the 8 gram increase in average birth weight may be understated.

Nevertheless, our estimates provide an important first step in understanding the effects of the Clean Water Act on health. Incorporating the birth weight benefits from cleaner surface water, as well as other infant, adolescent and adult health effects, is important for a full accounting of the benefits of the CWA.[26] More generally, this research documents the importance of policies targeting cleaner water through sewage treatment in protecting health and shows that the complementarity between clean drinking water and sewerage initiatives for improving health holds well into the twentieth century.

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[26] Although our study faces measurement error challenges and we cannot provide a full accounting of all relevant health benefits, we conduct a rough back-of-the-envelope calculation in Appendix Section A.6 to quantify the benefits of the effects on birth weight.

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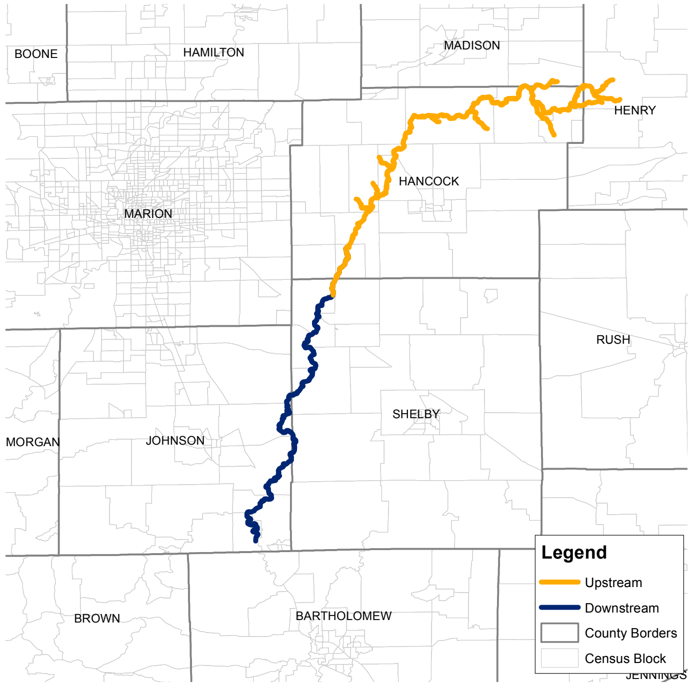
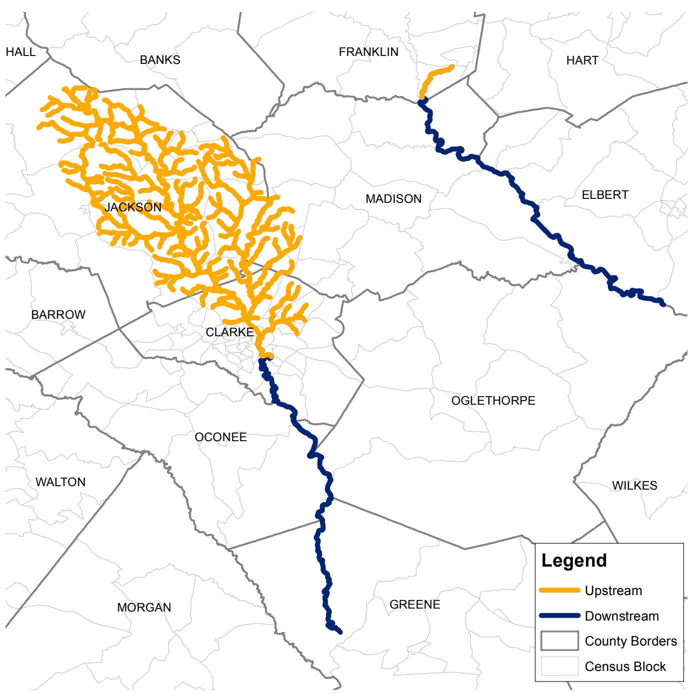
Figures



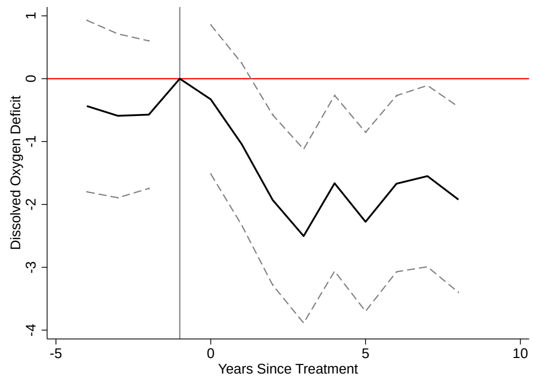
(a) Example 1: Indiana



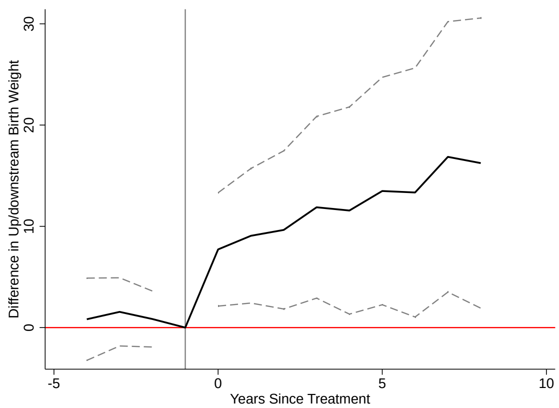
(b) Example 2: Georgia

Figure 1: Defining Upstream and Downstream Counties

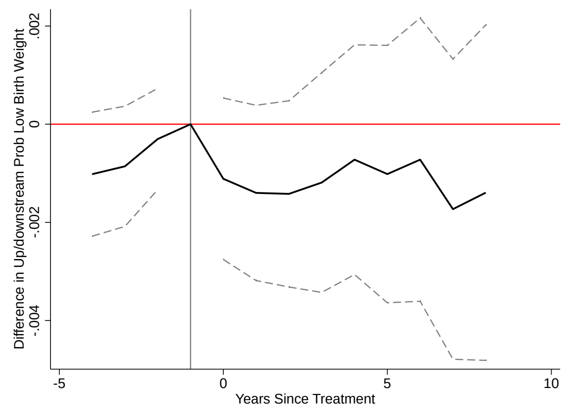
Notes: The figures show waterways within 25 miles downstream of a treated facility in dark blue and 25 miles upstream in medium yellow. County boundaries are in dark grey and census block boundaries are in light gray.



