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Publication Date

2022-12-16

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Peer reviewed

Cleaner Waters and Urbanization

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Manuscript accepted August 2023 at
Journal of Environmental Economics and Management

Abstract

The Clean Water Act (CWA) addresses nonpoint source pollution primarily by funding public works projects. Our study evaluates changes in rural watersheds before and after CWA projects are implemented, compared to watersheds without funding. We find that projects significantly reduce water pollution, with corresponding increases in human population and residential construction. Using housing values, we estimate that economic benefits exceed government costs by at least fourfold. Over half of this benefit is attributable to new housing. Our findings show that pollution can impede urbanization, suggesting more broadly that residential development is an important mechanism of revealed preference for environmental quality.

JEL: H41, O44, Q53, Q56, R23

Keywords: water pollution, public works, rural development, environmental valuation

*Ren: qren4@ucsc.edu. West (corresponding author): westj@ucsc.edu. We thank Alex Porteous for helpful discussions about the EPA's Grants Reporting and Tracking System. This manuscript benefited from comments by editor Klaus Moeltner and several anonymous reviewers at *Journal of Environmental Economics and Management*, and seminar participants at UC-Santa Cruz. The conclusions and any errors in this work are those of the authors. This research did not receive any specific grant from funding agencies.

1 Introduction

A vast literature uses housing prices to quantify the economic benefits of reducing pollution. Hedonic valuation is intuitive and empirically tractable: people should pay higher prices for homes that have better environmental amenities. Given the right assumptions, these relative differences in prices represent people’s willingness to pay for reductions in pollution (Bishop et al., 2020). Total social benefit can then be calculated by multiplying the estimated price effect(s) by the stock of homes (e.g. Chay and Greenstone, 2005; Gamper-Rabindran and Timmins, 2013). This approach seems sensible for urban areas; if housing supply is highly inelastic, improvements in environmental quality should primarily lead to higher prices (Kahn and Walsh, 2015). However, this approach might significantly underestimate economic benefits in rural and suburban areas, where undeveloped land can be repurposed to build new housing (Taylor and Druckenmiller, 2022).

We examine this possibility in the context of surface water pollution, testing whether the U.S. Clean Water Act Section 319(h) program increases residential development. Since 1990, Section 319 has provided annual funding to state water quality agencies for nonpoint source pollution projects. Most of this pollution is due to agricultural and other runoff, and this pollution is typically very salient. Specific projects take many forms, such as sediment retention basins, riparian fencing for livestock, and treatments for algae blooms. The vast majority of projects are in rural and suburban areas, and the “watershed-based” approach provides very localized treatments (EPA, 2011). Social benefits can accrue through numerous mechanisms, including recreational and fishing potential, drinking water quality, and aesthetic value. There is ample scope for new construction in rural areas and anecdotal evidence that these public works projects attract new residents. These factors make the Section 319 program an ideal setting to test our urbanization hypothesis: does reducing surface water pollution lead to increased residential development in rural areas?

Using data from a variety of government sources, our study evaluates changes in rural watersheds before and after Section 319 projects are implemented, compared to changes in watersheds without any projects. We first show that average reductions in surface water pollution from 1990 to 2020 are 68 percent larger in watersheds with projects, despite very similar trends (and average levels) for treated and never-treated watersheds before the start of the Section 319 program. This large average treatment effect is highly robust across different econometric models and analyses. Next, we show that Section 319 projects increase treated watersheds’ total population and housing units by about ten percent. We also find significant positive effects for housing values. Altogether, there is strong evidence that

reducing water pollution causes increased residential development. Finally, we use these estimates to conduct a cost-benefit analysis. We calculate that Section 319 program benefits are \$7.62 per dollar of federal Section 319 cost and \$4.28 per dollar of total government costs, with about 56 percent of the benefit accruing through new home construction.

Our paper makes several contributions. Most directly, we show that the Clean Water Act Section 319 program significantly reduces water pollution. Although state governments have conducted case studies for selected projects, to our knowledge we provide the first comprehensive nationwide evaluation. Broadly, there is a “dearth of economic research on water pollution” (Keiser and Shapiro, 2019a). Our study contributes to the “critical area” of research needed on nonpoint source pollution control (Olmstead, 2010).

In addition, we demonstrate by revealed-preference that the benefits of these public works projects greatly exceed costs. This favorable finding is an outlier in a literature that typically finds negative net-benefits for water quality policies (Keiser et al., 2019). Several factors could potentially reconcile this distinction. Nonpoint source pollution is the primary source of U.S. water quality impairments, and pollution programs have diminishing marginal benefits (Olmstead, 2010). Surface water pollution is also salient and directly affects amenity value. Compared to point source and municipal water pollution, the U.S. spends much less addressing nonpoint sources—the Section 319 program is one of only two major federal policies targeting nonpoint sources (Keiser et al., 2019; Keiser and Shapiro, 2019a).¹ Finally, hedonic valuations that focus only on the intensive margin of increased prices for existing homes may miss important categories of benefits (Keiser et al., 2019). In this study, we find that residential development is an important mechanism for economic benefits.

In doing so, we contribute evidence more generally on the determinants of housing supply. Natural resources and terrain directly influence development (Burchfield et al., 2006; Saiz, 2010). Zoning policies, land use regulations, and infrastructure investments also play a role (Glaeser et al., 2005; Glaeser and Ward, 2009; Fretz et al., 2022). Our findings help to address the “considerable” research gap on how pollution affects housing supply (Kuminoff et al., 2013).² Based on our estimates, quantifying valuation only through housing prices would fail to include more than half of the economic benefits of the Section 319 program.

¹In addition to Section 319, nonpoint source water pollution projects are also sponsored by the USDA through the U.S. Soil and Water Resources Conservation Act (RCA), discussed below in Section 4.

²A related literature considers how urbanization impacts pollution (e.g. Cropper and Griffiths, 1994; Glaeser and Kahn, 2010; Deng and Mendelsohn, 2021).

2 Data

Our study compiles data from several sources. We start with EPA’s Grants Reporting and Tracking System (GRTS), which describes each Clean Water Act Section 319 project. The most granular level of reporting for project locations is a 12-digit Hydrologic Unit Code, or “subwatershed,” which we use as our unit of analysis.³ Because project activities vary greatly and the same subwatershed may have multiple (possibly related) projects, we define a binary indicator for whether a subwatershed is “treated” with any Section 319 project. As shown in Figure 1, about 32 percent of subwatersheds are treated during 1990-2020.

To evaluate how these projects affect water pollution, we use data from EPA’s Storet and Storet Legacy Data Center, and USGS’s National Water Information System. We follow related literature in quantifying pollution as dissolved oxygen deficit, defined as 100 minus dissolved oxygen saturation in percentage points (Keiser and Shapiro, 2019b; Flynn and Marcus, 2023). Nonpoint source pollution increases dissolved oxygen deficits as microorganisms decompose pollutants. We restrict the sample to measurements from surface waters and assign these values to subwatersheds using the latitude and longitude of the monitoring site. The data provides fairly comprehensive but imperfect coverage, so we impute missing dissolved oxygen deficits within-subwatershed for about 33 percent of subwatershed-year observations in order to form a balanced panel spanning 1970-2020.⁴

For population and housing characteristics, we use data from the Integrated Public Use Microdata Series (IPUMS, Manson et al., 2021). The United States has been fully Tracted since 1990, and we use complete counts of population and housing at the Census Block level from the 1990, 2000, 2010 and 2020 decennial censuses. We additionally use Census Tract-level average and total owner-occupied housing values from the 1990 and 2000 census long form and the 2006-2010 and 2016-2020 American Community Survey (ACS) 5-year waves.⁵ We map these characteristics to the subwatershed level by spatially joining subwatershed and Census Block geodatabases, following Ren and West (2022a) in using subwatershed-block population weights to assign Tract-level housing values.

The vast majority of Section 319 projects are in rural areas. Because our study focuses

³The U.S. Geological Survey (USGS) divides the country into contiguous hydrologic units at various scales using a nested structure: region, subregion, basin, subbasin, watershed, and subwatershed. There are about 103,000 subwatersheds, with an average area of 106 square kilometers.

⁴See Ren and West (2022a) for additional discussion of the last observation carried forward imputation. Appendix A shows that our results are robust to using the unbalanced panel with only non-imputed data.

