CONSEQUENCES OF THE CLEAN WATER ACT AND THE DEMAND FOR WATER QUALITY

By

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Consequences of the Clean Water Act and the Demand for Water Quality*

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Abstract

Since the 1972 U.S. Clean Water Act, government and industry have invested over $1 trillion to abate water pollution, or $100 per person-year. Over half of U.S. stream and river miles, however, still violate pollution standards. We use the most comprehensive set of files ever compiled on water pollution and its determinants, including 50 million pollution readings from 170,000 monitoring sites, to study water pollution's trends, causes, and welfare consequences. We have three main findings. First, water pollution concentrations have fallen substantially since 1972, though were declining at faster rates before then. Second, the Clean Water Act's grants to municipal wastewater treatment plants caused some of these declines. Third, the grants' estimated effects on housing values are generally smaller than the grants' costs.

JEL: H23, H54, H70, Q50, R31

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1 Introduction

The 1972 U.S. Clean Water Act sought "to restore and maintain the chemical, physical, and biological integrity of the Nation's waters." This paper quantifies changes in water pollution since before 1972, studies the causes of any changes, and analyzes the welfare consequences of any changes.

The Clean Water Act addressed a classic externality. Textbooks since at least Stigler (1952; 1966) have illustrated the concept of an externality through the story of a plant dumping waste in a river and harming people downstream. The immediate impetus for the Clean Water Act was a 1969 fire on the Cuyahoga River, which had fires every decade since 1868 though has had no fires since 1972. Time (1969) described it vividly:

> "Anyone who falls into the Cuyahoga does not drown," Cleveland's citizens joke grimly. "He decays." The Federal Water Pollution Control Administration dryly notes: "The lower Cuyahoga has no visible life, not even low forms such as leeches and sludge worms that usually thrive on wastes. It is also literally a fire hazard."

Despite the potential to address a serious market failure, the Clean Water Act has been one of the most controversial regulations in U.S. history, for at least two reasons. First, it is unclear whether the Clean Water Act has been effective, or even whether water pollution has decreased at all. An analysis in the 1990s summarized, "As we approached the twenty-year anniversary of [The Clean Water Act], no comprehensive analysis was available to answer basic questions: How much cleaner are our rivers than they were two decades ago?" (Adler, Landman, and Cameron 1993). Other writers echo these sentiments (Knopman and Smith 1993; Powell 1995; Harrington 2004; Hayward 2011). Today over half of U.S. river and stream miles violate state water quality standards (USEPA 2016), but it is not known if water quality was even worse before the Clean Water Act. William Ruckelshaus, the first head of the U.S. Environmental Protection Agency, nicely summarized what *is* known about water pollution today: "even if all of our waters are not swimmable or fishable, at least they are not flammable" (Mehan III 2010).

The second controversy is whether the Clean Water Act's benefits have exceeded its costs, which have been enormous. Since 1972, government and industry have spent over $1 trillion to abate water pollution, or over $100 per person-year. This is more than the U.S. has spent on air pollution abatement (see Appendix A). In the mid-1970s, Clean Water Act funding of municipal wastewater treatment plants was the single largest public works program in the U.S. (USEPA 1975). These costs were large in part because the Clean Water Act had very ambitious targets: to make <u>all</u> U.S. waters fishable and swimmable by 1983; to have <u>zero</u> water pollution discharge by 1985; and to prohibit discharge of toxic amounts of toxic pollutants.

Controversy over these costs and potentially smaller benefits began even before the law was passed. Council of Economic Advisers chair Paul McCracken described the Clean Water Act as an "inefficient use of national resources that would not produce balancing [of] social and economic benefits" (Barfield 1971). The EPA's chief legal officer wrote that advocates of the zero discharge standard had "no estimates at all of what the costs might be" (Quarles 1976). President Nixon actually vetoed the Clean Water Act and described its costs as "unconscionable," though Congress later overruled the veto (Nixon 1972).

Large costs could be outweighed by large benefits, but existing cost-benefit analyses of the Clean Water Act have not estimated positive benefit/cost ratios. One influential study concluded that in 1985, the Clean Water Act's annual costs were twice the Act's benefits (Freeman 2000). Other researchers have reached similar conclusions (Lyon and Farrow 1995). Even the U.S. Environmental Projection Agency (2000a; 2000c)'s evaluation of the Clean Water Act – its own regulation – estimated costs larger than benefits, though they do mention several types of unmeasured benefits.

These controversies have been largely academic, but they have spilled over into politics. The U.S. Supreme Court's 2001 and 2006 *SWANCC* and *Rapanos* decisions removed Clean Water Act regulation for nearly half of U.S. rivers and streams. In 2015, the Obama Administration proposed a Clean Water Rule (also called the Waters of the United States Rule) which would reinstate many of those regulations. This Rule has met fierce political opposition, and twenty-seven states have sued to vacate it.

This paper seeks to shed light on these controversies using the most comprehensive set of files ever compiled in academia or government on water pollution and its determinants. These files include several datasets that largely have not been used in economic research, including the National Hydrography Dataset, which is a georeferenced atlas mapping all U.S. surface waters; the Clean Watershed Needs Survey, which is a panel description of the country's wastewater treatment plants; a historic extract of the Grants Information and Control System describing each of 35,000 Clean Water Act grants the federal government gave cities; the Survey of Water Use in Manufacturing, a confidential plant-level dataset of large industrial water users which was recently recovered from a decommissioned government mainframe (Becker 2015); and around 50 million water pollution readings at over 170,000 pollution monitoring sites during the years 1962-2001 from three data repositories—Storet Legacy, Modern Storet and the National Water Information System (NWIS). Discovering, obtaining, and compiling these data has been a serious undertaking involving three Freedom of Information Act requests, software development in C++ with a full-time programmer specialized in hydrological routing models, and extensive discussions with engineers and hydrologists from the U.S. Geological Survey (USGS), the EPA, and engineering consultancies. These data enable a more extensive analysis of water pollution and its regulation than has previously been possible.

The analysis obtains three sets of results. First, we study how water pollution changed in the period 1962-2001. We find that most types of water pollution declined, though the rate of decrease slowed over time. Between 1972 and 2001, for example, the share of waters that met standards for fishing grew by 11 percentage points, and dissolved oxygen saturation (an omnibus measure of water quality we describe in detail later) increased by an average of 5 percentage points. We find similar patterns both in well-documented networks of a few monitoring sites and in the full sample of 170,000 monitoring sites. Our finding of decreases in most pollutants implies that the prevalence of such violations was even greater before the Clean Water Act. Two trends are particularly interesting because they may reflect air and climate pollution. The pH of rivers and lakes has increased at a similar rate to the pH of rainwater, likely in part due to decreased sulfur air pollution. In other words, less acid rain may have led to less acidic rivers and lakes. Additionally, the temperature of rivers and lakes increased by about 1 degree F every 40 years, which is consistent with climate change.

Second, the paper asks how the Clean Water Act's grants to municipal wastewater treatment plants contributed to these trends. The Clean Water Act had two main components—grants for wastewater treatment plants and permits for industry. The analysis focuses on the first component though controls for potential confounding effects of the second. We answer this question using a triple-difference research design. We compare water pollution before versus after Clean Water Act investments occurred, upstream versus downstream of recipient plants, and between plants receiving grants in early versus late years. To define upstream and downstream waters, we analyze a set of 70 million nodes that collectively describe the entire U.S. river network. We show that in the cross-section, water pollution jumps dramatically as a river passes a treatment plant.

We then find that each grant decreases the probability that downriver areas violate standards for being fishable by about half a percentage point. These changes are concentrated within 25 miles downstream of the treatment plant and they persist for around 30 years. We use the results to study the cost-effectiveness of these Clean Water Act grants. Through these grants, it cost around \$1.5 million (\$2014) per year to make one river-mile fishable, and around \$0.5 million per year to increase the dissolved oxygen saturation in a river-mile by ten percentage points. We do not find substantial heterogeneity in cost-effectiveness across regions or types of grants, though there is imprecise evidence that grants to states with decentralized authority to administer Clean Water Act effluent permits were more cost-effective. We also use annual municipal financial records and find that one dollar of a federal grant project led to approximately one additional dollar of local sewerage capital spending, implying limited crowding-in or crowding-out of local expenditure.

Third, the paper asks how residents valued these grants. We analyze housing units within a 25 mile radius of affected river segments, for two reasons—95 percent of recreational trips have a destination within this distance, and several other channels for benefits of water quality such as odor and appearance are likely to affect housing units within this radius. We find that a grant's estimated effects on home values are about 25 percent of the grant's costs. Put another way, while the average grant project cost around \$35 million (\$2014), the estimated effect of a grant on the value of housing within 25 miles of the affected river is around \$9 million. We find limited heterogeneity in these numbers across regions and types of grants, though grants to areas where outdoor fishing or swimming is common, to cities with high amenity levels, or to states with pro-environmental views have slightly higher estimated ratios of measured benefits to costs.

We discuss several reasons why these hedonic estimates could be interpreted as a lower bound on willingness to pay for these grants, including that people may have incomplete information about changes in water pollution and their welfare (including health) implications; they exclude nonuse ("existence") values; they abstract from general equilibrium effects; and they exclude the five percent of most distant recreational trips. One interpretation of these results is that the benefits of these Clean Water Act grants exceed their costs if these unmeasured components of willingness to pay exceed the components of willingness to pay that we measure by a factor of three or more.

Two aspects of the research design are worth highlighting. The first deals with comparison groups. Because water pollution flows in a known direction, areas upstream of a treatment plant provide a natural counterfactual for areas downstream of a plant. For this reason, our preferred estimates of how Clean Water Act grants affect water pollution use a triple-difference estimator comparing upstream and downstream areas. But because residents who live upstream of treatment plants can benefit from clean water downstream of treatment plants (e.g., by traveling for recreation), upstream homes could benefit from grants. Hence our preferred housing estimates come from difference-in-difference regressions analyzing homes within a 25 mile radius of river segments that are downstream of treatment plants. We do report both the double-difference and triple-difference estimators for both outcomes, and obtain generally similar conclusions.

Second, as in most settings, our identifying assumptions cannot be tested directly, since we cannot observe a counterfactual world without Clean Water Act grants. We do, however, provide several indirect tests of the identifying assumptions, all of which support the validity of the research design. First, we report event study graphs in time which test for pre-trends in outcomes (pollution or home values) in the years preceding a grant. Second, we report two different research designs—a triple-difference estimator which uses upstream areas as a counterfactual for downstream areas, and a differences-in-differences estimate focused only on downstream areas. Third, we assess whether grants affect pollutants closely related to municipal waste (e.g., biochemical oxygen demand and dissolved oxygen deficits) more than they affect pollutants that are less closely related (e.g., lead, mercury, and phenols). Fourth, we separately estimate the effect of a plant receiving one, two, three, four, or five or more grants, and find a positive dose-response function for most pollutants. Finally, we estimate specifications controlling for particularly important potential confounding variables, including industrial water pollution sources, air pollution regulations, and local population totals.