(a) Pollution



(b) Birth Weight



(c) Probability of Low Birth Weight

Figure 2: Pollution and Infant Health Event Studies

Notes: Sub-figure (a) plots the θ_t and η_t from estimating $Q_{pdy} = \sum_{t=-5}^{-2} \theta_t 1\{y - y_p^* = t\} * d_d * t_p + \sum_{t=0}^{9} \eta_t 1\{y - y_p^* = t\} * d_d * t_p + \sum_{t=-5}^{-2} \pi_t 1\{y - y_p^* = t\} * d_d + \sum_{t=0}^{9} \gamma_t 1\{y - y_p^* = t\} * d_d + \beta W_{pdy} + \phi W_{pdy} * t_p + \alpha_{py} + \alpha_{pd} + \epsilon_{pdy}$. Q_{pdy} measures dissolved oxygen deficit, d_d is a dummy equaling one for observations downstream from a facility, and t_p is an indicator that equals one for non-compliant facilities. The model includes facility-by-downstream fixed effects and facility-by-year fixed effects, α_{pd} and α_{py}, as well as controls for temperature. Sub-figures (b) and (c) plot the θ_t and η_t from estimating $\Delta Y_{py} = \sum_{t=-5}^{-2} \theta_t 1\{y - y_p^* = t\} * t_p + \sum_{t=0}^{9} \eta_t 1\{y - y_p^* = t\} * pct_{py} * t_p + \sum_{t=-4}^{-2} \pi_t 1\{y - y_p^* = t\} + \sum_{t=0}^{9} \gamma_t 1\{y - y_p^* = t\} * pct_{py} + \beta X_{py} + \phi X_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py}$. pct_{py} is a continuous variable that takes values from zero to one, and indicates the percent of downstream counties' populations living within a mile of a treated waterway in year y. The model includes facility and year fixed effects, α_p and α_y respectively, as well as demographic controls. t_p is an indicator that equals one for non-compliant facilities. The dependent variable is the difference in birth weight between up and downstream counties in year y in sub-figure (b), 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 (c).
Source: USEPA (1968-1988); National Center for Health Statistics (1968-1988a)

Tables

Table 1: Effects on Surface Water Pollution

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

95% confidence intervals in brackets

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

Notes: This table describes the effects of Clean Water Act grants on downstream pollution. Columns 1, 2 and 3 estimate equation 1 for areas up and downstream from all facilities in our sample, non-compliant facilities, and all other facilities respectively. Column 4 presents estimates from the associated triple difference: $Q_{pdy} = \gamma_0^{DD} g_y * d_d + \gamma^{DDD} g_y * d_d * t_p + \beta W_{pdy} + \phi W_{pdy} * t_p + \alpha_{py} + \alpha_{pd} + \epsilon_{pdy}$ where t_p is a dummy variable equaling one for observations from non-compliant facilities. 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. All regressions include controls for water temperature, as well as facility-by-downstream and facility-by-year fixed effects, α_{pd} and α_{py}.
Source: (USEPA, 1968-1988)

Table 2: Effects on Demographic Changes

	non-compliant (1)	compliant (2)	DDD (3)
Panel A.		percent non-white	
pct downstream	-0.0223***	-0.0176***	-0.0176***
	[-0.0281,-0.0165]	[-0.0229,-0.0123]	[-0.0229,-0.0123]
pct downstream X non-compliant			-0.00471
			[-0.0126,0.00313]
mean	.116	.105	.11
Panel B.		mother's age	
pct downstream	0.126***	0.0784**	0.0784**
	[0.0557,0.197]	[0.0149,0.142]	[0.0150,0.142]
pct downstream X non-compliant			0.0479
			[-0.0470,0.143]
mean	24.563	24.569	24.566
Panel C.		probability first or second birth	
pct downstream	-0.00210	0.00109	0.00109
	[-0.00916,0.00496]	[-0.00390,0.00608]	[-0.00390,0.00608]
pct downstream X non-compliant			-0.00319
			[-0.0118,0.00545]
mean	.653	.645	.648
Panel D.		probability third or higher birth	
pct downstream	-0.0105***	-0.00618***	-0.00618***
	[-0.0145,-0.00646]	[-0.00965,-0.00271]	[-0.00964,-0.00271]
pct downstream X non-compliant			-0.00429
			[-0.00958,0.00100]
mean	.338	.347	.343
unit and year fixed effects	X	X	X
collapsed to facility level	X	X	X
N	34188	48132	82320

95% confidence intervals in brackets

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

Notes: Columns 1 and 2 present results from estimating $\Delta x_{py} = \gamma pct_{py} + \alpha_p + \alpha_y + \epsilon_{py}$ on subsamples of non-compliant and compliant facilities. Δx_{py} is a measure of the difference between demographic characteristic in counties up and downstream from facility p in year y, and pct_{py} is a continuous variable that takes values from zero to one, and indicates the percent of downstream counties' populations living within a mile of a treated waterway in year y. The model includes facility and year fixed effects, α_p and α_y. Column 3 presents estimates of the associated triple difference, $\Delta x_{py} = \gamma_0^{DD} pct_{py} + \gamma^{DDD} pct_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py}$, where t_p is an indicator that equals one for non-compliant facilities. Each panel represents a different demographic variable. Means of each variable in 1970 from up and downstream counties are reported at the bottom of each panel.
Source: National Center for Health Statistics (1968-1988a)

Table 3: Effects on Health at Birth

	full sample	full sample	full sample	full sample	non-compliant	compliant	DDD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A	county average birth weight						
pct downstream	12.80***	6.718***	7.134***	8.999***	13.36***	5.153**	5.153**
	[6.709,18.89]	[2.034,11.40]	[2.444,11.82]	[5.721,12.28]	[8.012,18.72]	[1.129,9.177]	[1.130,9.176]
pct downstream X non-compliant							8.211**
							[1.519,14.90]
Panel B	probability birth weight $<$ 2500 grams						
pct downstream	-0.00288***	-0.000874*	-0.000963*	-0.00177***	-0.00216***	-0.00138**	-0.00138**
	[-0.00419,-0.00156]	[-0.00190,0.000152]	[-0.00198,0.0000584]	[-0.00256,-0.000985]	[-0.00334,-0.000979]	[-0.00244,-0.000325]	[-0.00244,-0.000325]
pct downstream X non-compliant							-0.000780
							[-0.00236,0.000803]
unit and year fixed effects	X	X	X	X	X	X	X
demographic controls		X	X	X	X	X	X
up/downstream counties only			X	X	X	X	X
collapsed to county level	X	X	X				
collapsed to facility level				X	X	X	X
N	64239	64239	64008	82320	34188	48132	82320

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

Notes: This table describes the effects of Clean Water Act grants on downstream infant health. 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. Columns 1-3 present estimates from equation 2. "pct downstream" is a continuous variable that takes values from zero to one, and indicates the proportion of the population that lived within a mile of a treated waterway in each year. All estimates include unit and year fixed effects. Demographic controls include the percent of a county's births in a given birth order bin, and county averages of mother's age and race and child gender. Columns 1 and 2 use data from every county in the US, while columns 3-7 restrict the sample to counties that are up or downstream from a wastewater treatment facility. Columns 5 and 6 restrict the sample to non-compliant facilities (those that were required to make treatment technology upgrades) and compliant facilities (those that were not), respectively. In columns 1-3, data is collapsed to the county level. In columns 4-7, data is collapsed to the facility level. Columns 4-6 estimate equation 3. Column 7 estimates the associated triple difference from equation 4. All regressions are weighted by number of births.
Source: National Center for Health Statistics (1968-1988a)