⁵The census data provide housing counts for a set of price ranges. To determine total value, we use the midpoint of each range, e.g. \$95,000 for the \$90,000 to \$99,999 bin. We then sum the value for all homes.

on urbanization, we restrict our analysis to subwatersheds that are “rural” when treatment begins. Using the Census Bureau’s urban/rural distinction, we include only subwatersheds with no “urban” Census Blocks in 1990. This results in a balanced panel of 3,995,646 surface water pollution observations for 78,346 rural subwatersheds during 1970-2020. Housing values are only defined in populated areas, so we further restrict the population and housing sample to subwatersheds with positive population and housing in all four decennial years, resulting in a balanced panel with 247,912 observations covering 61,978 subwatersheds in 1990, 2000, 2010 and 2020.

Table A1 presents summary statistics for the two panel datasets. About one-third of subwatersheds are treated by at least one Section 319 project. The median and mean year of initial funding is 2008. Note that we observe very few subwatershed treatments prior to 2002, when the EPA started requiring projects to be geolocated. For the water pollution sample in Panel [A], the average dissolved oxygen deficit is 12.94 percent, with a standard deviation of 16.7. Panel [B] shows that populated subwatersheds have 604 people and 280 homes on average during 1990-2020. The average subwatershed has 148 owner-occupied housing units, with an average value of 179,288 and total value of 30.97 million (2020\$).⁶

3 Results

3.1 Clean Water Act Section 319 projects reduce water pollution

We estimate the effects of CWA Section 319 projects by comparing the change in outcomes in treated subwatersheds before and after projects are implemented, relative to the change in subwatersheds without any projects. Section 319 grants are not randomly assigned. For the estimates to have a causal interpretation, the identifying assumption is that the *change* in outcomes in untreated subwatersheds serves as a credible counterfactual for the change in outcomes in treated subwatersheds.

Figure A1 provides some support for this parallel trends assumption. In 1970, the average dissolved oxygen deficit is 15.02 percent for eventually-treated subwatersheds, compared to 14.85 percent for never-treated subwatersheds. At the start of the Section 319 program in 1990, to-be-treated subwatersheds’ average deficit is 12.79, compared to 12.66 for the never-treated. Thus, the pretreatment difference between groups is 0.17 percentage points in 1970 and 0.13 pp in 1990, a very stable and small difference (about one percent of the sample

⁶This 53 percent of homes being owner-occupied is close to the national rate (U.S. Census Bureau, 2022).

mean).⁷ In contrast, by the end of the posttreatment period in 2020, the average deficit is 9.11 percent for treated subwatersheds and 10.44 for untreated subwatersheds, a difference of -1.33 percentage points. From 1970 to 1990, the difference-in-differences is -0.04 pp, and from 1990 to 2020 it is -1.46 pp.

To examine these patterns more dynamically, we use the full panel for years 1970-2020 and regress dissolved oxygen deficit on subwatershed fixed effects, year fixed effects, and a set of indicators for years before or after a subwatershed is first treated. Figure 2 plots the resulting point estimates and 95 percent confidence intervals, with standard errors two-way clustered by subwatershed and year.⁸ All pretreatment estimates are insignificant and close to zero, further supporting the identification strategy. Following treatment, water pollution in treated subwatersheds is significantly reduced compared to the counterfactual, with the treatment effect growing in magnitude over time. This pattern reflects the purpose of many projects is to mitigate pollution, which should yield accumulating improvements.

We quantify this effect in Table 1. Motivated by the dynamic pattern shown above, our preferred regression model is the long differences specification of Equation (1). We also estimate the canonical two-way fixed effects (TWFE) specification of Equation (2).

$$\Delta y_{is,2020,1990} = \Delta \text{treated}_{i,2020,1990} \delta + \Delta \phi_{s,2020,1990} + \Delta \epsilon_{is,2020,1990} \quad (1)$$

$$y_{ist} = \text{treated}_{it} \beta + \theta_i + \psi_{st} + v_{ist} \quad (2)$$

The long differences specification has one observation per subwatershed, where $\Delta y_{is,2020,1990}$ is the change in dissolved oxygen deficit between 1990 and 2020 for subwatershed i located in state s , $\Delta \text{treated}_{i,2020,1990}$ indicates whether the subwatershed is ever treated between 1990 and 2020, $\Delta \phi_{s,2020,1990}$ is equivalent to a linear time trend for each state, and $\Delta \epsilon_{is,2020,1990}$ is the error term. In the TWFE model, y_{ist} is the dissolved oxygen deficit of subwatershed i in year t , treated_{it} indicates whether the subwatershed is treated as of year t , θ_i are subwatershed fixed effects, ψ_{st} are state-by-year fixed effects, and v_{ist} is the error term.

The first two columns present long differences results. The estimate is -1.46 percentage points ($\text{se} = 0.153$) in Column (1), which omits the state fixed effects. Column (2) shows a very similar estimate of -1.5 , or 11.6 percent of the sample mean. As a point of comparison, average dissolved oxygen deficits fell by 2.22 pp in untreated subwatersheds be-

⁷As a more rigorous test of the parallel trends assumption, we conduct a Wald test using the methods described in (and R package provided by) Sant’Anna and Zhao (2020) and Callaway and Sant’Anna (2021). The p-value from this test is 0.795, indicating a statistically insignificant difference in pre-trends.

⁸Figure A2 shows a nearly identical pattern using a shorter panel from 1990-2020.

tween 1990 and 2020 (from Figure A1), so treatment reduces pollution by an additional 67.7 percent. Columns (3) and (4) present the two-way fixed effects results. Compared to the long differences, these regressions show somewhat smaller estimates, but are still statistically significant. This attenuation is expected for a treatment effect that accumulates over time. In fact, all estimates in Table 1 likely understate the longer-run effects. Regardless, we find that Section 319 projects cause economically significant reductions in water pollution.⁹

Not all subwatersheds are treated simultaneously, with Section 319 projects implemented throughout 1990-2020 (especially 2002-2020). Estimates from two-way fixed effects models may be biased when there are staggered treatments (Meer and West, 2016; Goodman-Bacon, 2021; Sun and Abraham, 2021). This potential bias is another reason to favor the long differences models, which avoid these concerns. Notwithstanding, two-thirds of subwatersheds are never-treated and only 7.9 percent of observations are treated. Figure A3 plots the distribution of treatment timing. Despite the staggering, all subwatersheds have at least 20 pretreatment observations and treatment timing is compact, with a mean of 2008 and standard deviation of 4.4 years. To formally examine the identifying variation, we use the “Goodman-Bacon decomposition” (2021). Figure A4 shows that 90 percent of regression weight is from comparing treated to untreated, and only 1.9 percent of weight is from “forbidden comparisons” between later-treated and earlier-treated subwatersheds. These exercises further support a causal interpretation.

3.2 Section 319 projects increase housing development and value

Next, we explore whether Section 319 projects increase treated subwatersheds’ human population and housing density. This evidence speaks to the fundamental question of our study: does reducing water pollution encourage residential development? We also evaluate housing value to use in Section 4 for our cost-benefit analysis of the Section 319 program.

To examine these relationships, we estimate Equations (1) and (2) using the population and housing sample.¹⁰ Recall that this balanced panel has one observation per populated subwatershed in 1990, 2000, 2010, and 2020.¹¹ For outcomes, we use Census full counts of log-population and log-housing units, along with owner-occupied housing units’ log-count, log-average value, and log-total value. Table 2 presents the results, with long differences regressions in Panel [A] and two-way fixed effects regressions in Panel [B].

⁹Table A2 verifies results are similar in the unbalanced panel of non-imputed dissolved oxygen values.

¹⁰Again using the methods of Sant’Anna and Zhao (2020) and Callaway and Sant’Anna (2021), we find support for parallel trends in residential development, e.g. the pre-trends p-value for housing units is 0.313.

¹¹Table A3 verifies that the pollution results are robust to using this subset of populated subwatersheds.

The long differences estimates show that treatment increases a subwatershed’s total population and housing units by about ten percent. At the sample mean, these effects equate to about 58 more people and 29 new housing units. The estimated increase in owner-occupied homes is somewhat smaller, at around four percent. This discrepancy could be due to measurement error in mapping Tract-level data to subwatersheds or the five-year nature of the ACS data. Alternatively, Section 319 projects might lead to relatively more construction of multifamily (rental) dwellings; for instance, the site of a major infrastructure project might be an appealing location to build apartments. Projects could also encourage increased development of seasonal or vacation homes. The final two columns show treatment effects of about three percent for average owner-occupied home value and about seven percent for total value. In Panel [B], the two-way fixed effects estimates are also statistically significant but somewhat smaller in magnitude, as one would expect for a dynamic treatment effect.