More broadly, this paper departs from the literature in four primary ways. This is the first study to quantify national changes in water pollution since before the Clean Water Act using a dense network of monitoring sites. Trends are important both in their own right and because measuring water pollution is one step towards measuring its national economic costs (Muller, Mendelsohn, and Nordhaus 2011). Some studies measure trends in water pollution for small sets of monitoring sites (e.g., Smith, Alexander, and Wolman 1983; USEPA 2000b). Smith and Wolloh (2012) study one measure of pollution (dissolved oxygen) in lakes beginning after the Clean Water Act and use data from one of the repositories we analyze. They conclude that "nothing has changed" since 1975. We find similar trends for the pollutant they study in lakes, though we show that other pollutants are declining in lakes and that most pollutants are declining in other types of waters. This is also the first national estimate of temperature trends in U.S. rivers using a dense and long-term network of monitoring sites, which is relevant for learning about climate change. One study estimates river temperature trends using 18 sites in the Northwestern U.S. from the NWIS water quality data network that we use, and finds that air temperatures account for 90 percent of this river temperature trend (Isaak, Wollrab, Horan, and Chandler 2012).

This paper also provides the first national estimate of how Clean Water Act investments affected ambient pollution concentrations. We use these estimates to calculate the cost effectiveness of these investments. Water pollution research typically uses ex ante engineering simulations, rather than actual observed data on water pollution, to assess the effects of water quality policies (Wu, Adams, Kling, and Tanaka 2004; Rabotyagov, Campbell, White, Arnold, Atwood, Norfleet, Kling, Gassman, Valcu, Richardson, Turner, and Rabalais 2014). Far more economic research focuses on air pollution than on water pollution regulation.[1] A few studies do investigate how water pollution affects emissions of a single pollutant in specific settings, such as analyses of several dozen wastewater treatment plants in one state (Earnhart 2004a,b) or a study of a phosphate ban in dishwasher detergent (Cohen and Keiser 2015). Emissions in those studies are self-reported by the regulated plants. Abroad, water pollution in China and India is much worse than in the U.S. Recent research finds that India's water pollution regulations, which have similar structure to the U.S. Clean Water Act, are ineffective (Ebenstein 2012; Greenstone and Hanna 2014). It is unclear whether the failure of these water pollution regulations in developing countries reflects their regulatory context, or whether it reflects broader challenges regulating water pollution. Several studies find that ambient water pollution increases with political boundaries, though generally without directly observing regulation (Sigman 2002; Lipscomb and Mobarak Forthcoming; Kahn, Li, and Zhao 2015). Some work investigates how fracking wells and the pollution they send to wastewater treatment plants affects water quality (Olmstead, Muehlenbachs, Shih, Chu, and Krupnick 2013).

Third, this study provides the first estimate of the effects of water pollution regulation on home values. Existing estimates of willingness-to-pay for water quality use travel cost methods, hedonics, or stated preference (i.e., contingent valuation; Kuwayama and Olmstead (2015) list many individual studies).[2] Travel cost methods observe the distance people travel to visit recreational sites and associated time and pecuniary costs, then infer willingness-to-pay for visiting these sites. Travel cost studies typically rely on observational and cross-sectional variation in pollution and focus on a single county or other limited area (e.g., Smith and Desvousges 1986). The literature has emphasized that such studies may suffer from omitted variable bias because unobserved disamenities like factories or roads contribute to pollution and

[1] Olmstead (2010) attributes the imbalance between research on air and water pollution to three explanations: air pollution, unlike surface water pollution, has large and direct consequences for human health; policymakers have implemented many market-based mechanisms to regulate air pollution but few for water pollution; and most areas of industrialized countries already have effective basic drinking water treatment and sanitation. We hypothesize two additional reasons for the imbalance in research between air and water pollution: ambient air pollution data are much more widely available and better documented than ambient water pollution data; and air pollution regulation has better-understood variation over time and space which is amenable to empirical econometric analysis than water pollution regulation has.

[2] Some research looks at drinking water pollution and health or home values (Snow 1855; Cutler and Miller 2005; Currie, Zivin, Meckel, Neidell, and Schlenker 2013; Muehlenbachs, Spiller, and Timmins 2015), but we focus on ambient pollution in rivers and lakes, which is generally distinct from drinking water quality. The only studies we know on surface water pollution and health focus on China and India (Ebenstein 2012; Greenstone and Hanna 2014), and a study of the Boston area around 1900 (Alsan and Goldin 2015). Watson (2006) finds that sanitation investments in U.S. Indian reservations decreased infant mortality, though the analysis pools all investments (including drinking water treatment, wastewater treatment plant construction and upgrades, household sanitation infrastructure like latrines, and others) so does not separately identify health consequences of investments in wastewater treatment plants.

directly discourage recreational visits (Leggett and Bockstael 2000; Murdock 2006; Moeltner and von Haefen 2011). Such omitted variables are important for studying air pollution, though their importance for water pollution is unknown.[3] Several authors note that limited water quality variation within housing markets has restricted the use of hedonic models (Leggett and Bockstael 2000; Palmquist and Smith 2002). Most cost-benefit analyses of the Clean Water Act rely on stated preferences (Carson and Mitchell 1993; Lyon and Farrow 1995; USEPA 2000a), which are controversial (Hausman 2012; Kling, Phaneuf, and Zhao 2012).

Finally, this work sheds light on regulation and policy design more generally. We believe this is the first empirical study of the efficiency of subsidizing use of pollution control equipment. This policy instrument is common in many countries for a variety of pollutants.[4] Theoretical research has lamented the poor incentives of such subsidies (Kohn 1992; Aidt 1998; Fredriksson 1998).[5] The only econometric analysis we know of such policies, however, tests how the French policy of jointly taxing industrial air pollution and subsidizing abatement technologies affected emissions, using data from 226 plants (Millock and Nauges 2006). That study does not quantify efficiency or separately identify the effect of the pollution tax from the effect of the abatement subsidy. Our analysis of heterogeneity in cost-effectiveness and benefit-cost ratios also provides a new domain to consider recent research on spatially differentiated policy (Muller and Mendelsohn 2009), a design which thus far has focused mostly on air pollution.

The paper proceeds as follows. Section 2 provides a background on the Clean Water Act and water pollution. Section 3 describes the data sources. Section 4 describes the econometric and economic models. Section 5 describes water pollution trends. Section 6 analyzes how the Clean Water Act's grants to municipal wastewater treatment plants affected water pollution. Section 7 discusses grants' effects on housing. Section 8 concludes.

[3] The only panel study we know is Hausman, Leonard, and McFadden (1995)'s use of recall questions to study changes in recreation around the Exxon Valdez spill. Keiser (2016) uses upstream ambient pollution as instruments for local lake pollution to address omitted variables and measurement error. Concurrent work is studying panel data on lakes in Iowa (Herriges, Kling, and Phaneuf 2015). A few hedonic studies address these concerns through the use of property or lake fixed-effects (Mendelsohn, Hellerstein, Huguenin, Unsworth, and Brazee 1992; Walsh, Milon, and Scrogin 2011).

[4] Countries including Brazil, France, India, Japan, South Korea, Sweden, and the U.S. subsidize municipal water pollution abatement investments. Many countries have subsidized air pollution abatement investments for transportation (e.g., adding catalytic converters), including Cyprus, Germany, Hong Kong, the Netherlands, and Sweden. The U.S. Clean Coal program and France directly subsidize industrial air pollution equipment. Many countries allow accelerated depreciation of pollution abatement capital costs for taxes.

[5] A larger body of theoretical research studies payments for decreasing the level of pollution emitted (Baumol and Oates 1988), subsidies to the use of clean types of production (Mestelman 1982; Fullerton and Mohr 2003), or subsidies to research on clean technologies (Acemoglu, Akcigit, Hanley, and Kerr 2016). More empirical research studies these policies, and they can have similar incentives as subsidies to pollution control equipment.

2 Background on the Clean Water Act and Water Pollution

2.1 Clean Water Act Background

A brief background on the Clean Water Act may help explain our analysis and results.[6] Our data begin in 1962, and policies before the Clean Water Act may contribute to some of the water pollution patterns we observe before 1972. The U.S. Congress passed major water pollution control laws in 1948, 1956, 1961, 1965, 1966, and 1970. Many earlier laws, like the Clean Water Act, supported municipal wastewater treatment and industrial abatement, but provided funds an order of magnitude below the funds distributed by the Clean Water Act. By 1966, all 50 states had passed some type of water pollution legislation, but the level of enforcement varied greatly across states (Hines 1967).

One impetus for the 1972 Clean Water Act was concern about incentives for local governments to impose weak regulation in order to attract industry. Another concern was that previous laws had left much pollution decision-making power to states, and not all states strongly supported or enforced water pollution regulation (Freeman 2000).

Like many other federal environmental regulations, the Clean Water Act retained large roles for state-level implementation, and the effectiveness of that implementation most likely varied across states. While a simple formula determined the level of grant funds that each state received, each state designed the priority lists determining which plants received grants. States with decentralized authority also oversaw writing of permits for municipal plants, monitoring and enforcement of violations, and other activities (Sigman 2003, 2005). We report sensitivity analyses which investigate how the effectiveness of grants varied with decentralization of authority to manage permits.

Also like other regulation, the Clean Water Act targeted municipal waste treatment and industrial pollution sources, sometimes called "point sources." But much water pollution comes from urban runoff and agriculture, the most important "non-point" pollution sources. The Clean Water Act had minor provisions for these sources, but has largely exempted them from regulation. We briefly analyze trends in agricultural pollutants, and comment on the relevance of the relative lack of regulating non-point sources for interpreting our cost-effectiveness numbers.

Most of this paper focuses on the Clean Water Act grants program, but as mentioned earlier, the Clean Water Act had a second important component—distributing and enforcing permits limiting industrial water pollution, managed through the National Pollutant Discharge Elimination System (NPDES). NPDES aims to cover every source which directly discharges pollution into U.S. waters. Some plants are part of a separate "Pretreatment Program," in which they discharge untreated or lightly-treated wastewater through sewers to wastewater treatment plants, then pay fees to the treatment plant.[7] The

[6] The 1972 law was formally called the Federal Water Pollution Control Amendments, though we follow common practice in referring to it as the Clean Water Act.