A Appendix: Additional Results

A.1 Additional Figures

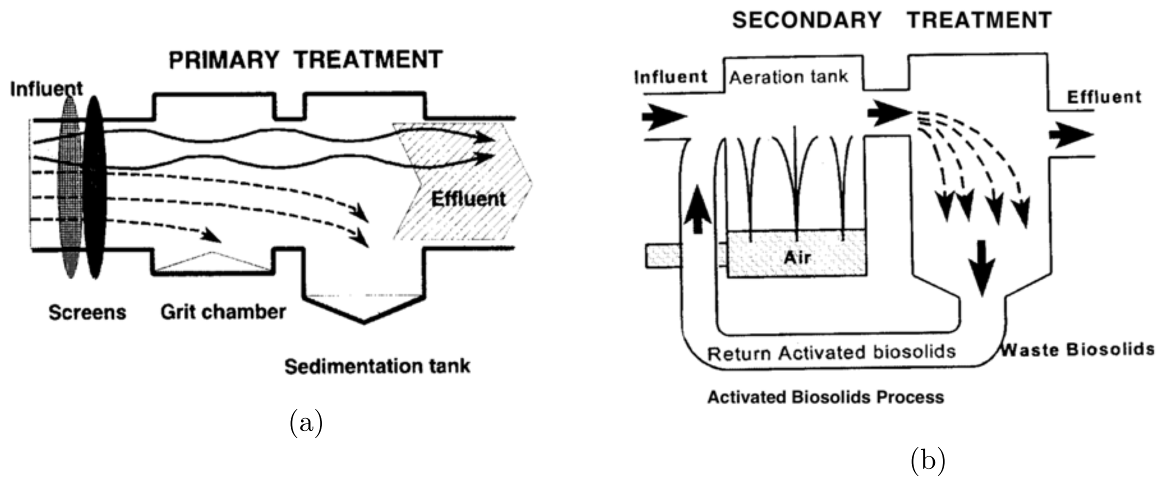
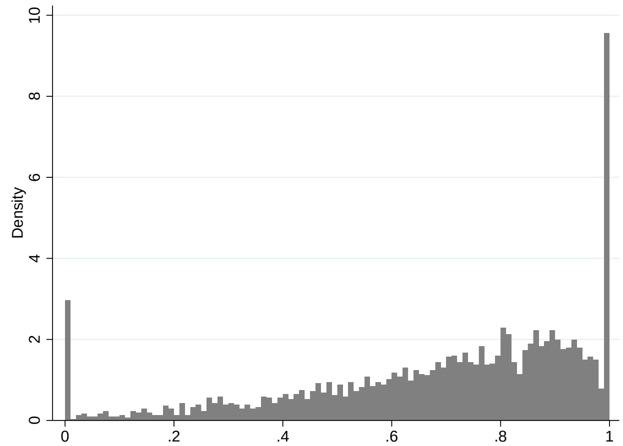


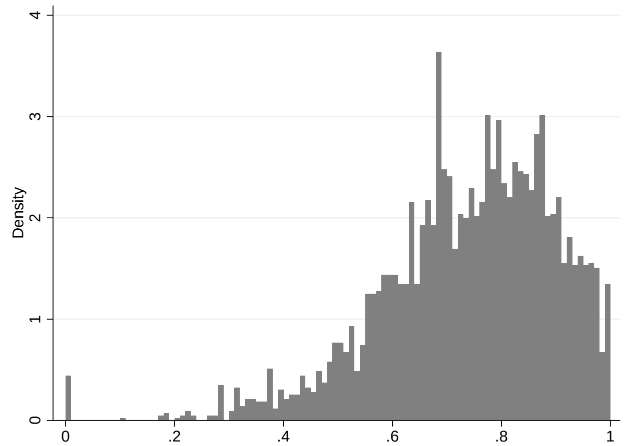
Figure A1: Primary vs Secondary Treatment Technology

Source: USEPA (1998)

Figure A2: Timing of First Grant

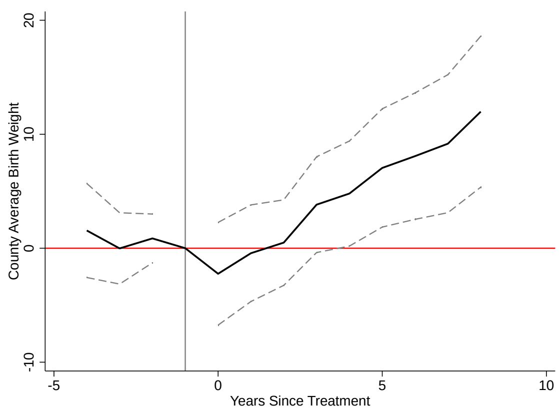


(a) County Level Treatment

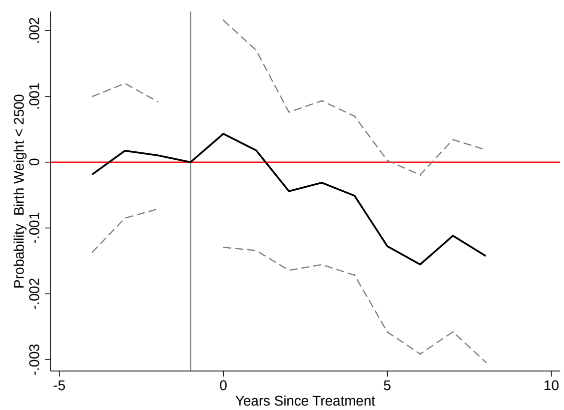


(b) Facility Level Treatment

Figure A3: Percent of Population Living Within a Mile of a Treated Waterway in 1988



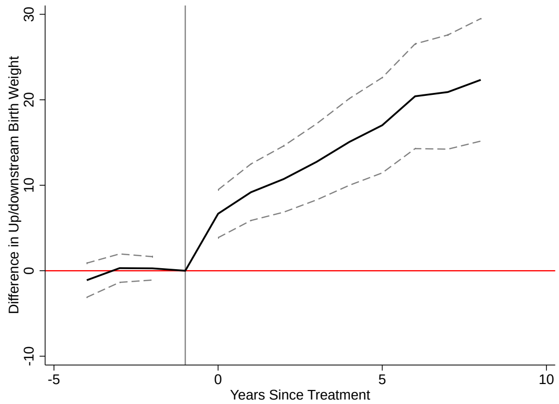
(a) Birth Weight



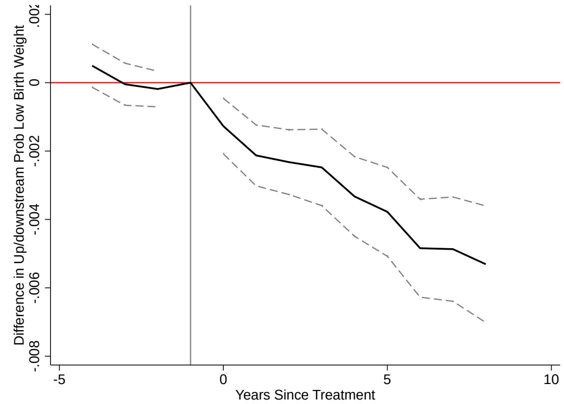
(b) Probability of Low Birth Weight

Figure A4: Birth Outcomes Downstream from Grant Facilities

Notes: These figures plot the π_t and γ_t from estimating $Y_{cy} = \sum_{t=-5}^{-2} \pi_t 1\{y - y_c^* = t\} + \sum_{t=0}^{9} \gamma_t 1\{y - y_c^* = t\} * pct_{cy} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy}$. pct_{cy} is a continuous variable that takes values from zero to one, and indicates the percent of county c's population living within a mile of a treated waterway in year y. The model includes county and year fixed effects, α_c and α_y respectively, as well as controls for the percent of a county's births of a given birth order, and county averages of mother's age and race and child gender. The estimates are weighted by total number of births in a county-year. The dependent variable is the the average birth weight in county c in year y in sub-figure (a), and the probability of being born weighing less than 2500 grams in county c in year y in sub-figure (b).
Source: National Center for Health Statistics (1968-1988a)