Collectively, the results in Table 2 provide strong support for our hypothesis. People have a positive valuation of cleaner waters, and a primary mechanism of this valuation is to increase residential development and urbanization in areas with less water pollution.¹²

4 Cost-benefit analysis

We use these estimates to conduct a back-of-the-envelope cost-benefit analysis of the CWA Section 319 program. EPA provides total Section 319 costs for each year, but we observe few projects prior to 2002, as discussed above. Because we can more accurately quantify benefits post-2002, Table 3 presents results for both the full 1990-2020 period and for 2002-2020.¹³

Total owner-occupied home value for the average subwatershed is 30.97 million (2020\$). If we assume that treatment effects are homogeneous (in natural logs), then the estimated log-increase of 0.066 translates to \$2.11 million in benefit per subwatershed. With 23,091 rural subwatersheds treated, this aggregates to \$48.8 billion in added housing value for the full period and \$46.39 billion for projects during 2002-2020. Under the conservative assumption that new homes are valued at the average for all homes, then about 56 percent of the total

¹²The results in Tables 1 and 2 imply that a one percent improvement in water quality leads to a 0.25 percent increase in average housing value and a 0.57 percent increase in total housing value (including new construction). Although large, these elasticities are well within the range of the literature. A recent meta-analysis by Guignet et al. (2022) includes 598 estimated elasticities between water pollution and housing values. Our estimates of 0.25 and 0.57 would fall, respectively, at the 89th and 94th percentiles among the values provided by Guignet et al. (2022), or the 79th and 89th percentiles restricted to positive elasticities.

¹³Tables A4 and A5 show that the results in Tables 1 and 2 are robust to dropping subwatersheds treated prior to 2002. Any unobserved projects should attenuate estimated effects towards zero.

benefit is attributable to net housing construction.¹⁴

The second panel shows costs. The national total Section 319 funding (in 2020\$) is \$6.4 billion for 1990-2020 and \$4.28 billion for 2002-2020. In the GRTS data, state and local spending averages \$0.783 per federal dollar. This brings total government spending to \$11.42 billion during 1990-2020 and \$7.98 billion during 2002-2020. Comparing benefits to costs, these back-of-the-envelope calculations show a ratio of economic value added to federal expenditures of 7.62 during the full period and 10.83 during 2002-2020. Using total government expenditures, the respective benefit-cost ratios are 4.28 and 5.82.

These calculations will overstate net benefits if there are unobserved social costs—for example, if a community builds a golf course concurrently with implementing a Section 319 project, and the golf course also increases housing value.¹⁵ Our calculations could also be (upward or downward) biased from heterogeneity in treatment effects or from measurement error in the Census data on home values (Bishop et al., 2020). On the other hand, we calculate value-added only for owner-occupied homes, omitting benefits for renters. We also include Section 319 costs for both rural and urban areas but benefits only for rural subwatersheds; these grants likely provide at least some benefit to urban populations. Furthermore, property valuation fails to capture some social benefits, such as people traveling to cleaner water for recreation (Kuwayama et al., 2022). Finally, we reiterate that our estimates likely understate the longer-run effects of a treatment that decreases pollution over time. Even divided by four, the benefit-cost ratios calculated here exceed one.

5 Conclusions

In this paper, we investigate how reducing surface water pollution affects residential development, with a specific evaluation of the U.S. Clean Water Act’s Section 319 nonpoint source pollution program. We compare changes in watersheds before and after they receive Section 319 projects, relative to watersheds that never receive projects.

We find that projects are highly effective at reducing pollution, with corresponding increases in human population, housing units, and home values. Incorporating the estimates into a back-of-the-envelope cost-benefit analysis, we calculate that program benefits are \$7.62

¹⁴This can be calculated as $0.037/0.066$ or alternatively as:
 $(179288 * (\exp(\log(148) + 0.037) - 148)) / ((179288 * (\exp(\log(148) + 0.037) - 148)) + (148 * (\exp(\log(179288) + 0.029) - 179288)))$

¹⁵As mentioned above, some USDA funding through the U.S. Soil and Water Resources Conservation Act (RCA) also pertains to nonpoint source water pollution. Total RCA spending is several billion dollars annually, which could potentially greatly impact the cost-benefit calculation. In Appendix B, we provide evidence that the effect of Section 319 projects on home values is robust to controlling for RCA spending.

per dollar of federal Section 319 cost and \$4.28 per dollar of total government costs. More than half of the benefit accrues through new home construction.

Evidence of benefits exceeding costs is rare in the water policy literature. Our outlier finding could be because the Section 319 program is one of the only U.S. policies addressing nonpoint source pollution—the primary source of the country’s water quality impairments. Surface water pollution is also highly salient and directly impacts amenity value. More broadly, our study suggests that housing construction can be at least as important a dimension of environmental valuation as increased home values for existing homes.

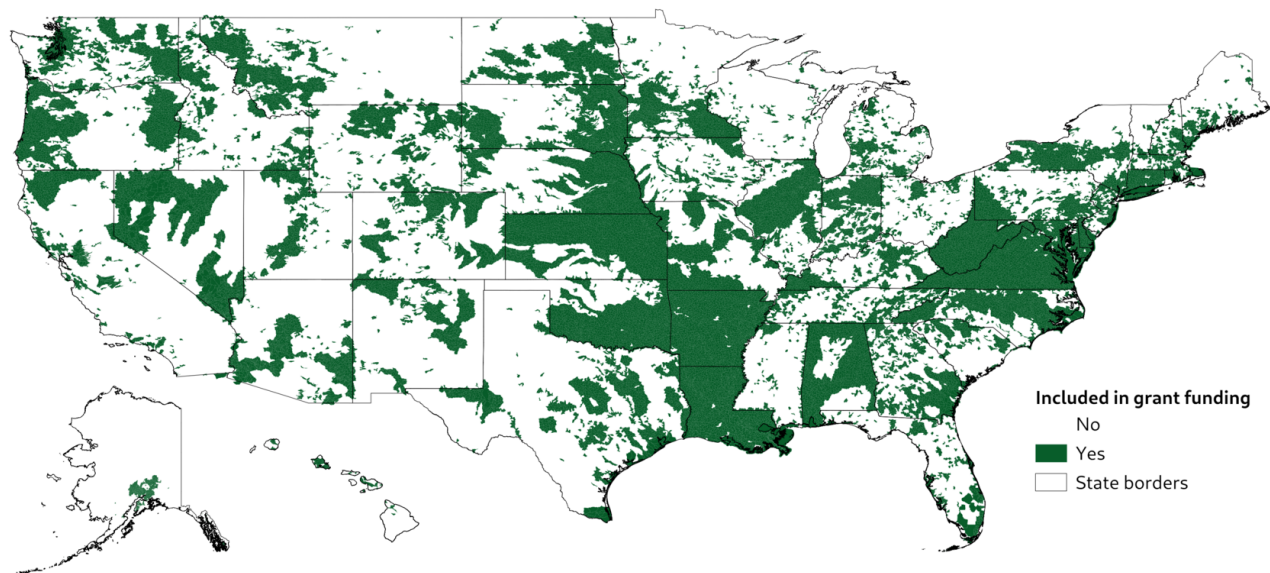
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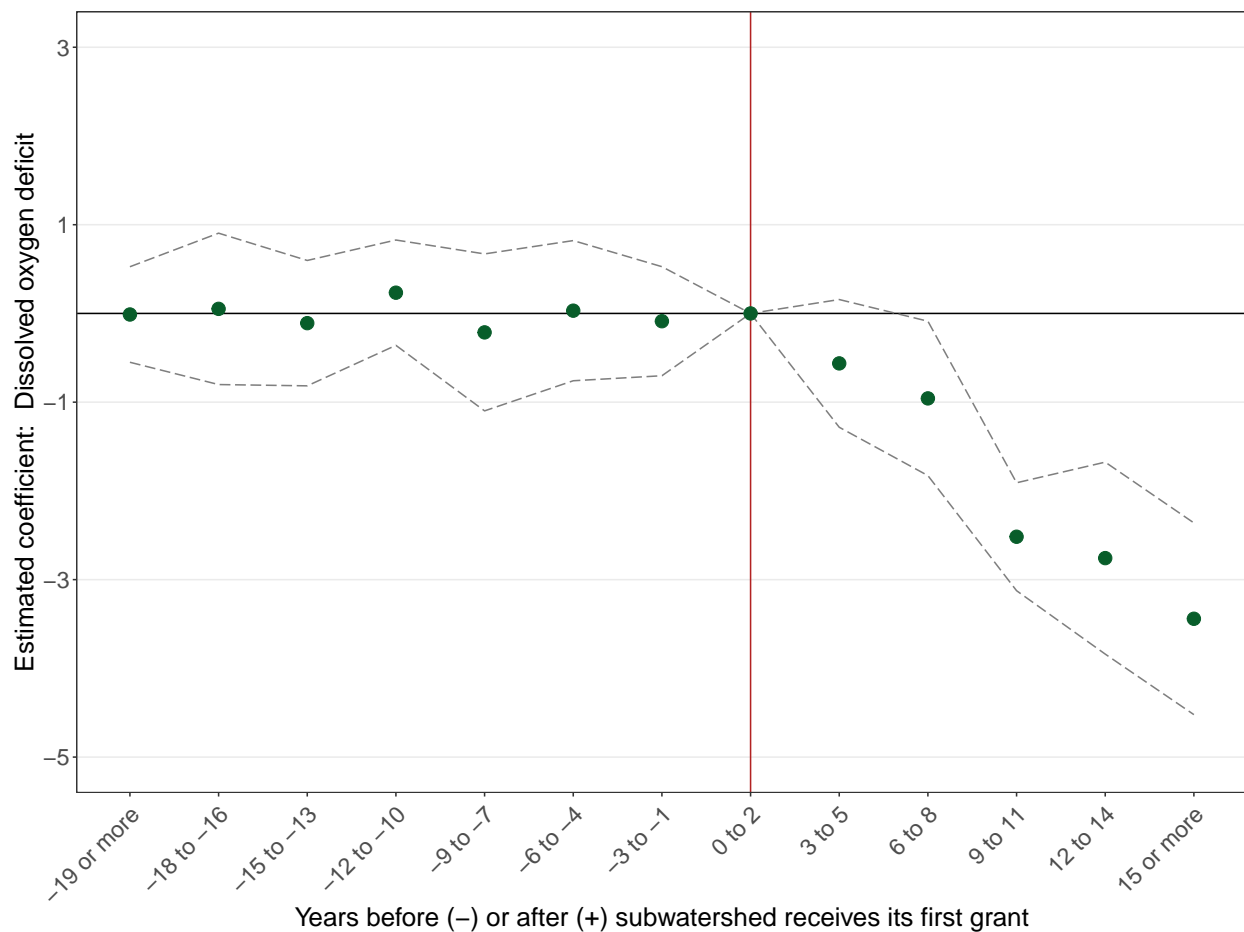
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Figure 1: Map of subwatershed grant award funding inclusion during 1990-2020