[7] The wastewater treatment plants which are the focus of this paper also receive effluent permits through the NPDES program. Because those permits may be related to the federal grants we study here, our analysis of grants may also reflect NPDES permits

permits were distributed in the early 1970s. Because this was a national program affecting all plants and industries at about the same time, we include a variety of fixed effects in regressions that are designed to control for this program and other potential concurrent environmental regulations. We also obtain historic data on large industrial water users around the time of the Clean Water Act, which provides a control used in some sensitivity analyses.

2.2 Wastewater Treatment Background

Explaining the function of wastewater treatment plants may help also clarify our analysis. In most cities and towns, sewers convey wastewater to a municipal wastewater treatment plant which treats the waste and then discharges it to surface waters. Ninety-eight percent of treatment plants are publicly owned (USEPA 2002). The abatement technology in treatment plants initially only included screens to remove large objects. As technology improved during the twentieth century, treatment plants began allowing wastewater to settle before discharging, then plants began applying bacteria that degrade sludge and organic matter, and finally they began using more advanced technologies to balance the chemical composition of water. Abatement technologies falling into these categories are generally called raw, primary, secondary, and tertiary treatment, respectively. The Clean Water Act required all municipal treatment plants to have at least secondary treatment by 1977 and correspondingly offered cities subsidies for investment in treatment plants.

This investment in wastewater treatment was not cheap. Projects funded by Clean Water Act grants cost about $680 billion in total over their lifetimes ($2014)—about $185 billion in federal grant funds, $75 billion in municipal matching funds, and $420 billion in operation and maintenance costs. Grants covered new treatment plants, improvement of existing plants, and upgrades to sewers (USEPA 1975). Local governments paid about a fourth of most grant projects' capital costs.[8] The 1987 Clean Water Act Amendments converted these grants into a system of subsidized loans called the Clean Water State Revolving Fund, which continues today.

The U.S. did not come close to meeting the Clean Water Act's goal of having every plant install secondary treatment by 1977. Only a third of large plants met this deadline, though abatement technologies improved over time. In 1978, for example, nearly a third of all plants lacked secondary treatment, and by 1996, almost none did. The treatment technology used in wastewater treatment plants, however, had been improving steadily before the Clean Water Act (USEPA 2000b).

Because this paper exploits the timing and location of grants to identify the effect of the Clean Water Act's grants program, it is useful to clarify how grants were distributed. The allocation of wastewater spending across states came from formulas depending on state population, forecast population, and

distributed to wastewater treatment plants.

[8]The federal government paid 75 percent of the capital cost for most construction projects awarded through September 1984, and 55 percent thereafter; local governments paid the rest of the capital costs. Beginning in 1977, grants provided a higher 85 percent subsidy to projects using "innovative" technology, such as those sending wastewater through constructed wetlands for treatment. This extra subsidy fell to 75 percent in 1984, and about 8 percent of projects received the subsidy for innovative technology (USGAO 1994).

wastewater treatment needs (CBO 1985). Within a state, grants were distributed according to a "priority list" that each state submitted annually to the EPA. States had to base a priority list on seven criteria (USEPA 1980, p. 8):

> 1. [T]he severity of the pollution problem; 2. [T]he existing population affected; 3. [T]he need for preservation of high quality waters; 4. [A]t the State's option, the specific category of need... 5. ... [T]echniques meeting innovative and alternative guidelines... 6. [O]ther criteria, consistent with these, may be considered (including the special needs of small and rural communities). The state may not consider: the project area's development needs not related to pollution abatement; the geographical region within the State; or future population growth projections; and 7. [I]n addition to the criteria listed above, the State must consider ... total funds available; and other management criteria.

States had to publicly offer information concerning their priority systems and the ranking of particular projects, including a public hearing to discuss the lists (USEPA 1976, 1981). Funds moved slowly and EPA estimated that it took two to ten years from project conception to finishing construction, with a mean of five years.

This paper's triple-difference regressions assume that in the absence of a grant, areas downstream and upstream of plants receiving grants would have had a similar evolution of pollution concentrations and home values. The statutory requirement quoted above, which forbid states from considering population growth projections or other development needs, gives some support for this identifying assumption. Ultimately, however, the allocation of state funds to individual plants is an empirical question. As discussed in the introduction, the empirical sections provide a number of tests for the validity of the research design.

2.3 Water Pollution Background

This paper emphasizes two measures of water quality – the dissolved oxygen saturation of water, and whether waters are fishable – though also reports results for other measures. We focus on dissolved oxygen saturation because it is the most common omnibus measure of water quality in research, because it responds to a wide variety of pollutants, and because it is a continuous (rather than binary) measure of pollution which alleviates concerns about failing to measure inframarginal changes in water quality. Most aquatic life requires dissolved oxygen to survive. Water can absorb dissolved oxygen from the air, but loses dissolved oxygen when microorganisms consume oxygen in order to decompose pollution. Dissolved oxygen levels move inversely with temperature. Dissolved oxygen saturation represents the dissolved oxygen level divided by the maximum oxygen level expected given the water temperature, so implicitly adjusts for water temperature. Actual dissolved oxygen saturation is bounded below at zero (describing water with no oxygen) but is not bounded above, since waters can exceed 100 percent saturation. Dissolved oxygen deficits are defined as 100 minus dissolved oxygen saturation.

We focus also on the fishable standard because making water safe for fishing is a major goal of the

Clean Water Act and because recreational fishing is believed to be a main reason why people value water quality. We use a definition of whether waters are "fishable" that was developed in the early 1980s by William Vaughan for Resources for the Future (RFF), and adapted by the USEPA (2000a) to study the Clean Water Act. This definition has several appealing features. It distills several published water quality criteria from between 1966 and 1979, which are appropriate to the period we study. It particularly reflected state water quality standards. We reviewed current state-specific standards of "fishable," and found that they are generally close to this definition. Finally, it is a widely-used interpretation of "fishable." In this definition, water is "fishable" if pollution is below a threshold, based on four measures: biochemical oxygen demand (BOD), dissolved oxygen saturation, fecal coliforms, and total suspended solids (TSS). To implement these definitions in the data, we pool data from these pollutants and define a dummy for whether a raw pollution reading exceeds the relevant standard.[9]

We also report estimates for whether waters are swimmable, and we report separate results for the other pollutants that are part of the "fishable" and "swimmable" definitions—biochemical oxygen demand (BOD), fecal coliforms, and total suspended solids (TSS). These pollutants merit interest in their own right because BOD, fecal coliforms, and TSS are a majority of the five "conventional pollutants" the Clean Water Act targeted. The other "conventional" pollutants are pH, which we analyze in Appendix Table 4, and oil and grease, a pollutant for which we have little data. We define all pollutants so that lower levels of the pollutant represent cleaner water (so we report the share of waters that are "not fishable" or "not swimmable," and we report dissolved oxygen deficits).

Describing these other pollutants may help interpret results. BOD measures the amount of oxygen consumed by decomposing organic matter. Fecal coliforms proxy for the presence of pathogenic bacteria, viruses, and protozoa like E. coli or Enterococcus that cause human illness and are unsafe for human contact. Pathogens including fecal coliforms are the most common reason why water quality violates state standards today (USEPA 2016). TSS measures the quantity of solids in water that is trapped by a filter.[10] Municipal sources in the early 1980s were estimated to account for about 20 percent of national BOD emissions and less than one percent of national TSS emissions (Gianessi and Peskin 1981), though municipal sources may account for a larger share of emissions in urban areas. Most TSS comes from agriculture and urban runoff, and TSS concentrations are highest in the Midwest (Appendix Figure 2a).

We also report a few results for three additional groups of pollutants: industrial pollutants like lead, mercury, and phenols; nutrients like nitrogen and phosphorus; and other general water quality measures

[9] "Fishable" readings have BOD below 2.4 mg/L, dissolved oxygen above 64 percent saturation (equivalently, dissolved oxygen deficits below 36 percent), fecal coliforms below 1000 MPN/100mL, and TSS below 50 mg/L. "Swimmable" waters must have BOD below 1.5 mg/L, dissolved oxygen above 83 percent saturation (equivalently, dissolved oxygen deficits below 17 percent), fecal coliforms below 200 MPN/100mL, and TSS below 10 mg/L. The definition also includes standards for boating and drinking water that we do not analyze.

[10] We analyze all these physical pollutants in levels, though Appendix Tables 3 and 6 show results also in logs. Fecal coliforms are approximately lognormally distributed, and BOD and TSS are somewhat skewed (see Appendix Figure 1). Specifying these pollutants in logs would implicitly assume that the percentage change in a river's pollution due to a grant is the same for a river with a high background concentration as for a river with a low background pollution concentration. We specify these pollutants in levels since this assumption does not seem accurate. Other water pollution research generally specifies BOD and TSS in levels. Some papers specify fecal coliforms in logs while others do not.

like temperature. We use a standardized criterion, described in Appendix B, to choose pollutants for this appendix table.[11] We show these additional pollutants because they merit interest directly, and because some like lead, mercury, and phenols help test our research design since grants to treatment plants are unlikely to affect them.

One important question for defining our analysis sample is how far these pollutants travel downstream. We focus on a distance of 25 miles for several reasons. First, the only engineering study we found on this question (USEPA 2001) limited its analysis to 25 miles downstream of point sources for BOD. They chose this distance to reflect 15 watershed-specific studies designed to remedy pollution problems. Second, an interview with a wastewater regulation specialist at the Iowa Department of Natural Resources suggested that effects of treatment plants on dissolved oxygen would be concentrated within 20 miles downriver. Third, estimated effects of grants on whether rivers are fishable out to 100 miles downstream of a treatment plant only show effects within 25 miles (Appendix Table 6).

3 Data

We use eight types of data: spatial data on rivers and lakes; municipal sources of water pollution; Clean Water Act grants; ambient levels of water pollution; census tract-level housing and population characteristics; recreational travel distances; municipal financial records; and other environmental data. This section describes each dataset. It then briefly discusses how we measure distances along rivers between plants, monitoring sites, houses, and city centers. Except where otherwise noted, all data cover the years 1962 to 2001. This section describes the most important features of these data; Appendix B provides additional details.

Spatial Data on Rivers and Lakes. We use data from the National Hydrography Dataset Plus, Version 2.1 (NHD), an electronic atlas mapping all U.S. surface waters. NHD organizes the U.S. into approximately 200 river basins, 2,000 watersheds, 70,000 named rivers, 3.5 million stream and river miles, and 70 million river nodes. A river in these data consists of a set of river nodes (i.e., points) connected by straight lines. NHD forms a network describing the flow direction of each river or stream segment and helps us follow water pollution upstream or downstream. These data let us determine the exact surface water (e.g., the Mississippi River) where each pollution monitoring site or treatment plant is located, the exact location on that surface water, the distance along the river upstream or downstream from other monitoring sites or plants, and the census tracts nearby. Panel A of Figure 1 shows U.S. streams, rivers, and lakes, colored by their distance from the ocean, Great Lakes, or other terminus. (See additional details in Appendix B.2.)