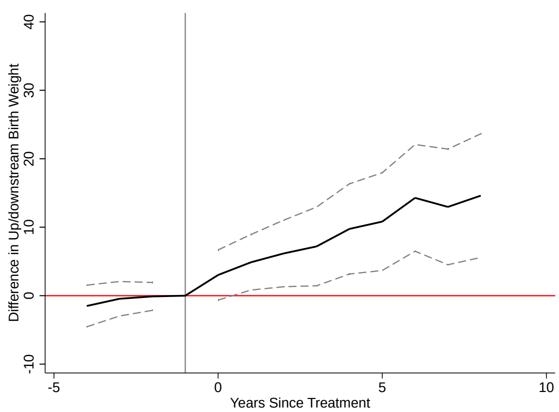
(a) Birth Weight



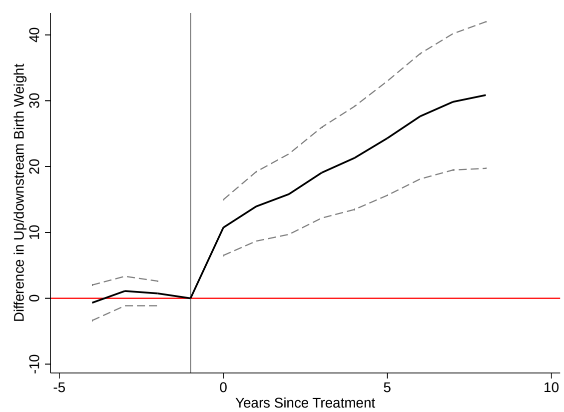
(b) Probability of Low Birth Weight

Figure A5: Difference in Birth Outcomes Up and Downstream from Grant Facilities

Notes: These figure plot the π_t and γ_t from estimating $\Delta Y_{py} = \sum_{t=-5}^{-2} \pi_t 1\{y - y_p^* = t\} + \sum_{t=0}^{9} \gamma_t 1\{y - y_p^* = t\} * pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py}$. pct_{py} is a continuous variable that takes values from zero to one, and indicates the percent of downstream counties' populations living within a mile of a treated waterway in year y. The model includes facility and year fixed effects, α_p and α_y respectively, as well as controls for the percent of up and downstream counties' births of a given birth order, and averages of up and downstream mother's age and race and child gender. The estimates are weighted by total number of births in counties up and downstream from facility p in year y. The dependent variable is the difference in birth weight between up and downstream counties in year y in sub-figure (a), and the difference in the probability of being born weighing less than 2500 grams between up and downstream counties in year y in sub-figure (b).
Source: National Center for Health Statistics (1968-1988a)



(a) Compliant



(b) Non-Compliant

Figure A6: Event Studies by Compliance

Notes: The figures plot the event study estimates from Figure 2b separately in panels (a) and (b) for compliant and non-compliant facilities, t_p. The model includes facility and year fixed effects, α_p and α_y respectively, as well as demographic controls. The dependent variable is the difference in birth weight between up and downstream counties in year y. Source: National Center for Health Statistics (1968-1988a)

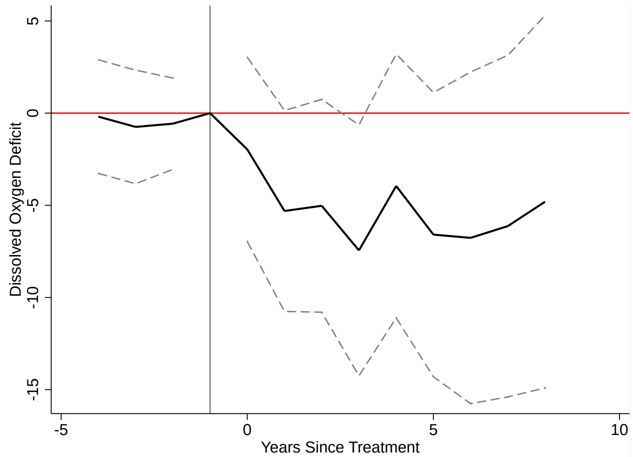


Figure A7: First Stage

A.2 Additional Tables

Table A1: Agents of Waterborne or Water-based Disease

Bacteria	Protozoa	Viruses
Vibrio cholerae	*Giardia lamblia*	Norovirus
Salmonella spp.	*Cryptosporidium parvum*	Sapprovirus
Shigella spp.	*Entamoeba histolitica*	Poliovirus
Toigenic *Escherichia coli*	*Cyclospora cayetanensis*	Coxsackievirus
Campylobacter spp.	*Isospora belli*	Echovirus
Yersinia enterocolitica	Microsporidia	Paraechovirus
Legionella	*Ballantidium coli*	Enteroviruses 69-91
Helicobacter pylori	*Toxoplasma gondii*	Reovirus
	Naegleria fowleri	Adenovirus
		Hepatitis A & E
		Rotavirus
		Astrovirus
		Picobirnavirus
		Coronavirus

Source: Reynolds et al. (2008)

Table A2: 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. These means are calculated using individial birth data from 1970, two years before the CWA came into effect.
Source: National Center for Health Statistics (1968-1988a)

Table A3: Effect on Across the Birth Weight Distribution

	(1) bw < 1000	(2) bw < 1500	(3) 1500 < bw < 2500	(4) bw > 2500
pct pop 1 mile	-0.000320*	-0.000496**	-0.000378	0.000874*
	(0.000174)	(0.000210)	(0.000439)	(0.000523)
Observations	64239	64239	64239	64239

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Notes: This table presents re-estimates our difference-in-differences results from Column 2 of Table 3 on different bins of birth weight. Column 1 shows the effect on Extremely Low Birth Weight (ELBW), defined as births below 1,000 grams. Column 2 shows the effect on Very Low Birth Weight, defined as births below 1,500 grams. Column 3 shows the effect on births between 1,500 and 2,500 grams, which includes births classified as Low Birth Weight but not VLBW or ELBW. Column 4 shows the effect on births above 2,500 grams.

Table A4: First Stage

	(1) non-compliant	(2) compliant	(3) DDD	(4) DDD	(5) DDD
pct pop 1 mile	-3.946***	-0.132	-0.132	-0.271	0.659
	(1.496)	(1.908)	(1.908)	(0.767)	(1.907)
pct pop 1 mile X non-compliant			-3.814	-1.789*	-3.704
			(2.424)	(1.078)	(2.440)
demographic controls	X	X	X	X	
unit fixed effects	X	X	X	X	X
year fixed effects	X	X	X	X	X
collapsed to facility level	X	X	X	X	X
weighted	X	X	X		X
N	12201	11378	23579	23579	23579

Standard errors in parentheses

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

Table A5: Alternative Small Bandwidths

	(1) 25 miles downstream .5 mile buffer	(2) 25 miles downstream 1.5 mile buffer
	county average birth weight	
pct pop .5 miles	10.70**	
	[1.961,19.44]	
pct pop 1.5 miles		6.621**
		[1.081,12.16]
demographic controls	X	X
unit and year fixed effects	X	X
collapsed to facility level	X	X
N	82320	82320

95% confidence intervals in brackets

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

Notes: This table presents (weighted) estimates from the following model: $\Delta Y_{py} = \gamma_0^{DD} pct_{py} + \gamma^{DDD} pct_{py} * t_p + \beta X_{py} + \phi X_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py}$. pct_{py} is a continuous variable that takes values from zero to one, and indicates the proportion of downstream counties' populations that lived within some bandwidth of a treated waterway in a given year. In column 1, this bandwidth is .5 miles, and in column 2, it is 1.5 miles.