Notes: The figure plots whether each subwatershed is treated by any Clean Water Act Section 319 project between 1990-2020. Funding decisions are made by state governments each year. There are about 103,000 subwatersheds in total, and about 32 percent of subwatersheds are included in at least one grant-funded project.

Figure 2: Event study estimates for surface water pollution in rural subwatersheds



Notes: The figure plots point estimates and 95 percent confidence intervals from a regression of dissolved oxygen deficit on the set of indicators shown for years before or after a subwatershed is first treated by a Clean Water Act Section 319 project. The regression includes subwatershed fixed effects and year fixed effects. Each observation is a subwatershed-year tuple in a balanced panel for years 1970-2020. Only rural subwatersheds are included, with rural/urban status defined as of 1990. Dissolved oxygen deficit equals 100 minus dissolved oxygen saturation, measured as a percentage. A larger value indicates more polluted water. About 32 percent of rural subwatersheds are included in a grant award made between 1990-2020. Standard errors for the confidence intervals are two-way clustered by subwatershed and year.

Table 1: Effects of CWA Section 319 projects on surface water pollution in rural subwatersheds

Dependent variable: dissolved oxygen deficit				
	Long differences regressions		Two-way fixed effects regressions	
	(1)	(2)	(3)	(4)
Subwatershed is treated	-1.462*** (0.153)	-1.504*** (0.170)	-1.060*** (0.169)	-0.514*** (0.152)
State linear time trends		Yes		
Subwatershed fixed effects			Yes	Yes
Year fixed effects			Yes	Yes
State \times year fixed effects				Yes
Dependent variable mean	12.944	12.944	12.944	12.944
Number of subwatersheds	78,346	78,346	78,346	78,346
Observations	78,346	78,346	3,995,646	3,995,646

Notes: Each column presents estimates from a separate regression. Columns (1) and (2) use one observation per subwatershed of the within-subwatershed change from 1990 to 2020. Columns (3) and (4) use a balanced panel for years 1970-2020, where an observation is a subwatershed-year tuple. Only rural subwatersheds are included, with rural/urban status defined as of 1990. The dependent variable is dissolved oxygen deficit, which equals 100 minus dissolved oxygen saturation, measured in percentage points. Standard errors in parentheses are two-way clustered by subwatershed and year for Columns (3) and (4).

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2: Effects of CWA Section 319 projects on population and housing in rural subwatersheds

	Dependent variable (all are in natural logs)				
	Census full count		ACS/Census long form owner-occupied housing		
	(1) Population	(2) Housing units	(3) Housing units	(4) Average value	(5) Total value
Panel [A]: Long differences regressions: one observation per subwatershed of the change from 1990 to 2020					
Subwatershed is treated	0.092*** (0.010)	0.099*** (0.009)	0.037*** (0.010)	0.029*** (0.003)	0.066*** (0.011)
Panel [B]: Two-way fixed effects regressions: balanced panel for years 1990, 2000, 2010, and 2020					
Subwatershed is treated	0.053*** (0.006)	0.059*** (0.005)	0.016** (0.007)	0.006*** (0.002)	0.021*** (0.007)
State time trends (Panel [A])	Yes	Yes	Yes	Yes	Yes
Subwatershed FE (Panel [B])	Yes	Yes	Yes	Yes	Yes
State \times year FE (Panel [B])	Yes	Yes	Yes	Yes	Yes
Number of subwatersheds	61,978	61,978	61,978	61,978	61,978
Observations (Panel [B])	247,912	247,912	247,912	247,912	247,912

Notes: Each cell presents estimates from a separate regression. Panel [A] uses one observation per subwatershed of the within-subwatershed change from 1990 to 2020. Panel [B] uses a balanced panel for years 1990, 2000, 2010, and 2020, where an observation is a subwatershed-year tuple. Only rural subwatersheds with positive population and housing throughout 1990-2020 are included, with rural/urban status defined as of 1990. Standard errors in parentheses are clustered by subwatershed for Panel [B].

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Cost-benefit analysis of the CWA Section 319 program

	Subwatersheds funded during		Source
	1990 - 2020	2002 - 2020	
Benefits			
Estimated log-increase in owner-occupied housing units	0.037	0.036	Table 2, Table A5
Estimated log-increase in average owner-occupied housing value	0.029	0.029	Table 2, Table A5
Estimated log-increase in total owner-occupied housing value	0.066	0.065	Table 2, Table A5
Number of owner-occupied housing units per subwatershed	148	148	Table A1
Average value of owner-occupied housing units (2020\$)	179,288	179,288	Table A1
Total owner-occ. housing value per subwatershed (M 2020\$)	30.974	30.974	Table A1
Increase in own-occ. housing value per subwatershed (M 2020\$)	2.113	2.080	Calculated here
Share of value added from new housing (percent)	56.160	55.472	Calculated here
Total number of rural subwatersheds treated	23,091	22,299	Table A1
Total increase in value from new housing (B 2020\$)	27.404	25.731	Calculated here
Total increase in value of existing housing (B 2020\$)	21.393	20.655	Calculated here
Total increase in housing value (B 2020\$)	48.797	46.386	Calculated here
Costs			
Total Clean Water Act Section 319 federal funding (B 2020\$)	6.402	4.283	EPA (CPI-adj.)
Average state and local expenditures per federal dollar (\$)	0.783	0.862	EPA GRTS
Total federal and non-federal expenditures (B 2020\$)	11.415	7.975	Calculated here
Ratios			
Ratio of value added to federal expenditures	7.622	10.830	Calculated here
Ratio of value added to federal and non-federal expenditures	4.275	5.816	Calculated here

Notes: These back-of-the-envelope calculations assume homogeneity in treatment effects for owner-occupied housing value. The calculated share of value added from new housing assumes that new homes are sold at the average housing value.