Municipal Sources of Water Pollution. We created a panel census of U.S. municipal water pollution treatment plants. The data come from the EPA and are called the Clean Watershed Needs Survey (CWNS). EPA staff sent us complete computer-readable files and codebooks for these data from

[11] Applying such a stringent criterion is important—one of our repositories alone, Storet Legacy, includes 16,000 different measures of water pollution.

their internal systems. Most years report federal grant identifying codes and the latitude and longitude of discharge. The data are complete and have accurate panel identifiers in 1978 and then biennially beginning in 1984.[12] Panel B of Figure 1 shows the location of each treatment plant, and shows that relatively more treatment plants are located in densely populated areas.

Clean Water Act Grants. We filed two Freedom of Information Act requests to obtain details on each of the 35,000 Clean Water Act grants that the federal government gave to these plants. These records come from the EPA's internal archived version of the Grants Information and Control System (GICS). The data list the grant award date, grant amount, total project cost (including both federal and local capital expenditures), name of the overseeing government authority (city, county, state, or special district), a grant identifier code, and the name of the recipient treatment plant. The data report on grants given to 8,000 different local governments. The data also include grants in the years 1957-1971 given under predecessor laws to the Clean Water Act. The grants were concentrated in the 1970s. Grants decreased throughout the 1980s and nearly stopped after 1987. For simplicity, our analysis counts multiple grants to a single treatment plant in a given calendar year as a single grant. (See additional detail in Appendix B.4.)

Ambient Levels of Water Pollution. We use water pollution readings from three federal data repositories: Storet Legacy, Modern Storet, and the National Water Information System (NWIS).[13] Storet Legacy contains data from the early 20th century through 1998. Storet Legacy is large—the raw data include 18,000 separate data files and 200 million pollution readings. Modern Storet is similar to Storet Legacy but covers more recent years. The Storet repositories have data from many local organizations. USGS national and state offices collect a large share of NWIS readings. In addition to describing these data in more detail, Appendix B.3 discusses the steps we have taken to clean these data, including limiting to rivers/streams and lakes, limiting to scientifically comparable methods of measuring each pollutant, winsorizing at the 99th percentile, excluding readings specific to hurricanes and other non-routine events, and others.

Basic descriptive statistics help characterize the data (Appendix Table 1). The analysis sample includes 10.5 million observations on the four main pollutants and 37 million observations on the additional pollutants discussed in Appendix Table 4. Levels of BOD, fecal coliforms, and dissolved oxygen deficits are substantially lower in the U.S. than in India or China (Greenstone and Hanna 2014). Among the four main pollutants, about half the data describe dissolved oxygen. The data come from 170,000 distinct monitoring sites. If all the data came from monitoring sites that reported data for short periods of time, it would be more difficult to measure long-run trends accurately. Fortunately, 45 percent of the data come from monitoring sites that report readings in at least three of the four decades we analyze (the decade 1962-1971 is most often missing); about a fourth of readings come from monitoring sites that only

[12]The 1980 and 1982 surveys have incorrect plant identifier codes. The 1976 survey is incomplete. Plant longitude and latitude are listed beginning in 1984.

[13]We considered a fourth repository, the Sustaining the Earth's Watersheds: Agricultural Research Data System (STEWARDS), managed by the USDA. We did not use these data because they focus on years 1990 and later, mainly measure pesticides, and have a small sample.

report in one decade.

No sampling design explains why certain areas and years were monitored more than others. In some cases, hydrologists purposefully designed representative samples of U.S. waters. At least four such networks are in these data: the Hydrologic Benchmark Network, the National Stream Quality Accounting Network, the National Water-Quality Assessment, and the National Water Quality Network (HBN, NASQAN, NAWQA, and NWQN). The first three this paper discusses in detail later. The fourth was collected by the Public Health Service beginning in 1957 (USPHS 1961) and focuses on years before the Clean Water Act. In other cases, sampling locations and frequency were chosen by local governments or non-governmental organizations. Some states like Massachusetts have relatively dense monitoring networks, while others like Texas have less dense networks (Figure 1, Panel C). Individual rivers are also visible in the pattern of monitoring sites. Cities have visibly greater density of monitoring sites. We explore the sensitivity of our results to restricting estimates to metro areas only, to long-term monitoring sites which operate over most of the sample period, and to the networks of monitoring sites that have well-documented design and good data quality, and find similar pollution trends in these subsamples.

Census Tract Data. We use the Geolytics Neighborhood Change Database (NCDB), which Geolytics built from the 1970, 1980, 1990, and 2000 Censuses of Population and Housing. The 1970 census only included metro areas in tracts, so these tract-level data for 1970 are restricted to metro areas, and so much of our analysis is as well.

We use these census data because they have national coverage and also because transaction-level records that county assessor offices maintain, such as those aggregated by Dataquick or CoreLogic and used in other economics studies, generally do not extend back to the 1970s when Clean Water Act investments were concentrated. In addition to describing these data in more detail, Appendix B.5 discusses what is known about the quality of the Census self-reported data as compared to actual transactions, including concerns about measurement error and inertia.

Recreational Travel Distances. Improving water quality in a particular river segment may affect neighboring homes that benefit from the nearby amenity value. This improvement may also affect more distant homes for residents who travel for recreation. We seek to determine a distance around a river that covers most individuals who travel to participate in recreation at this river. We obtain estimates of this distance from the Nationwide Personal Transportation Survey (NPTS) for years 1983, 1990, and 1995. This survey is the only source we know that provides a large nationally representative sample of recreational activities and travel distances over the period we study.[14] The survey picks a day and has respondents list all trips, their purposes, and the driving distances in miles. We limit trip purposes to "vacation" or "other social or recreation." In these data, the 95th percentile of one-way distance from home to recreational destinations is 33.7 miles. This distance is similar in all three years of the survey, and we calculate 33.7 from the unweighted mean across years.

This distance represents the distance traveled along roads; but the radius we use to calculate the

[14] The National Survey of Recreation and the Environment and its predecessor, the National Recreation Survey, do not systematically summarize trips taken and travel distances. Many travel demand papers use small surveys that report distance traveled to a specific lake or for a specific narrow region.

distance of homes from rivers represents a great circle distance (i.e., the shortest direct path along the ground). Making the great circle and road distances comparable requires an estimate of how road distances typically compare to great circle distances. We are aware of two such estimates. First, the 2009 National Household Travel Survey (the successor to the NPTS) reports both the great-circle distance between a person's home and the person's workplace, and also the distance by road. On average, the ratio of the road distance to the great circle distance is 1.4. Second, a recent study compared driving distance versus straight-line (i.e., great circle) distance for travel from a representative sample of about 70,000 locations in the U.S. to the nearest community hospital, and the average ratio was also 1.4 (Boscoe, Henry, and Zdeb 2012). Considering these two, we estimate that the straight-line (great circle) distance between homes and rivers which covers ninety-five percent of recreational trips is 25 miles ($\approx$33.7/1.4).

Municipal Financial Records. To examine the pass-through of federal Clean Water Act grants to municipal spending on wastewater treatment, we use data from the 1970-2001 Annual Survey of State and Local Government Finances and the Census of Governments. These data report annual capital and total expenditures for sewerage (a category including wastewater treatment), separately for each local government.[15] For use as a control variable in some specifications, we obtain population data for most of these cities from the 1970-2000 decennial censuses, then linearly interpolate between years. The final sample includes 199 cities; in addition to describing these data in more detail, Appendix B.6 discusses the main sample restrictions, including requiring a balanced panel and accurate links to the grants data. Given this relatively small sample of cities, we do report a set of estimates which weight by the inverse propensity score to provide estimates more representative of all cities, but the small sample should be considered when assessing external validity.

Other Environmental Data. We use a few other environmental data sources. One sensitivity analysis controls for nearby industrial sources of water pollution. This is a potentially important control because regulation of industrial sources was the second main component of the Clean Water Act. We are not aware of any complete data on industrial water pollution sources around the year 1972, so we use two distinct controls as imperfect proxies. The first is a list of the manufacturing plants that used large amounts of water in 1972. We obtain these data from the confidential 1973 Survey of Water Use in Manufacturing (SWUM) microdata, accessed through a Census Research Data Center. The second control is a count of the cumulative number of plants in a county holding industrial effluent (NPDES) permits. We filed a Freedom of Information Act request to obtain a historic copy of the EPA database which keeps records of industrial pollution sources—the Permit Compliance System, now called the Integrated Compliance Information System. Appendix B.7 describes more information on these sources, along with additional data on weather and nonattainment designations. Finally, Appendix B.8 describes data used to consider heterogeneity across different groups of grants by several dimensions: grant size, baseline abatement technologies, baseline pollution, Clean Water Act state decentralization,[16] prevalence

[15] The "year" in these data refers to each local government's fiscal year. We convert the data to calendar years using data from these surveys on the month when each government's fiscal year ends, assuming that government expenditure is evenly distributed across months. For the few governments that don't report when their fiscal year ends, we assume they report by calendar year.

[16] Our measure of decentralization indicates whether a state holds authority to administer National Pollutant Discharge Eli-

of local outdoor fishing and swimming, local environmental views, declining older urban areas (Glaeser and Gyourko 2005), and high amenity areas (Albouy 2016).

Spatial Links. We construct four types of links between datasets. The first involves linking each pollution monitoring site and treatment plant to the river or lake where it monitors. The second involves measuring distances along rivers between treatment plants and pollution monitoring sites. The third involves measuring distances of census tracts from rivers. The fourth involves linking grants to individual plants in the CWNS. Appendix C provides details of each step.

4 Economic and Econometric Models

Because this paper has three research questions (water pollution's trends, causes, and welfare consequences), we discuss the econometric details and then results separately for each research question. For most analyses, we describe both a flexible version used for graphs and which includes separate indicators for years or distance bins, and a parametric version of the regression used for tables. Except where otherwise noted, regressions are clustered by watershed. Appendix Tables 3, 6, and 8 also report results from two-way clustering by watershed and year. A watershed is defined by the USGS as an area of land in which all water within it drains to one point. Where relevant, watersheds or counties are defined by the treatment plant's location.

4.1 Econometrics: Water Pollution Trends

We use the following equation to assess year-by-year changes in water pollution:

$$Q_{icy} = \sum_{\tau=1963}^{\tau=2001} \alpha_\tau 1[y_y = \tau] + X'_{icy}\beta + \delta_i + \epsilon_{icy} \tag{1}$$

Each observation in this analysis is an individual water pollution reading at monitoring site i, hour and calendar day-of-year c, and year y. The variable Q_{icy} represents the level of water pollution. We estimate this equation separately for each pollutant. The matrix X_{icy} includes cubic polynomials in time of day and in day of year. In sensitivity analyses, X_{icy} also includes air temperature and precipitation. The fixed effects δ_i control for all time-invariant determinants of water pollution specific to monitoring site i. The error term ϵ_{icy} includes other determinants of water pollution. We plot the year-by-year coefficients $\alpha_{1963} \ldots \alpha_{2001}$ plus the constant. The year-specific points in graphs can be interpreted as mean national patterns of water pollution, controlling for time and monitoring site characteristics.