Table A6: Drop Top Quartile of Land Area

	(1)
pct pop 1 mile	5.429**
	(2.515)
demographic controls	X
unit and year fixed effects	X
collapsed to county level	X
observations	48174

Standard errors in parentheses

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

Notes: This table reproduces difference-in-difference estimates from Column 2 of Table 3 after dropping the counties in the top quartile of land area (i.e. counties with the largest geographic area).

Table A7: Correlation of Treatment Variables

	(1)
	pct pop public water
pct downstream	0.927***
	(0.00944)
Observations	8463

Standard errors in parentheses

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

Notes: This table shows the correlation between the percent of the population living in a treated public water system's service area and the percent of the population living within a mile of a treated waterway by presenting estimates from the following model: $pws_{cy} = \beta pct_{cy}$ where pws_{cy} is a variable that takes values between zero and one and indicates the proportion of county population population living in a treated public water system's service area.

A.3 Heterogeneity

We examine the heterogeneity of our estimates across race in Table A8 by estimating equation 4 on sub-samples of white and non-white births from counties with sizable non-white populations.[27] The point estimates for both white and non-white births are similar to the estimates of effects on average birth weight for any race, and results by race are not statistically distinguishable.

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

[27] 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.

especially true if we think there is a convex relationship between pollution and health.

We address this in columns 3 and 4 of Table A8. In column 3, we drop all observations from facilities that received a grant after 1976 and re-estimate equation 3, 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.

Table A8: Heterogeneous Effects

	(1) white	(2) nonwhite	(3) early grants	(4) later grants
pct downstream 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 equation 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.4 Mortality

Using data from National Center for Health Statistics (1968-1988b), we re-estimate equation 4 with mortality as the dependent variable in Table A9. Columns 1-6 presents estimates from different age bins, and column 7 estimates the effect on mortality of child bearing age women. While these estimates are noisy, we find no significant effect of treatment on mortality for any group.

Table A9: Mortality Triple Difference

	(1) under 1	(2) 1-19	(3) 20-44	(4) 45-64	(5) 65-84	(6) 85+	(7) women 15-44
pct downstream X non-compliant	0.389	10.11	-14.51	-3.723	-35.34	-19.66	1.607
	[-19.65,20.43]	[-10.01,30.23]	[-63.08,34.06]	[-43.27,35.82]	[-119.9,49.17]	[-68.25,28.93]	[-8.503,11.72]
demographic controls	X	X	X	X	X	X	X
unit and year fixed effects	X	X	X	X	X	X	X
collapsed to facility level	X	X	X	X	X	X	X
N	82320	82320	82320	82320	82320	82320	82320

95% confidence intervals in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Notes: This table presents (weighted) estimates from the following model: $\Delta Y_{py} = \gamma pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py}$. The dependent variable is the difference in mortality between counties up and downstream from facility p in year y. Columns 1-6 presents estimates from different age bins, and column 7 estimates the effect on mortality of child bearing age women.
Source: National Center for Health Statistics (1968-1988b); Solley et al. (1988)

A.5 Public Water

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.[28]

We show that our results are driven by counties that had some public water systems that drew from surface water sources in Table A10. Column 1 of Table A10 re-estimates equation 4 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.[29]

We disaggregate these results further in Table A11 by estimating a triple difference where the first difference comes from where and when CWA grants were distributed, the second difference comes from if a birth occurred up or downstream from a wastewater treatment facility, and the third difference comes from whether downstream public water systems drew from surface or groundwater. Panels A and B estimate this triple difference on a sample of non-compliant facilities. We see strongly significant increases in birth weight and marginally significant decreases in the probability of low birth weight in areas that drew from surface water sources. Our estimates for areas that drew exclusively from groundwater are statistically insignificant and wrong-signed, and the birth weight effect in areas that drew from surface water is statistically greater than the effect in areas that only drew from groundwater. In Panels C and D, we re-estimate these specifications on samples of compliant facilities. These estimates can be thought of as a placebo test since these facilities experienced no improvement in downstream water quality. We find no significant effects of treatment in areas whose community water systems drew from either surface or ground water sources, as we would have expected. This suggests that our results are almost completely driven by counties that are downstream from non-compliant facilities in which some public water systems draw from surface water.

We provide further evidence that the effect of CWA grants on birth weight is driven by reduced contamination of publicly provided water in Table A12. Rather than defining the treated population as the percent of a county's population living within 1 mile of a treated waterway, we instead leverage information on the location of community water system service areas to define the treated population as the percent of the county's population served by a public drinking water system that is near a treated waterway. We calculate this using

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

[29] Columns 6 and 7 of Table A2 suggest that communities served by surface and groundwater systems serve similar populations.

maps of public water supply areas from 8 states (see Section C.2 for details on this data). This reduces the estimation sample by 86% (from 64,239 to 8,463 county-year observations). Due to reduced sample size, our results from this specification are less precise than our main results, however, the effects on both birth weight and probability of low birth weight are right-signed, and the effect on birth weight is significant at the 10 percent level and statistically indistinguishable from our main estimates.[30] We showed that this treatment measure is correlated with the percent of the population living within a mile of a treated waterway for theses eight states in Table A7, which suggests that some of our main results are driven by this public water channel.

Note that, if populations are receiving publicly provided drinking water from other counties, our county-level measure of treatment may not accurately describe treated populations. We do not have data on the locations of public water system's source wells, but, while water service areas and county borders do not always perfectly align, community water systems generally serve areas no larger than counties (USEPA, 1997).

Table A10: Effects by Public Water Source

	Surface Water	Ground Water
	(1)	(2)
Panel A	county average birth weight	
pct downstream X non-compliant	8.893**	-5.137
	[1.874,15.91]	[-21.34,11.06]
Panel B	probability birth weight < 2500 grams	
pct downstream 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 7 of Table 3 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)

[30] While estimates in Table A12 are slightly smaller than those from the full sample, we re-estimate equation 2 on the sample of states that we have public water supply data for in Table A13 and find similar estimates for this reduced sample with our main specification.

Table A11: Public Water Source Triple Difference

	Surface	Ground	DDD
	(1)	(2)	(3)
Panel A. Non-compliant	county average birth weight		
pct downstream	10.15***	-7.879	-7.879
	[5.927,14.38]	[-20.35,4.597]	[-20.23,4.473]
pct downstream X surface			18.03***
			[4.976,31.09]
N	30009	4200	34209
Panel B. Non-compliant	probability birth weight $<$ 2500 grams		
pct downstream	-0.000872*	0.00103	0.00103
	[-0.00182,0.0000796]	[-0.00192,0.00399]	[-0.00189,0.00396]
pct downstream X surface			-0.00190
			[-0.00498,0.00117]
N	30009	4200	34209
Panel C. Compliant	county average birth weight		
pct downstream	3.111	3.110	3.110
	[-0.861,7.083]	[-4.426,10.65]	[-4.402,10.62]
pct downstream X surface			0.000404
			[-8.497,8.498]
N	37023	11088	48111
Panel D. Compliant	probability birth weight $<$ 2500 grams		
pct downstream	-0.000333	-0.00183	-0.00183
	[-0.00138,0.000714]	[-0.00419,0.000522]	[-0.00418,0.000515]
pct downstream X surface			0.00150
			[-0.00107,0.00407]
N	37023	11088	48111
demographic controls	X	X	X
unit and year fixed effects	X	X	X
collapsed to facility level	X	X	X