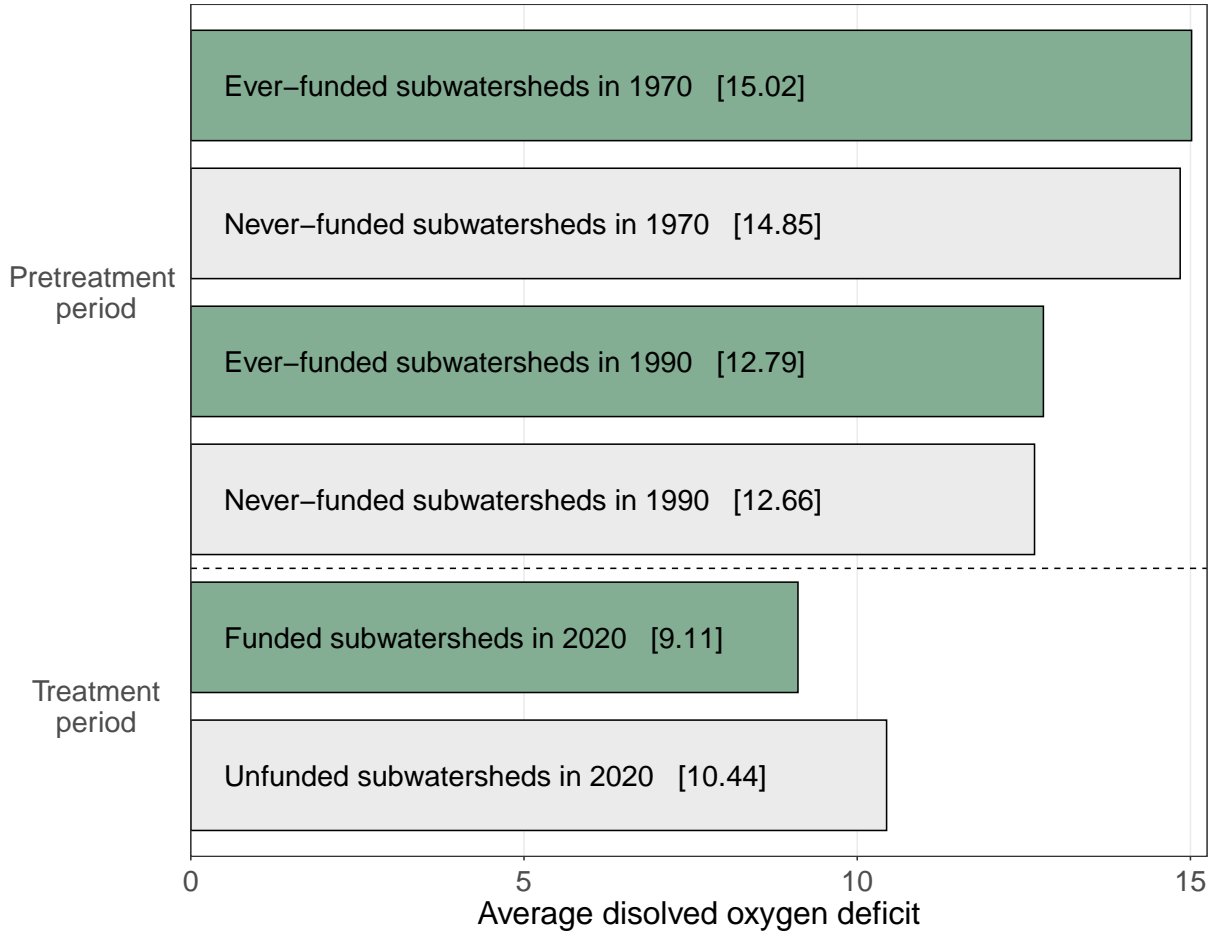
A Appendix tables and figures

Table A1: Summary statistics for rural subwatersheds

	Median	Mean	SD	Observations
Panel [A]: Surface water pollution sample: balanced annual panel for years 1970-2020				
Number of subwatersheds				78,346
Share of subwatersheds treated		0.324		78,346
Year of initial funding	2008	2008	4.399	25,391
Year of initial funding if post-2002	2009	2009	4.055	24,583
Subwatershed is treated indicator	0.000	0.079	0.270	3,995,646
Dissolved oxygen deficit (percent)	10.855	12.944	16.695	3,995,646
Panel [B]: Population and housing sample: balanced panel for years 1990, 2000, 2010, and 2020				
Number of subwatersheds				61,978
Share of subwatersheds treated		0.373		61,978
Year of initial funding	2008	2008	4.383	23,091
Year of initial funding if post-2002	2008	2009	4.017	22,299
Subwatershed is treated indicator	0.000	0.162	0.369	247,912
Dissolved oxygen deficit (percent)	10.170	11.912	16.632	247,912
Census full count				
Population	153	604	1,220	247,912
Housing units	82	280	541	247,912
ACS/Census long form				
Owner-occupied housing units	32	148	323	247,912
Average home value (2020\$)	150,396	179,288	115,617	247,912
Total home value (millions 2020\$)	4.397	30.974	103.098	247,912

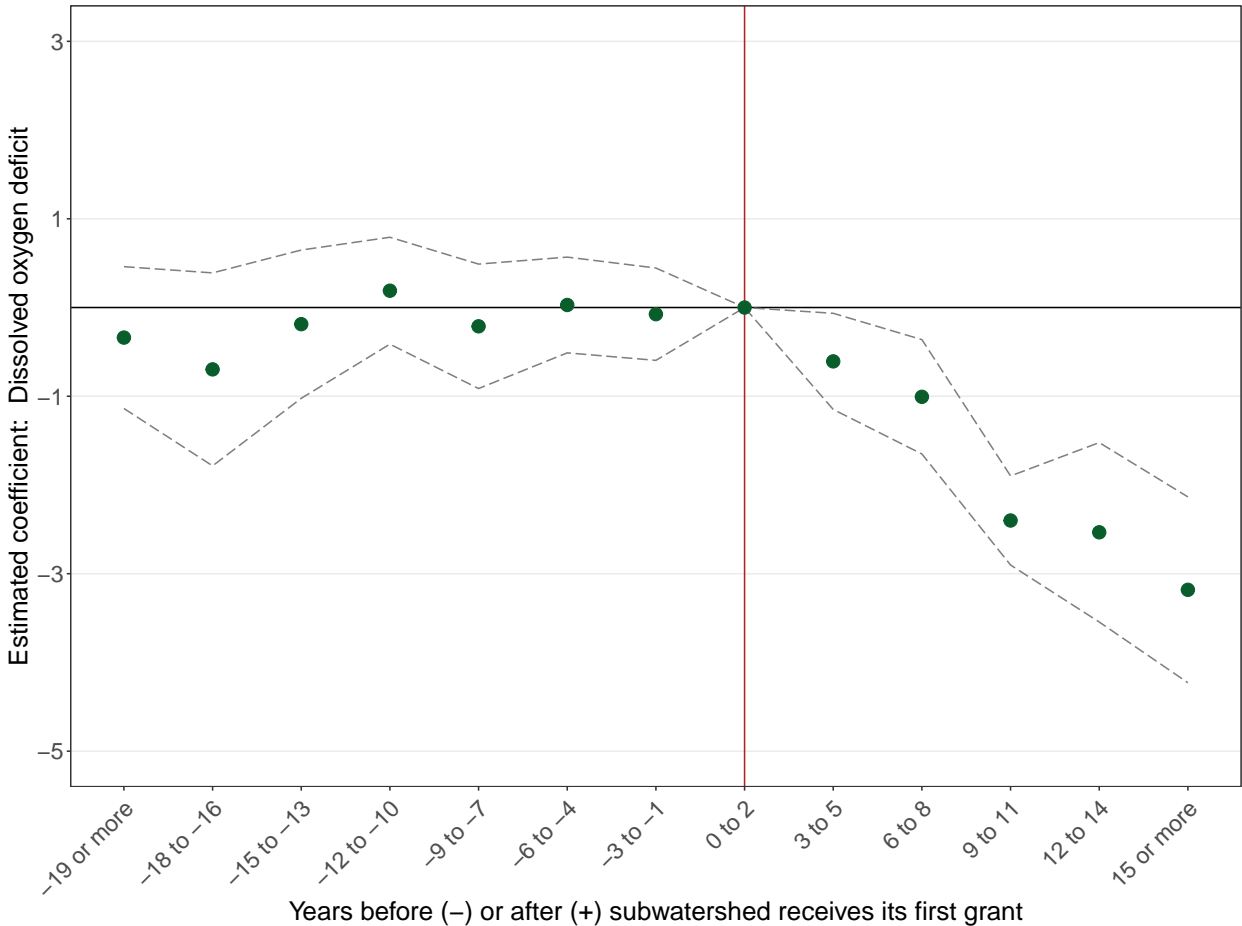
Notes: Each observation is a subwatershed-year tuple. Only rural subwatersheds are included, with rural/urban status defined as of 1990. The sample in Panel [B] is restricted from that in Panel [A] to subwatersheds during the four decennial census years that have positive population and housing throughout 1990-2020. Dissolved oxygen deficit equals 100 minus dissolved oxygen saturation, measured as a percentage. A larger value indicates more polluted water. Census full count population and housing units use Census Block-level data from the 1990, 2000, 2010, and 2020 decennial censuses. The ACS/Census long form variables use Census Tract-level data from the 1990 and 2000 decennial census long forms and the American Community Survey 5-year waves 2006-2010 and 2016-2020. Census data is assigned by spatially joining subwatersheds to Census Blocks and using subwatershed-block population weights to assign Tract-level values.