We also estimate linear water pollution trends using the following equation:

$$Q_{icy} = \alpha y_y + X'_{icy}\beta + \delta_i + \epsilon_{icy} \tag{2}$$

mination System (NPDES) permits.

The main coefficient of interest, α, represents the mean annual change in water pollution, conditional on the other controls in the regression. We also show specifications which interact the trend term y with an indicator $1[y \geq 1972]$ for whether an observation is year 1972 or later. This interaction measures how water pollution trends differed after versus before the Clean Water Act. We emphasize graphs based on equation (1) more than tables based on equation (2) for a few reasons—the graphs are more visually transparent; the nonlinear trends in graphs are crudely approximated with linear trends; and 30 years is a long post period.

4.2 Econometrics: Effects of Grants on Water Pollution

Appendix D discusses evidence on how water pollution changes as rivers pass treatment plants. This provides a test of the hypothesis that the data capture an important feature of the world—ambient water pollution in a river increases as the river passes a large polluting plant.

This section estimates how grants affect downstream water pollution, which is the paper's second main research question. It then assesses how grants affect municipal spending on wastewater treatment capital, which is useful for measuring the cost-effectiveness of the grants and, later, their costs versus benefits.

Effects of Clean Water Act Grants on Water Pollution

We use the following regression to estimate effects of Clean Water Act grants on water pollution:

$$Q_{pdy} = \gamma G_{py} d_d + X_{pdy}^{'} \beta + \eta_{pd} + \eta_{py} + \eta_{dwy} + \epsilon_{pdy} \tag{3}$$

This regression has two observations for each treatment plant p and year y, one observation describing mean water quality upstream ($d = 0$), and the other observation describing mean water quality downstream ($d = 1$). The variable G_{py} describes the cumulative number of grants that plant p had received by year y. This regression measures grants as a cumulative stock because they represent investment in durable capital. The main coefficient of interest, γ, represents the mean effect of each grant on downstream water pollution. We also explore other specifications for G, including limiting to grants for construction and not for planning or design, estimating effects separately for each possible number of cumulative grants, and others.

Equation (3) includes several important sets of controls. The matrix X_{pdy} includes temperature and precipitation controls. The plant-by-downstream fixed effects η_{pd} allow both upstream and downstream waters for each treatment plant to have different mean levels of water pollution. These fixed effects control for time-invariant sources of pollution like factories and farms, which may be only upstream or only downstream of a plant. The plant-by-year fixed effects η_{py} allow for water pollution to differ near each treatment plant in each year, and they control for forces like the growth of local industries, other environmental regulations, and changes in population density which affect both upstream and downstream pollution. The downstream-by-basin-by-year fixed effects η_{dwy} allow upstream and downstream water quality separately to differ by year in ways that are common to all plants in a river basin.[17] These fixed effects address the possibility that other point source pollutants and regulations are located near wastewater treatment plants and had water quality trends unrelated to the municipal grants.

Equation (3) focuses on the effect of the number of grants a plant has received, rather than the dollar value of these grants, for several reasons. (Appendix Table 6 reports similar effects of grant dollars.) First, it may be easier to think in discrete terms about the effect of a grant, rather than the effect of an arbitrary amount of money. Second, estimating these regressions in simple discrete terms makes the regression tables more easily comparable with event study graphs. Third, larger grants tend to go to more populated areas and larger rivers. Because it takes relatively larger investment to achieve a given change in pollution concentration for a more populated area and larger river, it is ambiguous whether grants of larger amount should have larger effects on pollution concentrations. Fourth, the distribution of cumulative grant amounts is highly skewed, with many zeros. Focusing on the number of grants rather than grant dollars avoids issues involved in log transformations (or other approaches) in the presence of many zeros.

A few other details of our approach are worth noting. Because the dependent variable is an average over different numbers of underlying pollution readings, in all regressions where each observation is plant-downstream-year tuple, we use generalized least squares weighted by the number of raw underlying pollution readings.[18] To maximize comparability between the treatment plant location and monitoring sites, we also restrict pollution data to monitoring sites located on the same river as the treatment plant. Finally, all estimates are limited to plants within 1 kilometer of a river node. Appendix Table 6 shows results with these assumptions relaxed.

The identifying assumption for equation (3) to provide an unbiased estimate of the parameter γ is that the grants×downstream interaction $G_{py}d$ is independent of the regression error, conditional on other explanatory variables:

$$E[G_{py}d_d \cdot \epsilon_{dpy} | X_{pdy}, \eta_{pd}, \eta_{py}, \eta_{dwy}] = 0$$

This assumption would be violated if, for example, grants or permits responded to unobserved shocks to variables like population which themselves affect pollution concentrations.[19]

We cannot test this assumption directly. However, we can provide several suggestive tests of its

[17] A water basin w is defined as a four-digit hydrologic unit code (HUC).

[18] Appendix Table 6 also reports unweighted estimates, which are broadly similar to the generalized least squares (GLS) estimates. GLS based on the number of underlying pollution readings in each plant×downstream×year is an efficient response to heteroskedasticity since we have grouped data. GLS estimates the effect for the average pollution reading rather than for the average plant×downstream×year. It is possible that areas with more pollution data may be of greater interest; for example, Panel C of Figure 1 shows generally more monitoring sites in more populated areas.

[19] This assumption could also fail if changes in governments' effectiveness at receiving grants correlated with governments' effectiveness at operating treatment plants. This does not seem consistent with our results since it would likely create pre-trends in pollution or home values (whereas we observe none). Our finding that benefits last about as long as engineering estimates suggest (30 years) and for exactly the expected pollutants also are not exactly what this story would predict. We also observe that each additional grant results in further decreases in pollution (Appendix Table 6), which would be a complicated story for the timing of government human capital to explain.

validity. One test is whether pre-trends are flat in the years before a facility receives a grant.[20]

$$Q_{pdy} = \sum_{\tau=-10}^{\tau=25} \gamma_\tau 1[G_{p,y+\tau} = 1]d_d + X'_{pdy}\beta + \eta_{pd} + \eta_{py} + \eta_{dwy} + \epsilon_{pdy} \tag{4}$$

Here τ indexes years since a grant was received.[21] A second test is to compare difference-in-difference estimates, which resemble equation (3) but only use data on downstream areas, against triple-difference estimates. A third test is to compare estimates of grants' effects on pollutants known to be related to treatment plants (e.g., BOD and dissolved oxygen) against estimated effects on other pollutants (e.g., lead, mercury, and phenols). A fourth test is to measure whether each additional grant (one, versus two, versus three, etc.) that a plant receives is associated with additional decreases in pollution. A fifth test is to assess sensitivity to adding controls for important potential confounding variables: population, industrial water pollution sources, and other air pollution regulations.[22]

Pass-through of Clean Water Act Grants to Municipal Expenditure

How does a dollar of Clean Water Act grants affect municipal spending on wastewater treatment? Grants could have complete pass-through, so a federal grant of one dollar increases municipal spending on wastewater treatment by a dollar. Grants could also have incomplete pass-through (crowding out municipal expenditure) or more than complete pass-through (crowding in).

We study this question primarily because it can increase the accuracy of cost-effectiveness and cost-benefit analyses. If, for example an additional dollar of federal grant funds lead cities to spend much less than a dollar on wastewater treatment, then the spending due to grants is much less than our cost data imply. The question of how federal grants affect municipal spending is also important in the fiscal federalism literature (see reviews in Oates (1999) and Lutz (2010)). Finally, this analysis provides some evidence on the quality of the grants data, since the grants data come from a completely different source than the municipal expenditure data.

To estimate the pass-through of Clean Water Act grants to local expenditure, we regress cumulative municipal sewerage capital expenditures E_{cy} in city c and year y on cumulative Clean Water Act grant

[20]In standard event study settings, one event time indicator must be excluded as a reference category. In our setting, a treatment plant can receive many grants, so no reference category is needed in estimating equation (4). To ease interpretation, we recenter graphs vertically so the time period before treatment has outcome zero.

[21]As in most event study analyses, only a subset of event study indicators are observed for all grants. Because most grants were given in the 1970s, we observe water pollution up to 10 years before and 15-25 years after most grants.

[22]Farms, confined animal feeding operations (CAFOs), and other agricultural or "non-point" sources are not a likely source of confounding variation during this time period since they were not regulated under the first few decades of the Clean Water Act. The Safe Drinking Water Act was passed in 1974, just after the Clean Water Act. It is not a likely source of confounding variation for several reasons. Its goal is to improve the quality of tap water, not ambient river water. It also focused on establishing water standards and overseeing local authorities that enforce those standards, rather than on providing grant funds to improve infrastructure.

dollars D_{cy} this city has received:

$$E_{cy} = \beta D_{cy} + \upsilon_c + \eta_{wy} + \epsilon_{cy} \tag{5}$$

The dependent and independent variables are cumulative because capital is a stock variable, and since local investment could occur in years after the grants are received. The regression includes city fixed effects υ_c and year fixed effects π_y. We also report specifications with river basin-by-year fixed effects η_{wy}. The value $\beta = 1$ implies complete pass-through (no crowding out or crowding in). Finding $\beta < 1$ implies incomplete pass-through (crowding out), while $\beta > 1$ implies more than complete pass-through (crowding in).

The definitions of these variables are important. Municipal expenditures E_{cy} include both expenditures funded by federal grants and those funded by other sources of revenue. As mentioned in Section 2.1, most grants require cities to pay 25 percent of the capital cost, though a small share require other copayments. We therefore report two sets of regressions—one where the variable D_{cy} includes only federal grant funds, and another where the variable D_{cy} includes both federal grant funds and the required municipal capital contribution. We also report specifications that weight by the inverse propensity score for inclusion in the balanced panel of cities, and discuss models controlling for population and city-year revenue.

4.3 Demand for Water Quality

Hedonic Model

A few definitions and a graph convey essential features of the hedonic model. A house i is described by a vector of its J different characteristics, $(z_1, \ldots, z_J)$. The home's price is $P_i = P(z_1, \ldots, z_J)$. The marginal implicit price of attribute j is the marginal change in home price due to a marginal increase in attribute j, all else constant: $P_{z_j} \equiv \partial P / \partial z_j$. The key feature of this hedonic price schedule $P(\cdot)$ is that it reflects the equilibrium of firms that supply housing and consumers that demand housing. We assume that housing markets are competitive and that each consumer rents one house.