95% confidence intervals in brackets

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

Notes: This table describes the effects of Clean Water Act grants on birth outcomes depending on public water source. Column 1 estimates $\Delta Y_{py} = \gamma pct_{py} + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py}$ for facilities whose downstream counties had some public water systems that drew from surface water, and column 2 re-estimates this specification for counties whose public water systems only drew from groundwater. Column 3 estimates the associated triple difference: $\Delta Y_{py} = \gamma_0^{DD} pct_{py} + \gamma^{DDD} pct_{py} * s_p + \beta X_{py} + \phi X_{py} * s_p + \alpha_y * s_p p + \alpha_p + \alpha_y + \epsilon_{py}$ 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 A12: Exposure Defined by Percent on Public Water Supply

	(1) birth weight	(2) prob bw < 2500
pct pop public water	4.705*	-0.000224
	[-0.411,9.821]	[-0.00210,0.00165]
demographic controls	X	X
unit and year fixed effects	X	X
collapsed to county level	X	X
N	8463	8463

95% confidence intervals in brackets

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

Notes: In this table, we re-estimate the results in column 2 of Table 3 defining pct_{cy} as the percent of the population that is served by a public drinking water system that is near a treated waterway.
Source: National Center for Health Statistics (1968-1988a)

Table A13: Limit Sample to States with Public Water Supply Maps

	(1) birth weight	(2) prob bw < 2500
pct downstream	2.242	-0.000626
	[-4.038,8.522]	[-0.00268,0.00143]
demographic controls	X	X
unit and year fixed effects	X	X
collapsed to county level	X	X
N	8463	8463

95% confidence intervals in brackets

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

Notes: In this table, we re-estimate the results in column 2 of Table 3 on the eight states that we have public water supply data for.
Source: National Center for Health Statistics (1968-1988a)

A.6 Quantifying the Benefits to Infant Health

Our estimates suggest that reductions in pollution associated with CWA grants leading to an 8 gram increase in average birth weight in counties downstream from facilities that were required to make treatment technology upgrades. We use this information to quantify the benefits to one measure of health. We note that a full accounting of the health benefits would include many other infant health measures that are often studied in the literature (e.g., gestation length, SGA, neonatal mortality, maternal complications, etc.), as well as child, adolescent, and adult health measures.

About 56.4 million births occurred in treated counties between 1972 and 1988, and we estimate that about 32.1 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, it bounds improvements below a 0.263 percentage point reduction (Column 7 of Table 3). Given the measurement error that may be incorporated into our estimates due to data constraints, we think it is most helpful to use the upper bound of the confidence interval we estimate for low birth weight.

In terms of the costs associated with low birth weight, 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 Bharadwaj et al. (2018) finds that low birth weight reduces permanent labor income by 3.4 percent. We combine these estimates with the EPA's value of a statistical life (VSL) of $7.4 million and the census bureau's work-life earnings estimate of $2.4 million to calculate a rough back-of-the-envelope estimate.

While our estimates face measurement error that may attenuate the effects and a more comprehensive calculation of the health benefits of the CWA would include other potentially impacted health outcomes, we estimate that the upper-bound of the confidence interval on the effects on low birth weight generates benefits of about $32 billion. This is about 21 percent of the amount needed to make the CWA cost effective.[31] Future work should consider the effect of the CWA on additional measures of health to provide a more comprehensive cost-benefit analysis.

B Appendix: Robustness

B.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 4 defining treated waterways as those either 5 or 10 miles downstream from a treated facility in Table B1. The results are similar to those presented in Section 4.

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[31] In total, CWA grants to wastewater treatment facilities cost an estimated $153 billion (in 2014 dollars).

Table B1: Other Distances Downstream

	non-compliant	compliant	DDD
	(1)	(2)	(3)
Panel A. 5 miles downstream	county average birth weight		
pct downstream	14.68***	6.358***	6.358***
	[9.192,20.18]	[2.190,10.53]	[2.191,10.52]
pct downstream X non-compliant			8.326**
			[1.435,15.22]
N	35973	50379	86352
Panel B. 10 miles downstream	county average birth weight		
pct downstream	14.44***	6.167***	6.167***
	[8.986,19.90]	[2.023,10.31]	[2.024,10.31]
pct downstream 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: $bw_{py} = \gamma_0^{DD} pct_{py} + \gamma^{DDD} pct_{py} * t_p + \beta X_{py} + \phi X_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py}$. 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)

B.2 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, the third type of comparison can be wrong signed (Goodman-Bacon, 2021). 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. Note that 93 counties out of 3,064 total counties were never-treated. We can then estimate the following stacked difference-in-difference:

$$Y_{py} = \gamma^{stacked} pct_{py} + \alpha_{ps} + \alpha_{sy} + \epsilon_{psy} \tag{5}$$

p indexes facilities, y indexes years, and s indexes stacks. Facility-by-stack fixed effects, α_{ps}, are analogous to a unit fixed effect in our regressions in the main text. Year-by-stack fixed effects, α_{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 5 in Table B2. 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, our main results are closer to the results in column 1 than those in column 2.

Table B2: Stacked Difference in Difference

	(1) not yet treated	(2) never treated	(3) both
Panel A		county average birth weight	
pct downstream	5.209**	26.96***	5.458**
	[0.247,10.17]	[19.12,34.80]	[0.509,10.41]
Panel B		probability bw < 2500	
pct downstream	-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: $Y_{py} = \gamma^{stacked} pct_{psy} + \alpha_{ps} + \alpha_{sy} + \epsilon_{psy}$. 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)

B.3 Binary Treatment

Our main results define treatment with a continuous measure, so our results are identified in part off of comparisons between counties where a large proportion of the population is treated relative to counties where a small proportion is treated. Since we expect birth outcomes to improve homogeneously as more of the population becomes treated, there is nothing wrong with using this variation (Callaway et al., 2021), 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.

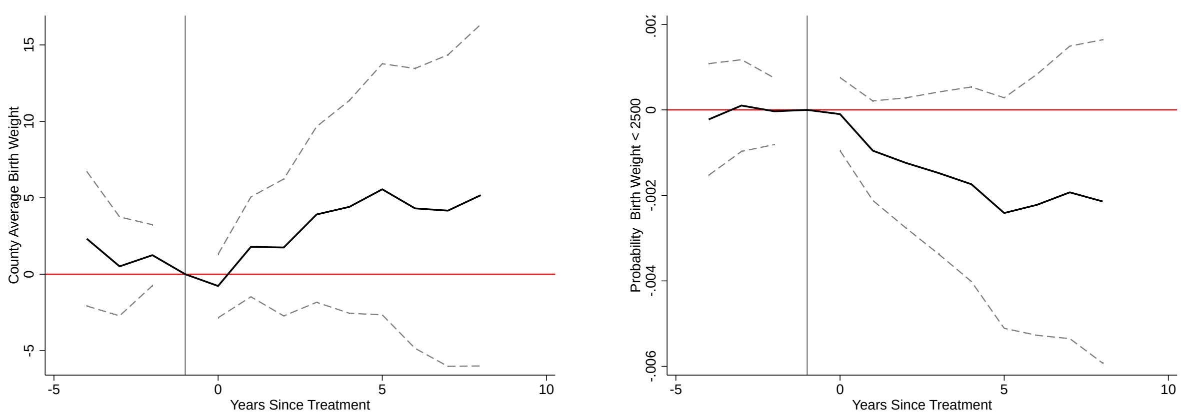
We first estimate the following event study

$$Y_{cy} = \sum_{t=-5}^{-2} \pi_t 1\{y - y_c^* = t\} + \sum_{t=0}^{9} \gamma_t 1\{y - y_c^* = t\} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy} \tag{6}$$

We present estimates of equation 6 with average birth weight and the probability of low birth weight in Figure B1. 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 B.2 in a more sophisticated way. To summarize these event studies, we use Callaway and Sant'Anna (2020) to estimate treatment effects in Table B3.