Figure A1: Average surface water pollution by subwatershed group and time period



Notes: This figure shows average dissolved oxygen deficit for two groups of subwatersheds in the three indicated time periods (1970, 1990, and 2020). The first group consists of subwatersheds that (eventually) are treated by a Clean Water Act Section 319 project between 1990 and 2020. The second group of subwatersheds is never treated. Only rural subwatersheds are included, with rural/urban status defined as of 1990. Dissolved oxygen deficit equals 100 minus dissolved oxygen saturation, measured in percentage points. A larger value indicates more polluted water.

Figure A2: Event study estimates for surface water pollution in rural subwatersheds:
Using a panel from 1990 - 2020



Notes: The figure reproduces Figure 2 using a shorter panel from 1990 through 2020.

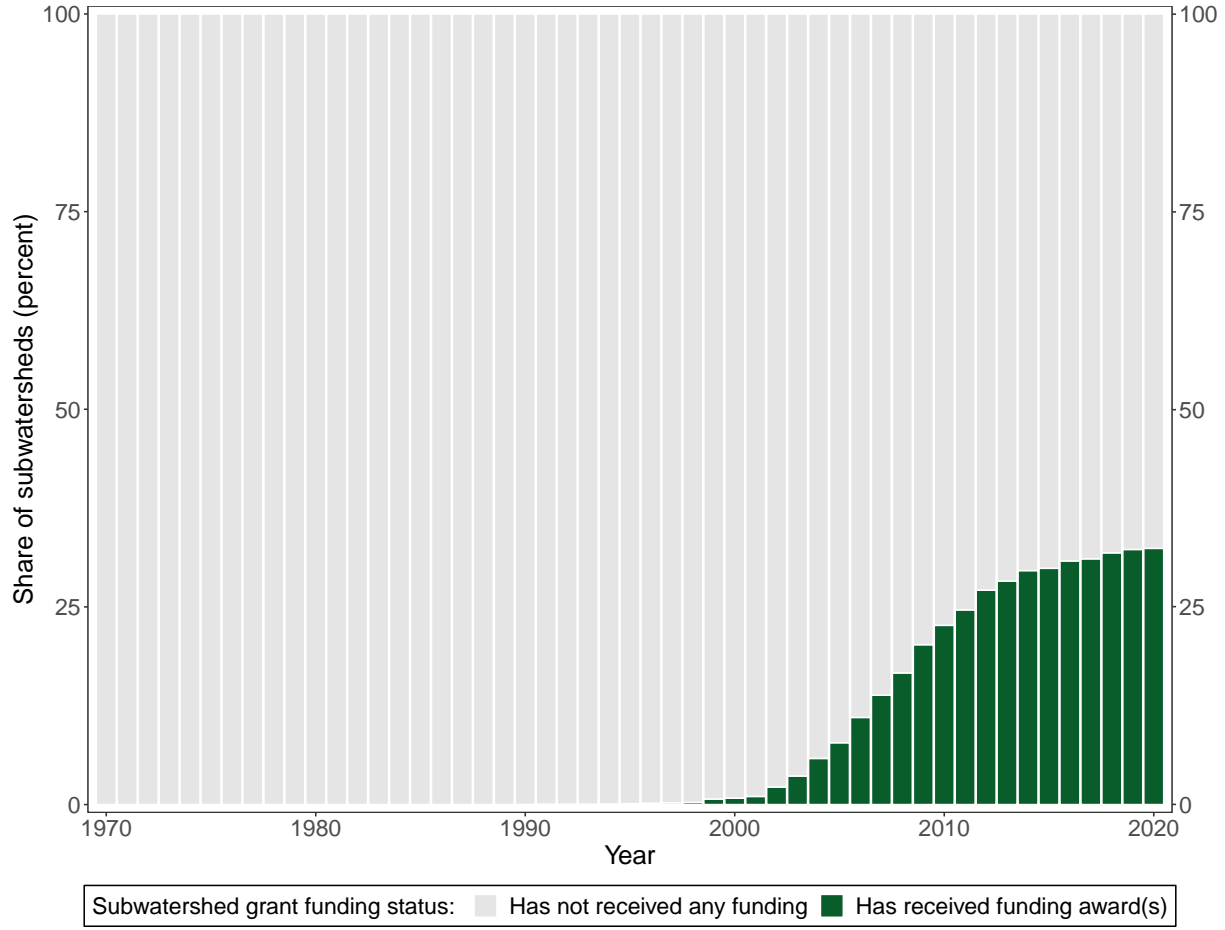
Table A2: Effects of CWA Section 319 projects on surface water pollution in rural subwatersheds:
Robustness checks using only non-imputed dissolved oxygen values

Dependent variable: dissolved oxygen deficit				
	Long differences regressions		Two-way fixed effects regressions	
	(1) LOCF imputation	(2) No Imputation	(3) LOCF imputation	(4) No Imputation
Subwatershed is treated	-1.504*** (0.170)	-1.290*** (0.192)	-0.514*** (0.152)	-0.807*** (0.184)
State linear time trends	Yes	Yes		
Subwatershed fixed effects			Yes	Yes
Year fixed effects			Yes	Yes
State \times year fixed effects			Yes	Yes
Dependent variable mean	12.944	12.518	12.944	12.518
Number of subwatersheds	78,346	36,332	78,346	78,346
Observations	78,346	36,332	3,995,646	2,672,658

Notes: Columns (1) and (3) reproduce, respectively, Columns (2) and (4) from Table 1. These estimations use a balanced panel which has within-subwatershed imputed dissolved oxygen deficit values for some observations. Columns (2) and (4) show results from estimations using the same specifications restricted to non-imputed dissolved oxygen deficit data.

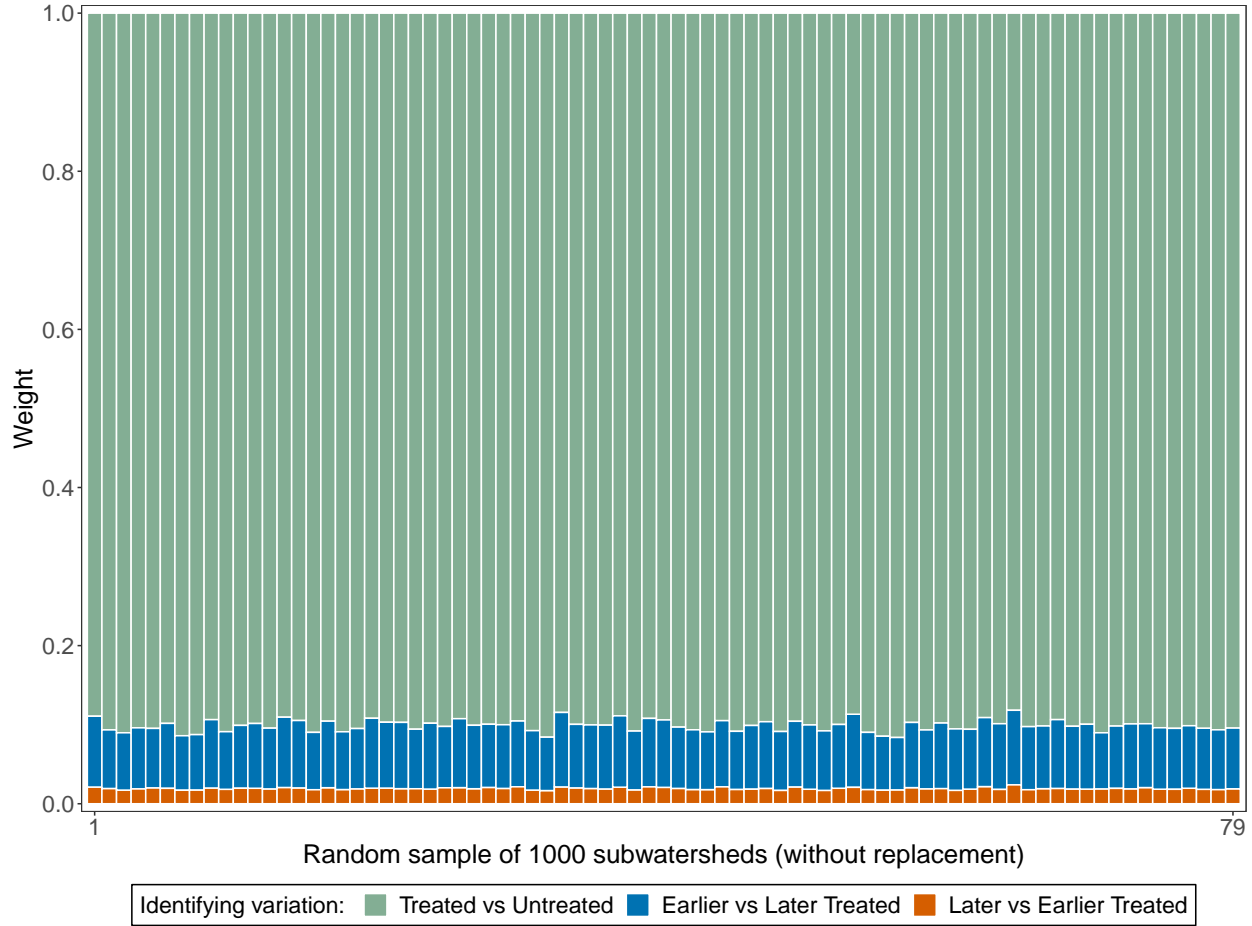
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure A3: Timing of treatment inclusion for rural subwatersheds