Appendix Figure 8 illustrates. The curve θ_1 describes the bid function of one type of consumer. The bid function is the consumer's indifference curve in the tradeoff between the price of a home and the amount of attribute j embodied in the home. The curve θ_2 describes the bid function for another type of consumer. The curve ϕ_1 describes the offer function of a firm, and ϕ_2 of another firm. The offer function is the firm's isoprofit curve in the tradeoff between home price and attribute j.

The hedonic price schedule provides information about willingness-to-pay for amenity j because it reflects the points of tangency between consumer bid curves and firm offer curves. This implies that the marginal implicit price of an amenity at a given point on the hedonic price schedule equals the marginal willingness to pay of the consumer who locates on that point of the hedonic price schedule.

Econometrics: Demand for Water Quality

To analyze how Clean Water Act grants affected home values, we use a differences-in-differences estimate comparing the change in the log mean value of homes within an 0.25, 1, or 25 mile radius in any direction of the downstream river, before versus after the plant receives a grant, and between plants receiving grants in early versus late years. We use this specification because homes upstream of a wastewater treatment plant may also benefit from improvements in water quality downstream of the treatment plant. Residents travel for recreation, and while water pollution flows downstream, the benefits of water quality improvements may affect both downstream and upstream areas. As a sensitivity analysis, we also report triple-difference estimates comparing homes within a 25 mile radius of the upstream segments against homes within a 25 mile radius of the downstream segments.

Specifically, we estimate the following regression model:

$$V_{py} = \gamma G_{py} + X^{'}_{py}\beta + \eta_p + \eta_{wy} + \epsilon_{py} \tag{6}$$

Here G_{py} represents the cumulative number of grants received by plant p in year y, V_{py} is the log mean value of homes within a 0.25, 1, or 25 mile radius of the portion of the river that is 25 miles downstream of treatment plant p, η_p are plant fixed effects, and η_{wy} are river basin-by-year fixed effects. Some specifications include controls X_{py} for house structure characteristics. Other specifications add year 1970 characteristics interacted with indicators for the year y of the observation.[23] We estimate the change in total housing units and total value of the housing stock.

A few points are worth noting. First, we limit the analysis to housing units within a twenty-five mile radius of downstream waters. As discussed earlier, this is designed to cover roughly ninety-five percent of recreational trips. Second, we limit regression estimates to the set of tracts reporting home values in all four years 1970, 1980, 1990, 2000. When we fit the change in home values, we do so both for only the balanced panel of tract-years reporting home values, and for all tract-years. Third, because the differences-in-differences specification used for home values does not use upstream areas as a counterfactual, it involves the stronger identifying assumption that areas with more and fewer grants would have had similar home price trends in the absence of the grants.[24] Fourth, to obtain regression estimates for the average housing unit, and to provide an efficient response to heteroskedasticity, we

[23] Structure characteristics are allowed to have different coefficients in each year, and include the following: number of bedrooms, number of housing units in building, number of stories in building, heating fuel, cooking fuel, hot water fuel, heating equipment type, sewer type, plumbing type, year built, air conditioning, kitchen, number of bathrooms, and water access. All variables are expressed as share of housing units in a plant-year cell with the indicated characteristic. All categorical variables (e.g., number of bedrooms) are expressed as the share of housing units with each possible category. The 1970 characteristics are the following: distance to central business district (see Appendix B.5 for details of definition and construction); share of population that is black; share of population over age 65; share of population under age 6; share with a college degree; share on public assistance; income per family; and all the 1970 structure characteristics.

[24] We focus on specifications including basin-by-year fixed effects and the interaction of baseline characteristics with year fixed effects, as shown in equation (6). Estimates without the basin-by-year controls are more positive for home values but not rents, but they are also more sensitive to specification, which is one indication that the within-basin comparison of equation (6) provides sharper identification.

include generalized least squares weights proportional to the number of total housing units in the plant-year observation and to the sampling probability.[25]

Finally, these regressions estimate the effect of improvements to wastewater treatment on home values within 25 miles of downstream river areas. Wastewater treatment plants themselves may be a disamenity due to noise, smell, appearance, and other reasons. We report one set of estimates which excludes homes within a 1-mile radius of the wastewater treatment plant, which is likely to remove potential local disamenities of the treatment plant itself.

5 Water Pollution Trends

5.1 Main Results

We begin with the paper's first main research question: how has water pollution changed since the Clean Water Act? We find large declines in most pollutants the Clean Water Act targeted. Dissolved oxygen deficits, and the share of waters that are not fishable, both decreased almost every year between 1962 and 1990 (Figure 2). After 1990, the trends approach zero.

The graphs show no visually obvious evidence of a mean-shift or trend-break discrete change in water pollution around 1972. The lack of such a trend break, however, tells us little about the Clean Water Act's effects, since Clean Water Act investments may take time to affect water pollution, expanded steadily during the 1970s, and may be effective even if they are not visually obvious from a national time series. These graphs also suggest that existing evaluations of the Clean Water Act, which typically consist of national trend reports based on data from after 1972, may reflect forces other than the Clean Water Act. In fact, using national time series comparisons to evaluate the Clean Water Act could imply that it has been counterproductive, since the rate of decrease in pollution slowed after 1972.

Year-by-year trends for the other pollutants in the main analysis – the share of waters that are not swimmable, BOD, fecal coliforms, and TSS – all show similar patterns (Appendix Figure 4). All these pollutants have declined over time; their rates of decline have slowed; and no pollutant shows a clear trend break in 1972.

These graphs all show water pollution trends that have slowed over time, and it is interesting to consider why trends may have slowed. One possible explanation involves declining returns to pollution abatement. At the same time, much oxygen-demanding pollution comes from agriculture and other "non-point" sources, and those sources have remained largely unregulated. Another potential explanation for the slowing trends is that "fishable" and "swimmable" are binary criteria, and dissolved oxygen saturation does not much exceed 100 percent. This explanation may be relevant for those outcomes, but is less

[25] The census long form has housing data and was collected from one in six households on average, but the exact proportion sampled varies across tracts. A separate issue is that the hedonic model describes attributes of individual housing units, but we use data on mean characteristics of census tracts. This point is addressed by using generalized least squares and weighting regressions by the number of underlying housing units. This would be numerically equivalent in levels and is similar though not equivalent in logs; see Appendix B for details.

relevant to explain the slowing trends in continuous variables like BOD, fecal coliforms, or TSS, each of which had mean levels far above zero even in 2001.

Regressions with linear trend and trend break specifications underscore these findings, subject to the caveats mentioned earlier about the linear approximation to a non-linear trend and the long post period. The share of waters that are not fishable fell on average by about half a percentage point per year, and the share that are not swimmable fell at the same rate (Table 1, Panel A). In total over the period 1972-2001, the share of waters that are not fishable and the share not swimmable each fell by 11 percentage points. Each of the four pollutants which are part of these fishable and swimmable definitions declined rapidly during this period. Fecal coliforms had the fastest rate of decrease, at 2.8 percent per year. BOD, dissolved oxygen deficits, and total suspended solids all declined more slowly, at about 1.5 percent per year.

Trends in all these pollutants since the Clean Water Act are large, but trends before the Clean Water Act were larger (Table 1, Panel B). For example, BOD was falling by 3 percent per year before the Clean Water Act and 1.5 percent after it. We find pre/post 1972 trend breaks of comparable magnitudes for all the other pollutants. We interpret these pre-1972 trends somewhat cautiously since, as discussed earlier, relatively few monitoring sites recorded data before the 1970s, and fewer long-term monitoring sites operated in the 1960s (Appendix Table 1).

The graphs show the national mean pollution in each year, but they abstract from heterogeneity across different parts of the U.S. Appendix Figure 2 shows national maps of each pollutant in the final decade, 1992-2001, and also shows decade-by-decade maps for fecal coliforms. The regional patterns of each pollutant make sense. Dissolved oxygen deficits are most severe in the South, where temperatures are hottest. Fecal coliforms have the greatest concentrations in the Northeast and Industrial Midwest, where population densities are high. TSS has the greatest concentrations in the Midwest, which is unsurprising since much TSS comes from agriculture. Fecal coliform concentrations were much greater in the 1960s than in the 1990s. Decreases in fecal coliforms are clearest in the South and Far West, and less clear in the Industrial Midwest and Northeast.

Our finding of substantial decreases in water pollution is novel and noteworthy, but also for these reasons worth scrutinizing. We estimate an extraordinary array of sensitivity analyses, including restricting to high-quality subsamples of the data, adding important controls, weighting by population, and many others. Most of these alternative approaches have similar sign, magnitude, and precision as the main results. Appendix Table 3 shows these results and Appendix E.1 explains each.

5.2 Other Pollutants

To provide a more complete picture of trends in water quality, we now discuss trends in three other groups of water quality measures: industrial pollutants; nutrients; and general measures of water quality (Appendix Table 4).[26] All three industrial pollutants have been declining at a rapid annual rate. Lead's

[26] Appendix B describes the rule we use to choose indicators for this list; it mainly reflects the pollutants used in the EPA's (1974c) first major water pollution report after the Clean Water Act.

decrease of about 11 percent per year may be related to air pollution regulations, such as prohibiting leaded gasoline. The decline in mercury is noteworthy given the recent controversy of the Mercury and Air Toxics Standards (MATS) policy that would regulate mercury from coal-fired power plants. Some nutrients like ammonia and phosphorus are declining, while others like nitrates are unchanged. Nutrients were not targeted in the original Clean Water Act, but are the focus of current regulation. Temperature is increasing by about 1 degree F per 40 years, which is consistent with effects from climate change. Electricity generating units and other sources do contribute to thermal pollution in rivers, but it is noteworthy that rapidly increasing temperature is such an outlier from decreasing pollution trends in most other water pollutants.

pH trends are particularly interesting. pH increased by 0.007 pH units per year, meaning that waters became more basic (less acidic). Rainwater monitors that are not in our data record increases of similar magnitude in the pH of rainwater over this period, and attribute it to declines in atmospheric sulfur air pollution (USEPA 2007). This is consistent with the idea that decreases in acidic sulfur air pollution contributed to decreases in acid water pollution, and could completely explain these pH trends.

6 Clean Water Act Grants and Water Pollution

These trends suggest that many types of water pollution have declined since the 1970s. Many forces besides the Clean Water Act, however, could have caused some of these changes, including improving technology, declining manufacturing, Coasian bargaining with neighbors, other regulation, or others.[27] This section investigates the extent to which the Clean Water Act grants to treatment plants caused these changes.