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 B1: Birth Outcomes Downstream from Grant Facilities (Binary Treatment)

Notes: These figures plot the π_t and γ_t from estimating $Y_{cy} = \sum_{t=-5}^{-2} \pi_t 1\{y - y_c^* = t\} + \sum_{t=0}^{9} \gamma_t 1\{y - y_c^* = t\} + \beta X_{cy} + \alpha_c + \alpha_y + \epsilon_{cy}$. 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 B3: Callaway and Sant'Anna (2020) 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 event study aggregations of group time average treatment effect estimates of the effect of being downstream from a facility that received a CWA grant on birth outcomes.
Source: National Center for Health Statistics (1968-1988a)

B.4 Flow Rate, Population Served, and Non-Treatment Technology Modifications

In our triple difference specification, we interact treatment with a variable that indicates whether plants were compliant with new treatment technology standards when the CWA came into effect. Compliance is strongly correlated with heterogeneity in the effect of grants, but there could be other attributes correlated with grant effectiveness. To argue that the difference in grant effectiveness is due to differences in compliance, we interact treatment with measures of these other characteristics in Table B4 by estimating equation 7.

$$\Delta Y_{py} = \gamma pct_{py} + \eta pct_{py} * t_p + \pi pct_{py} * Interact_p + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py} \tag{7}$$

In column 1, the interaction term is the flow rate of the receiving facility measured in millions of gallons per day. In column 2, it is the total population served by the facility. In column 3, it is a dummy variable that equals one for facilities that indicated that they would use grant money to pay for non-treatment technology related upgrades in the 1972 CWNS. Column 4 includes all of these interactions in one equation.[32] All other variables are defined analogously to those in equation 3.

The coefficients on all three of the interaction terms are insignificant, and all three are wrong signed in columns 1 through 3, showing that facility size, the size of the population served, and non-treatment technology upgrades are not driving the heterogeneity in our estimates. This is further evidence that improvements in downstream infant health are driven by upgrades to treatment technology.

[32] We do not have data on these interaction terms for all facilities.

Table B4: Other Interactions

	(1)	(2)	(3)	(4)
	county average birth weight			
pct downstream X non-compliant	6.464**	5.268**	5.389	6.736
	[0.664,12.26]	[0.143,10.39]	[-2.149,12.93]	[-2.078,15.55]
pct downstream	4.719*	7.304***	5.888	5.687
	[-0.507,9.945]	[2.763,11.84]	[-1.797,13.57]	[-2.950,14.32]
pct downstream X total flow	-0.0263			0.0347
	[-0.0652,0.0126]			[-0.0314,0.101]
pct downstream X population served		-0.00000700		-0.0000165
		[-0.0000184,0.00000441]		[-0.0000377,0.00000467]
pct downstream X other modification			-0.903	-2.871
			[-14.13,12.33]	[-16.76,11.02]
demographic controls	X	X	X	X
unit and year fixed effects	X	X	X	X
collapsed to facility level	X	X	X	X
N	35049	45864	30597	24717

95% confidence intervals in brackets

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

Notes: This table estimates $\Delta Y_{py} = \gamma pct_{py} + \eta pct_{py} * t_p + \pi pct_{py} * Interact_p + \beta X_{py} + \alpha_p + \alpha_y + \epsilon_{py}$ In column 1, the interaction term is is the flow rate of the receiving facility measured in millions of gallons per day. In column 2, it is the total population served by the facility. In column 3, it is a dummy variable that equals one for facilities that indicated that they would use grant money to pay for non-treatment technology related upgrades in the 1972 CWNS. Column four includes all of these interaction terms. All other variables are defined analogously to those in equation 3.
Source: National Center for Health Statistics (1968-1988a)

B.5 Unbalanced Event Study

In the main text, we look at effects up to eight years after treatment. Since we bin observations from greater than 8 years after treatment, we are only estimate balanced event study coefficients. We look at a longer post period by re-estimating the results in Figure 2b without binning these unbalanced endpoints in Figure B2. Since only early treated counties contribute to later event study coefficients, they should be interpreted with caution, however, these results suggest that the effect of CWA grants on infant health flattened out by 10 years after treatment, consistent with projects taking up to 10 years from grant application to project completion (USEPA, 2002).

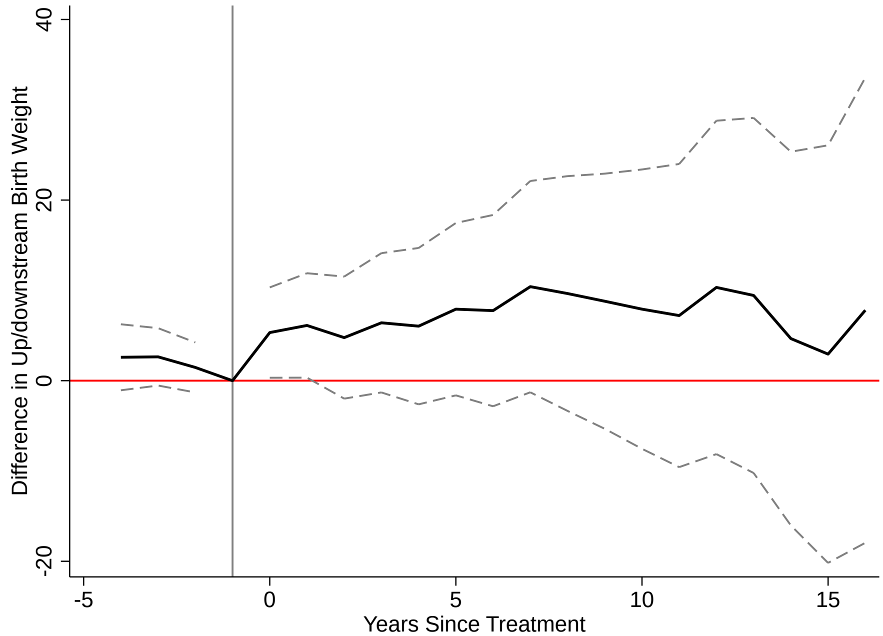


Figure B2: Birth Weight Triple Difference

Notes: These figures plot the θ_t and η_t from estimating $\Delta Y_{py} = \sum_{t=-5}^{-2} \theta_t 1\{y-y_p^* = t\} * t_p + \sum_{t=0}^{16} \eta_t 1\{y-y_p^* = t\} * pct_{py} * t_p + \sum_{t=-4}^{-2} \pi_t 1\{y-y_p^* = t\} + \sum_{t=0}^{16} \gamma_t 1\{y-y_p^* = t\} * pct_{py} + \beta X_{py} + \phi X_{py} * t_p + \alpha_y * t_p + \alpha_p + \alpha_y + \epsilon_{py}$. All variables are defined analogously to those in Figure 2. The dependent variable is the difference in birth weight between up and downstream counties in year y.
Source: National Center for Health Statistics (1968-1988a)

C Appendix: Additional Data Details

C.1 Birth Data Details

C.1.1 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 merged between 1968 and 1988. Changes are noted in Table C1.