Notes: About 32 percent of rural subwatersheds are included in a Clean Water Act Section 319 project between 1990-2020. The median and mean year of initial funding inclusion (if any) is 2008. For the full 1970-2020 panel, 7.9 percent of observations have a “subwatershed is treated” indicator status of one.

Figure A4: Identifying variation from the three types of 2×2 difference-in-differences comparisons for rural subwatersheds (Goodman-Bacon decomposition)



Notes: The figure plots the total regression weight for each type of difference-in-differences comparison, also known as the [Goodman-Bacon \(2021\)](#) decomposition, using regressions of dissolved oxygen deficit on an indicator for the subwatershed being included in a Clean Water Act Section 319 grant award. The regressions include subwatershed fixed effects and year fixed effects. Each observation is a subwatershed-year tuple in a balanced panel for years 1970-2020. Only rural subwatersheds are included, with rural/urban status defined as of 1990. For computational reasons, we use random draws (without replacement) of 1000 subwatershed units to split the full panel into 79 balanced panel subsets, and perform the decomposition separately for each subset. Overall, 90.12 percent of identifying variation is from comparisons of differences between treated and untreated units, 7.97 percent of regression weight is from comparisons of differences between earlier-treated and later-treated units, and only 1.91 percent of weight is from “forbidden comparisons” of differences between later-treated and earlier-treated units.

Table A3: Effects of CWA Section 319 projects on surface water pollution in rural subwatersheds: Robustness checks using subwatersheds with positive population and housing throughout 1990-2020

Dependent variable: dissolved oxygen deficit				
	Long differences regressions		Two-way fixed effects regressions	
	(1)	(2)	(3)	(4)
Subwatershed is treated	-1.094*** (0.167)	-1.269*** (0.179)	-0.904*** (0.170)	-0.368** (0.155)
State linear time trends		Yes		
Subwatershed fixed effects			Yes	Yes
Year fixed effects			Yes	Yes
State \times year fixed effects				Yes
Dependent variable mean	12.906	12.906	12.906	12.906
Number of subwatersheds	61,978	61,978	61,978	61,978
Observations	61,978	61,978	3,160,878	3,160,878

Notes: This table replicates Table 1 using the same sample of subwatershed units that is used in Table 2.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A4: Effects of CWA Section 319 projects on surface water pollution in rural subwatersheds:
Robustness checks dropping subwatersheds that were funded prior to 2002

Dependent variable: dissolved oxygen deficit				
	Long differences regressions		Two-way fixed effects regressions	
	(1)	(2)	(3)	(4)
Subwatershed is treated	-1.470*** (0.155)	-1.606*** (0.172)	-1.000*** (0.169)	-0.437*** (0.158)
State linear time trends		Yes		
Subwatershed fixed effects			Yes	Yes
Year fixed effects			Yes	Yes
State \times year fixed effects				Yes
Dependent variable mean	12.933	12.933	12.933	12.933
Number of subwatersheds	77,538	77,538	77,538	77,538
Observations	77,538	77,538	3,954,438	3,954,438

Notes: This table replicates Table 1, dropping the 808 subwatershed units that were funded prior to 2002 (41,208 observations).

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A5: Effects of CWA Section 319 projects on population and housing in rural subwatersheds:
Robustness checks dropping subwatersheds that were funded prior to 2002

	Dependent variable (all are in natural logs)				
	Census full count		ACS/Census long form owner-occupied housing		
	(1) Population	(2) Housing units	(3) Housing units	(4) Average value	(5) Total value
Panel [A]: Long differences regressions: one observation per subwatershed of the change from 1990 to 2020					
Subwatershed is treated	0.092*** (0.010)	0.100*** (0.009)	0.036*** (0.011)	0.029*** (0.003)	0.065*** (0.011)
Panel [B]: Two-way fixed effects regressions: balanced panel for years 1990, 2000, 2010, and 2020					
Subwatershed is treated	0.054*** (0.007)	0.060*** (0.006)	0.017** (0.007)	0.006*** (0.002)	0.022*** (0.007)
State time trends (Panel [A])	Yes	Yes	Yes	Yes	Yes
Subwatershed FE (Panel [B])	Yes	Yes	Yes	Yes	Yes
State \times year FE (Panel [B])	Yes	Yes	Yes	Yes	Yes
Number of subwatersheds	61,186	61,186	61,186	61,186	61,186
Observations (Panel [B])	244,744	244,744	244,744	244,744	244,744

Notes: This table replicates Table 2, dropping the 792 subwatershed units that were funded prior to 2002 (3,168 observations).
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

B Section 319 projects and USDA RCA programs

As discussed in the main text, the Clean Water Act Section 319 program is not the only source of funding for nonpoint source water pollution projects. In addition, some USDA funding through the U.S. Soil and Water Resources Conservation Act (RCA) also pertains to nonpoint source water pollution. Broadly, this strand of funding is used for protecting natural resources and enabling farmers to take protective actions. Because some of these USDA-funded projects may produce benefits in the same locations as the Section 319 projects that we study, this could potentially have important implications for our cost-benefit analysis.

In this appendix, we provide discussion about the comparison between Section 319 projects and USDA-funded programs. Then, we use state-level data on Section 319 projects and USDA RCA spending to estimate elasticities for total rural home value to both programs. The results of this exercise support that the effects our study finds for Section 319 projects are robust to controlling for RCA spending. Moreover, we find a much stronger effect on total home value from Section 319 projects than from the USDA funding.

B.1 RCA expenditures data

The data on RCA program expenditures is provided by the USDA Natural Resources Conservation Service (NRCS). Data is available from 2005 to 2022, disaggregated at the program by state by year level.¹⁶ The RCA covers broad programs targeting the conservation, protection, and enhancement of soil, water, and related natural resources. Some of the key programs are the Conservation Stewardship Program (CSP), the Environmental Quality Incentives Program (EQIP), and the Agricultural Conservation Easement Program (ACEP). Multiple RCA programs can include spending on nonpoint source pollution projects, which is not separated from other program spending. Following [Keiser et al. \(2019\)](#), we include both technical and financial expenditures pooled over the full set of RCA programs. Figure B1 shows the annual trend of the expenditures. In 2020 dollars, 3.93 billion of RCA funds were expended in 2005, with annual spending rising to 5.35 billion in 2020. We reiterate that it is unclear how much of this funding pertains to nonpoint source water pollution.

¹⁶Ideally, subwatershed or watershed level data would be of best use to isolate the variation of these programs. However, to our knowledge, the finest spatial disaggregation is state level. The data does not separate out values specifically for Hawaii, but a general group of “Hawaii/Pacific,” which accounts for only 0.6 percent of the total USDA RCA spending, so we exclude Hawaii in this analysis.

B.2 Comparison between Section 319 and RCA funding

USDA RCA-funded projects might yield benefits in the same locations as the Section 319 projects that we study. If some of the benefit we estimate for Section 319 projects is instead attributable to RCA spending, then our analysis would overstate the net-benefits for Section 319. To address this consideration, we test whether the estimated effects of Section 319 projects on housing values are robust to controlling for the RCA spending.