The magnitude of these grants' effects on water pollution is completely unknown. Grant money could be ineffective or wasted due to perverse incentives. Investment in abatement technology does not necessarily improve pollution—the abatement technology might not function, or pollution may still flow to surface waters without receiving treatment (for example, through combined sewer overflows).

Appendix D provides evidence on pollution levels around wastewater treatment plants. Both graphs and tables show large and statistically significant increases in pollution as a river passes a treatment plant, which suggest that the data behave as one might expect.

6.1 Effects of Clean Water Act Grants on Downstream Pollution

We now turn to the paper's second main research question: how did these Clean Water Act grants affect water pollution? These estimates come from regressions corresponding to equation (3). We find that these grants cause large and statistically significant decreases in pollution (Table 2). Each grant decreases dissolved oxygen deficits by 0.8 percentage points, and decreases the probability that downstream waters are not fishable by 0.7 percentage points. The other pollutants decrease as well — BOD falls by about

[27] Air pollution emissions have also declined in recent decades, and environmental regulation rather than trade or productivity appears to account for much of that decline (Shapiro and Walker 2014).

3.4 percent, fecal coliforms fall by 8.5 percent, and the probability that downstream waters are not swimmable by about half a percentage point. The point estimate implies that each grant decreases TSS by one percent, though is imprecise. TSS comes primarily from non-point sources like agriculture and urban runoff, so is less closely related to municipal wastewater.

Event study graphs support these results. These graphs are estimated from specifications corresponding to equation (4).[28] In years before a grant, the coefficients are all statistically indistinguishable from zero, have modest magnitude, and have no clear trend (Figure 3). This implies that pollution levels in upstream and downstream waters had similar trends before grants were received. In the years after a grant, downstream waters have 1-2 percent lower dissolved oxygen deficits, and become 1-2 percent less likely to violate fishing standards. These effects grow in magnitude over the first ten years, are statistically significant in this period, and remain negative for about 30 years after a grant. The gradual effect of the grants is unsurprising since EPA estimates that it took two to ten years after a grant is received for construction to finish. The 30-year duration of these benefits is also consistent with, though on the lower end of, engineering predictions. Two studies both report that concrete structures of treatment plants are expected to have a useful life of 50 years but mechanical and electrical components have a useful life of 15-25 years (American Society of Civil Engineers 2011, p. 15; USEPA 2002, p. 11).

Event study graphs for other pollutants are consistent with these results, though are less precise (Appendix Figure 6). Before a plant receives a grant, each pollutant has fairly similar trends between upstream and downstream areas. After a plant receives a grant, pollution visually declines for the swimmable standard; though period-by-period event study graphs for other pollutants are too imprecise to be informative.

Appendix Figure 7 shows the effect of a grant by distance downstream from a treatment plant. Less data is available to estimate effects separately for each 5-mile bin along the river, so estimates are correspondingly less precise. Each point in these graphs represents the difference in pollution after minus before a grant is received, at a given distance from the treatment plant.

We also consider a wide variety of sensitivity analyses, including all the sensitivity analyses used for studying water pollution trends; different estimates by distance downstream; different types of grants and plants; using grant amounts in dollars rather than number of grants; controlling for important potential confounding variables; and other rules for sample construction. Appendix Table 6 shows the results, and E.2 discusses each. Again they generally give similar qualitative conclusions as the main results, though exact point estimates vary.

[28] As discussed earlier, the analysis includes plants that never received a grant (which have all event study indicators $1[G_{p,y+\tau} = 1]$ equal to zero), plants that received a single grant (which in any observation have only a single event indicator equal to one), and plants that received more than one grant (which in any observation can have several event indicators equal to one). Since no reference category is required in this kind of event study setting where one observation can receive multiple treatments, for ease of interpretation, we recenter the graph line so the coefficient for the year before treatment $(\tau - 1)$ equals zero. This implies that coefficients in the graph can be interpreted as the pollution level in a given year, relative to the pollution level in the period before the treatment plant received a grant.

6.2 Grants' Effects on Water Pollution: Cost-Effectiveness

We now turn to estimate the cost-effectiveness of these grants. The cost-effectiveness is defined as the annual public expenditure required to decrease dissolved oxygen deficits in a river-mile by 10 percentage points or to make a river-mile fishable. These calculations combine our regression estimates and the cost data.[29]

These estimates are important. Even without the hedonic estimates of the next section, one can combine cost-effectiveness numbers with estimates from other studies of the value of clean waters to obtain a cost-benefit analysis of these grants. Moreover, we are not aware of any existing ex post estimates of the cost required to make a river-mile fishable or to decrease dissolved oxygen deficits.

Taking the ratio of total costs to improved river-miles yields the cost to increase dissolved oxygen saturation in a river-mile by 10 percentage points. Column (1) of Table 3 includes only waters on the same river as the treatment plant, as our main regression sample does. Column (2) includes all downstream river segments, and column (3) assumes that every treatment plant has 25 miles of downstream waters affected. The simplest specification of column (1) implies that it cost \$0.57 million per year to increase dissolved oxygen saturation in a river-mile by ten percent; the broadest specification of column (3) implies that it cost \$0.54 million per year. The annual cost to make a river-mile fishable ranges from \$1.8 million in the simplest specification of column (1) to \$1.5 million in the richest specification of column (3). Column (3) implies that the grants program made 16,000 river-miles fishable.

A few notes are important for interpreting these statistics. First, this is the average cost to supply water quality via Clean Water Act grants; the marginal cost, or the cost for a specific river, may differ. The next subsection investigates heterogeneity directly. Second, measuring cost-effectiveness is insufficient to reach conclusions about social welfare. Knowing whether these expenditures increased social welfare requires knowing peoples' value for these changes, which is the question of Section 7. Third, if some grant expenditures were lost to rents (e.g., corruption), then those expenditures represent transfers and not true economic costs. EPA did audit grants to minimize malfeasance. In the presence of such rents, our analysis could be interpreted as a cost-effectiveness analysis from the government's perspective.

6.3 Heterogeneity in Grants' Effects on Water Pollution and Cost-Effectiveness

For policy, it would be useful to identify types of grants that are particularly cost-effective. For several attributes of grants, we therefore estimate regressions like equation (3), but include an additional inte-

[29] The cost-effectiveness estimates for fishable regressions are based on Appendix Table 6, Row 13. The main regression estimates in Table 2 reflect the change in the share of pollution readings that are fishable and do not distinguish between cases where the share of readings that are fishable moved from 20 to 21 percent, or where it changed from 80 to 81 percent. The statistic we use reflects the binary cutoff of whether a majority of readings are fishable, which is more easily used to interpret the cost of making a river-mile fishable.

raction of the main downstream×grants term with a given binary characteristic of grants.[30] Appendix B.8 describes how we measure these characteristics.

Columns (1)-(2) of Appendix Table 7 report these estimates, and columns (5)-(6) use these regressions along with data on grant costs to estimate cost-effectiveness. Row 1 repeats the estimates for all grants discussed earlier. Row 2 finds that grant projects above the median size ($1.2 million) cause larger decreases in pollution. Because these larger grants cost more, however, columns (5)-(6) suggest they are slightly less cost effective. Row 3 analyzes grants for plants that initially had more advanced (secondary or tertiary) abatement technology. If plants face increasing marginal abatement costs, then grants given to plants with better initial technology might be less cost-effective.[31] Row 3 does not provide evidence to support this hypothesis, and the point estimates actually suggest that grants to plants with tertiary technology are more cost-effective. These estimates are imprecise, however, and we interpret them cautiously given the very poor quality and limited availability of the data on abatement technologies (see Appendix B.8 for details). Row 4 suggests that grants to more polluted areas decrease pollution more and are slightly more cost-effective, perhaps because areas with low initial pollution cannot decrease pollution much. Row 5 suggests that grants to state-years with decentralization authority to manage NPDES permits are more effective, and slightly more cost-effective.

Rows 6-8 of Appendix Table 7 study three additional dimensions of heterogeneity which are more relevant to housing markets, so are more of a focus of Section 6.5. We discuss them briefly here. Row 6 finds that grants to counties with a large share of people who do outdoor fishing or swimming are significantly more cost-effective.[32] These counties are generally rural, so may face lower wage and construction costs. Row 7 finds that states with pro-environmental views have slightly more cost-effective grants. Row 8 considers two sets of cities highlighted in the urban economics literature—declining older cities (Glaeser and Gyourko 2005), and high amenity cities (Albouy 2016). Both groups of cities have low cost effectiveness. High amenity areas may face high wages and construction costs, while declining urban areas may have governments which are less effective at managing grants.

Overall, this evidence does not suggest dramatic heterogeneity in cost-effectiveness. Compared to the mean grant, grants to declining urban areas are significantly less cost-effective, while grants to the generally rural counties where many people go fishing or swimming are significantly more effective. Most others are statistically indistinguishable from the mean grant, though there is some moderate (if statistically insignificant) heterogeneity in point estimates.

[30] Formally, if Z_{py} is a characteristic of plant p in year y, we add the controls $G_{py}d_dZ_{py}$ and $Z_{py}\eta_{dy}$ to equation (3). The term $Z_{py}\eta_{dy}$ allows the downstream-by-year fixed effects to vary with the binary characteristic Z_{py}.

[31] Advanced abatement technologies can target pollutants which more basic abatement technologies do not target. So it is plausible that the marginal abatement cost curve for an individual emitted pollutant is increasing, but the curve for ambient levels of an omnibus measure of water pollution like dissolved oxygen or fishability is not substantially increasing over the range of technologies we observe.

[32] The measure of swimming includes only natural water bodies and excludes pools.

6.4 Pass-Through of Clean Water Act Grants to Municipal Expenditure

We now study how grants affect municipal spending on wastewater treatment. This helps interpret our cost-effectiveness numbers since crowding out or in would change a grant's effective cost.

Table 4 reports estimates corresponding to equation (5). In Panel A, the main explanatory variable excludes required municipal contributions, while Panel B includes them. Column (1) reports a basic differences-in-differences regression with nominal dollars. Column (2) uses real dollars. A city may spend a grant in years after it is received, so real pass-through may be lower than nominal pass-through. Column (3) adds river basin-by-year fixed effects. Column (4) reweights estimates using the inverse of the estimated propensity score for inclusion in the balanced panel of cities.