Table C1: 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

C.1.2 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 C2 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 the results in Figure 2b on this sample in Figure C1. We then re-estimate the results presented in Table 3 on this sample and report the results in Table C3, which are similar to those reported in Section 4.

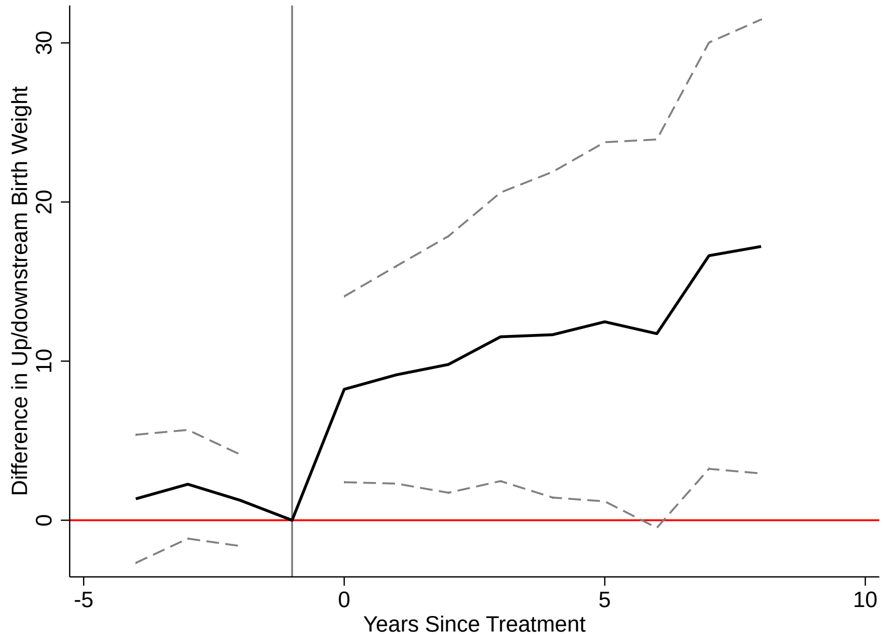


Figure C1: Birth Weight Triple Difference: Random Sample

Notes: This Figure re-estimates the results in Figure 2b 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 C2.
Soure: National Center for Health Statistics (1968-1988a)

Table C2: 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 C3: Triple Difference: Random Sample

	(1) non-compliant	(2) compliant	(3) DDD
pct downstream	12.38***	4.448**	4.448**
	[7.015,17.74]	[0.303,8.593]	[0.304,8.592]
pct downstream 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 Columns 5-7 in Panel A of Table 3 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)

C.2 Public Water Supply Data

Data from each state comes from different years and reflects different water sources. Data from each state is described below.

Arkansas

Arkansas data is from the Arkansas GIS office, and is a comprehensive geographic database of water utilities and services in the Arkansas public water system. A visual aid of water system boundaries overlaid on current digital aerial photography, associated road names, and landmarks, were verified by representatives of ADH to confirm the accuracy of the boundaries. First published in 2013, these maps were last updated in 2019 (Arkansas GIS Office, 2013).

Arizona

Arizona data is maintained by the Arizona Department of Water Resources (ADWR) and reflects community water systems as of 2020. To determine the service area, ADWR utilized primary data provided directly from the water system (i.e. PDF, shapefile, verbal definition). If primary data was unavailable, secondary data (i.e. Certificate of Convenience and Necessity (CCN), Census Designated Place shapefile from U.S Census Bureau) was utilized to determine service area boundaries (Arizona Department of Water Resources, 2020).

Connecticut

Cennecticut public water supply maps are maintained by the Connecticut State Department of Health (CT State Department of Public Health, 2020).

Kansas

Kansas public water maps are maintained by the The Kansas Water Office (KWO) and reflect public water supplies as of 2007 (Kansas Water Office, 2020).

New Jersey

New Jersey data comes from the Division of Science, Research, and Technology (DSRT) at the New Jersey Department of Environmental Protection (NJDEP). The maps shows all systems that piped water for human consumption to at least 15 service connections used year-round, or regularly served at least 25 year-round residents in 1998 (NJDEP, 2004).

North Carolina

North Carolina data comes from the NC Dept. of Environmental Quality, Division of Water Resources, Public Water Supply Section (PWSS), and contains maps of public water supply from 2017 (NCDEQ, 2017).

Pennsylvania

Pennsylvania maps show all areas served by a community water supply system that serves at least 15 service connections or 25 year-round residents, such as manufactured housing communities, municipal water systems, personal care homes and housing developments.

The locations were digitized from maps submitted with Annual Water Supply Report for 2000, 2001, 2002 and 2003 (PASDA, 2015).

Texas

Texas maps, maintained by the Texas Commission on Environmental Quality, show approximate relative locations of public water supply areas current to 2020 (Texas Commission on Environmental Quality, 2020).

C.3 Data on Wastewater Treatment Facilities

We begin with grant data from the EPA's Grant Information Control System, which we obtained through a Freedom of Information Act request. This data contains information on the year that the EPA distributed each grant, which municipality received the grant, the specific wastewater treatment facility the grant was designated for and the amount distributed. Keiser and Shapiro (2019a) uses the same data, and Appendix Section B.4 of Keiser and Shapiro (2019a) demonstrates its accuracy.

The 33,429 grants in our sample exclude grant records that do not include a specific facility code, as it is unclear to what extent these grants were precisely for wastewater treatment plants. We also drop grant records that are missing information on when they were distributed, which further restricts our sample to 29,898 grants.

We define whether a facility was in compliance with the CWA's capital mandate using the 1972 Clean Watershed Needs Survey, which we merge to our grant data with a unique facility code. The CWNS is an assessment of the capital investment that publicly-owned wastewater treatment facilities required to come into compliance with the Clean Water Act, and contains information on which community the facility serves, the number of residents served, the total wastewater flowing through the facility, the treatment technology currently in place, whether the facility needs to meet standards higher than the EPA's secondary treatment requirement, and whether they are currently in compliance with these requirements. This data was provided to us by the EPA's CWNS team, and is the same data that Jerch (2018) uses to define compliance with the CWA's capital mandate.

We use a facility's answer to Question 21 on the CWNS questionnaire to define compliance. Question 21b asks if a facility needs to meet treatment technology requirements that are more stringent than the EPA's secondary treatment requirement.[33] Question 21c then asks whether a facility is currently in compliance with both the EPAs secondary treatment mandate and any higher mandates.[34] We define facilities that answered "yes" on question 21c as "compliant", and those that answer no as "non-compliant". This defines facilities that satisfied the CWA's capital mandate when the CWA came into effect but did not satisfy more stringent state standards as non-compliant. When we use counties up and downstream from compliant facilities as an additional control group, we want to capture the effect of grants that were not bound by any capital mandate, so we do not want to define facilities that were still required to make upgrades as compliant, even if they are using secondary treatment.

Note that many facilities installed tertiary treatment after the CWA came into effect (USEPA, 2000). This increase was likely driven by municipalities bound by state standards or compelled by lawsuits to make upgrades beyond secondary treatment.

[33]In particular, it asks "What level of secondary treatment must the discharge of this pants meet by July 1, 1977? 1. Secondary treatment level as defined by the EPA, OR 2. Higher level of secondary treatment required by State."

[34]Question 21c asks "Does the discharge from this plant NOW meet the level of secondary treatment defined in 21b? 1. Yes, 2. No."