To do so, we estimate elasticities for state-level total rural housing value to Section 319 projects and USDA RCA funding. Because the RCA data are not available at the sub-state spatial level, i.e. for specific subwatersheds, we aggregate our subwatershed population and housing sample to the state by census year level, yielding one observation for each state in each year 1990, 2000, 2010, and 2020. Our outcome of interest is the natural log of total rural housing value, that is, the sum of the total housing value across the rural subwatersheds within a state for each observed year. The independent variables of interest are the natural log of Section 319-treated subwatersheds within the state and the natural log of cumulative RCA spending within the state. Similarly to the main analysis, we conduct the estimation using both the long differences model of Equation (3) and the two-way fixed effects model (TWFE) of Equation (4).

$$\Delta \log(y)_{s,2020,1990} = \Delta \log(\text{S319})_{s,2020,1990} \delta + \Delta \log(\text{RCA})_{s,2020,1990} \gamma + \Delta \epsilon_{s,2020,1990} \quad (3)$$

$$\log(y)_{st} = \log(\text{S319})_{st} \beta + \log(\text{RCA})_{st} \phi + \theta_s + \psi_t + v_{st} \quad (4)$$

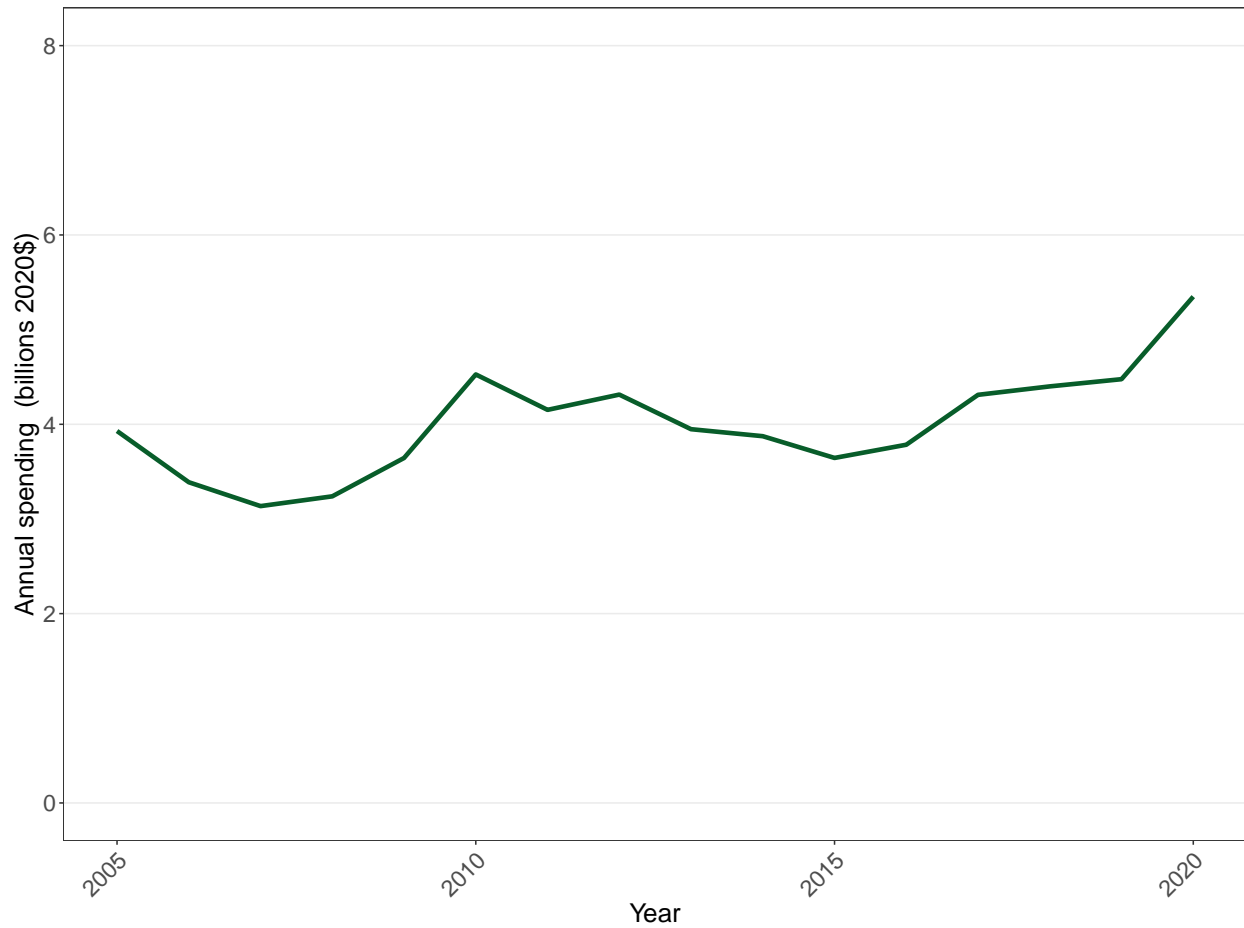
The long differences specification has one observation per state, where $\Delta \log(y)_{s,2020,1990}$ is the change in the natural log of total rural home value between 1990 and 2020 for state s , $\Delta \log(\text{S319})_{s,2020,1990}$ indicates the change in the log-number of treated subwatersheds in the state between 1990 and 2020, $\Delta \log(\text{RCA})_{s,2020,1990}$ is the change in log-total cumulative RCA spending in the state between 1990 and 2020, and $\Delta \epsilon_{s,2020,1990}$ is the error term. In the TWFE model, $\log(y)_{st}$ is the natural log of total rural home value for state s in year t , $\log(\text{S319})_{st}$ is the log-number of treated subwatersheds in the state as of year t , $\log(\text{RCA})_{st}$ is the log-total cumulative RCA spending in the state as of year t , θ_s are state fixed effects, ψ_t are year fixed effects, and v_{st} is the error term.

Table B1 presents the regression results. We first report the elasticity only for Section 319 projects in Column (1), setting $\gamma = 0$ and $\phi = 0$. As with our primary results in Table 2, there is a large and significant relationship between Section 319 projects and total rural home value. The long differences results in Panel [A] indicate that a one percent increase in the

number of treated subwatersheds in the state is associated with a 0.175 percent increase in the total rural home value. As we would expect and have seen throughout the results tables, the TWFE estimate is smaller at 0.05, but remains statistically significant. Column (2) shows the estimated elasticity only for RCA spending. Here, we observe much smaller, insignificant effects. Finally, Column (3) includes both independent variables in the regressions. The estimated elasticity for Section 319 projects remains similar in magnitude and significance to that in Column (1), despite controlling for RCA spending. There continues to be no positive and significant estimated elasticity for home values to RCA spending.

We caution readers not to interpret the estimates for RCA spending as showing that these programs do not add economic benefits, as measured by housing value. This state-level panel is not ideal for quantifying the effects of interventions that are implemented at much more spatially granular levels. However, we find it reassuring that the relationship between rural housing values and Section 319 projects remains highly robust to controlling for this major other policy that also targets similar sources of water pollution.

Figure B1: Annual expenditures for USDA-funded RCA programs



Notes: Data is from the USDA Natural Resources Conservation Service (NRCS). Following [Keiser et al. \(2019\)](#), both technical and financial expenditures are included, with spending summed across programs.

Table B1: Estimated elasticities for state-level total rural housing value to Section 319 projects and USDA Resources Conservation Act (RCA) funding

Dependent variable: Log(total home value)			
	(1)	(2)	(3)
Panel [A]: Long differences regressions: one observation per state of the change from 1990 to 2020			
Log(S319-treated subwatersheds)	0.175*** (0.037)		0.194*** (0.042)
Log(USDA RCA spending)		0.036 (0.028)	-0.024* (0.014)
Panel [B]: Two-way fixed effects regressions: balanced panel for years 1990, 2000, 2010, and 2020			
Log(S319-treated subwatersheds)	0.050** (0.019)		0.048** (0.020)
Log(USDA RCA spending)		0.019 (0.017)	0.007 (0.013)
State fixed effects (Panel [B])	Yes	Yes	Yes
Year FE (Panel [B])	Yes	Yes	Yes
States	50	50	50
Observations (Panel [B])	200	200	200

Notes: The USDA RCA spending data is from Natural Resources Conservation Service (NRCS), USDA. Panel [A] uses one observation per state of the within-state change from 1990 to 2020. Panel [B] uses a balanced panel for years 1990, 2000, 2010, and 2020, where an observation is a state-year tuple. Only rural subwatersheds with positive population and housing throughout 1990-2020 are included, with rural/urban status defined as of 1990. Standard errors in parentheses are clustered by state.

*** p<0.01, ** p<0.05, * p<0.1