The estimates in Table 4 are generally consistent with near complete pass-through, i.e., little or no crowding out or in beyond the required municipal capital copayment. Panel A does estimate pass-through above one, but this is expected since Panel A excludes the required municipal copayment. The Panel A pass-through estimates range from 1.15 to 1.27 in real terms or 1.53 in nominal, which mean that city expenditure increased by around the amount of the typical copay (which was typically a third of the federal grant). Panel B of Table 4 includes the local copayment in the main explanatory variable, and the estimates imply pass-through rates of 0.86 to 0.94 in real terms or 1.09 in nominal terms. The point estimates are near one, and all of these estimates are within a standard deviation of one, so fail to reject the hypothesis that the municipal wastewater investment exactly equals the cost listed in the grant project data.[33]

We emphasize a few caveats in interpreting Table 4. First, the analysis is based on only 199 cities. The inverse propensity score reweighted estimates are designed to reflect the entire population of US cities, though interpretation of these estimates should bear in mind their limited sample. Second, this city-level difference-in-difference estimate cannot use the upstream-downstream comparison that sharpens identification for the pollution estimates. The basin-by-year fixed effects and population and city revenue covariates do provide some additional useful controls.

Third, this analysis is different from the question of what municipal spending (and pollution and home values) would be in a world without the Clean Water Act. Our estimates are consistent with no crowdout for an individual grant, but it is plausible that the existence of the Clean Water Act decreases municipal investment in wastewater treatment in aggregate. Jondrow and Levy (1984) and CBO (1985) report national time-series patterns of municipal spending on sewerage capital and federal grants. Identification from a national time series is not especially compelling, since other national shocks like the 1973-5 and early 1980s recessions, high inflation, high interest rates, and the OPEC crisis make the 1960s a poor

[33]We also explored estimates controlling for city-year population or city-year municipal revenue. These controls could help address possible omitted variables bias due to city growth in these differences-in-differences regressions, but population and especially city-year total expenditure are potentially a case of bad controls (Angrist and Pischke 2009) since they are potentially affected by grants. Adding population or city revenue controls to the specification of column (4) in Table 4 gives estimates of 1.22 (0.30) or 0.91 (0.18) for Panel A, and 0.92 (0.22) or 0.68 (0.13) for Panel B. We discuss a range of pass-through estimates including these for cost-effectiveness and cost-benefit analysis.

counterfactual for the 1970s and 1980s.[34] But their data suggest that nationally, municipal revenue dedicated to wastewater capital spending was increasing in the 1960s and decreasing after 1972, which is consistent with aggregate crowdout. Combining the results of Table 4 with these patterns suggests that once the Clean Water Act began, cities became less likely to spend municipal funds on wastewater treatment capital. In this sense, the existence of the Clean Water Act did crowd out aggregate municipal investment in wastewater treatment. But municipal investments that occurred were closely connected to federal grant funds, and our point estimates imply that the level of grant costs reported in our data accurately represents the actual change in spending.[35]

Given these caveats, we now discuss how our cost-effectiveness estimates would change under different assumptions about crowd out.[36] Table 3 shows that it costs \$0.5 million annually to increase dissolved oxygen saturation in a river-mile by 10 percent, and \$1.5 million annually to make a river-mile fishable. Our real pass-through point estimate of 0.91 from column (4) of Table 3 implies cost-effectiveness numbers of \$0.45 million for oxygen and \$1.35 million for the fishable standard. The 95 percent confidence region for our real pass-through estimate ranges from 0.50 to 1.32, which implies a range of cost-effectiveness values between \$0.25 million and \$0.66 million for oxygen, and between \$0.75 million and \$1.98 million for fishable. All these estimates represent the cost per year to make a river mile fishable or to increase dissolved oxygen saturation by 10 percent for a year.

7 Demand for Water Quality

This analysis has shown that water pollution has declined dramatically over time and that the Clean Water Act grants contributed to this decline. We now turn to study how people valued these grants. We separate the analysis into several components. First, we discuss the main results. Second, we compare the effects of these grants on housing values to the grants' costs. Third, we assess heterogeneity in all these estimates. Finally, we discuss reasons why these estimates might be interpreted as a lower bound on willingness to pay.

7.1 Main Results

Table 5 analyzes how Clean Water Act grants affect housing. Column (1) shows estimates for homes within a quarter mile of downstream waters. Column (2) adds controls for dwelling characteristics, and for baseline covariates interacted with year fixed effects. Column (3) include all homes within 1 mile, and

[34] For example, a national trend-break time series analysis of our water pollution trends based on Figure 2 would suggest that the Clean Water Act actually increased water pollution, whereas our panel data analysis suggests the opposite.

[35] One story consistent with aggregate crowdout but no marginal crowdout is that for important wastewater treatment capital investments, cities invest when they get a grant, and they invest the grant amount. The existence of the grants program might deter cities from making these investments unilaterally, and so discourages municipal expenditure overall. This is the "aggregate crowd-out." But receiving an individual grant does not cause cities to provide funds beyond the required copay, and also does not discourage other small non-grant investments the city planned to make.

[36] See Kline and Walters (Forthcoming) for a related analysis in education.

column (4) includes homes within 25 miles.

Panel A reports estimates of how grants affect log mean home values. The positive coefficients in the richer specifications of columns (2) through (4) are consistent with increases in home values, though most are statistically insignificant. Column (4) implies that each grant increases mean home values within 25 miles of affected waters by three hundredths of a percentage point. The 0.25 or 1.0 mile estimates are slightly larger than the 25 mile estimate, which is consistent with the idea that residents nearer to the river benefit more from water quality. Panel B analyzes how grants affect log mean rental values. These estimates are generally smaller than the estimates for housing. The estimate in column (4), including homes within a 25 mile radius of downstream rivers, is small but actually negative.

Panels A and B reflect the classic hedonic model, with fixed housing stock. Panels C and D estimate the effect of grants on log housing units (panel C) or the log of the total value of the housing stock (panel D). In the presence of elastic housing, measuring only price effects (as in Panels A and B) could understate willingness-to-pay for local amenities. Moreover, many cities have had substantial waterfront development, which could be related to water quality.

Panels C and D suggest similar conclusions as Panels A and B. Most of these estimates are small and actually negative. One is marginally significant (Panel C, column 1), though the precision and point estimate diminish with the controls of column (2). Column (4) in of Panel D literally implies that each grant decreases the total value of the housing stock within a 25 mile radius of downstream waters by one point five hundredths of a percentage point.

Figure 4 shows event study graphs, which suggest similar conclusions as these regressions. Panel A shows modest evidence that in the years after a plant receives a grant, the values of homes within 0.25 miles of the downstream river increase. The increases are statistically insignificant in most years and small in magnitude. Panel B shows no evidence that homes within 25 miles of the downstream river increase after a treatment plant receives a grant.

We also report a range of sensitivity analyses, which are broadly in line with the main results. Estimates appear in Appendix Table 8 and discussion appears in Appendix E.3.

7.2 Measured Benefits and Costs

We now compare the ratio of a grant's effect on housing values (its "measured benefits") to its costs. The change in the value of housing is estimated by combining the regression estimates of Table 5 with the baseline value of housing and rents from the census. Grant costs include local and federal capital expenditures plus operating and maintenance costs over the 30 year lifespan over which we estimate grants to affect water pollution. We deflate operating and maintenance costs and rents at a rate of 7.85 percent (Peiser and Smith 1985).[37]

Column (1) of Table 6 includes only owned homes within a 1 mile radius of the downstream river segments; column (2) includes homes within a 25 mile radius; and column (3) adds rental units. The

[37]We include all capital and operating and maintenance costs in the measure of total grant project costs. The tables separately list the different components of costs, and Section 7.4 discusses possible effects of these costs on local taxes or fees.

1970 and 1980 censuses failed to define tracts for non-metro areas, so we lack home values and rents for these areas. Column (4) includes these non-metro areas by imputing home values and number of housing units for each non-metro tract in 1970 and 1980 as fitted values from a panel regression of log mean home values on year fixed effects and tract fixed effects.

Considering all owner-occupied homes within 25 miles of the river, the estimated ratio of the grants' aggregate effects on home values to the grants' costs is 0.25. Adding rental units in column (3) does not change this estimate out to two decimal points (though does at further decimals). The main regression sample includes only a balanced panel of tracts that appear in all four censuses between 1970-2000; imputing values for missing homes hardly changes the ratio in column (4). These confidence regions do not reject the hypothesis that the ratio of the change in home values to the grants' costs is zero. All four columns, however, reject the hypothesis that the change in home values equals the grants' costs.

We also consider alternative assumptions on the timing of homeowner beliefs. As discussed in Appendix B.5, evidence suggests that people may slowly update beliefs about housing values to reflect local public goods. We address this possibility in three alternative estimates. The first applies the change in rental values, which may more quickly reflect changes in local public goods, to both the value of owner-occupied and rented housing. Tenants do receive tenure discounts, though we are not aware of evidence that such discounts are systematically related to changes in local public goods. Second, we allow ten years for the effect of grants on home values to appear; formally, we define the cumulative number of grants relevant to home prices or rents in year t as the number of cumulative grants observed in year $t-10$ (Appendix Table 8, row 11). Third, we combine these approaches and apply estimated effects of grants on log rents to both rented and owner-occupied housing, but allow ten years for rents to reflect the effect of grants. Under these three approaches, the ratios of measured benefits to costs are -0.11 (0.16), 0.11 (0.31), and 0.11 (0.10), respectively. These are broadly similar to the main results.

7.3 Heterogeneity in Measured Benefits and Costs

We now analyze variation across groups of grants in the ratio of a grant's measured benefits to its costs. This is useful to determine what types and levels of investment may be particularly valuable. For several attributes of grants, we therefore estimate regressions like equation (6), but include an additional interaction of the main grants term with a given binary characteristic of grants.[38]

Columns (3) and (4) of Appendix Table 7 show regression estimates which allow the hedonic price function to differ across census regions and other divisions of the data. Column 7 shows the ratio of measured benefits to costs. Row 1 restates numbers for all grants, shown earlier. Rows 2-5 consider heterogeneity most relevant for grants' effects on pollution. The ratio of measured benefits to costs is not significantly different from that of the average grant for any of these rows. Row 6 considers grants to areas where a large share of people go fishing or swimming. The ratio of measured benefits to costs here is double the ratio for the mean grant. Row 7 finds that grants to states with pro-environmental views

[38]Formally, if Z_{py} is a characteristic of plant p in year y, we add the controls $G_{py}Z_{py}$ and $Z_{py}\eta_y$ to equation (3). The term $Z_{py}\eta_y$ allows year fixed effects to vary with the binary characteristic Z_{py}.

also have a greater ratio than that of the mean grant. Row 8 finds that grants to declining urban areas (Glaeser and Gyourko 2005) have slightly lower ratios, while the ratio for high amenity areas (Albouy 2016) is greater. Finally, row 9 tests for differences in the housing market response by census region. This specification finds that grants to the Northeast have smaller ratios, while grants to the south have larger ratios around 0.73. None of these ratios in rows 6-9 are significantly different than that of the mean grant.

The map in Appendix Figure 10 shows heterogeneity in the ratio of measured benefits to costs across U.S. counties. This map assumes the same hedonic price function nationally and reflects spatial heterogeneity in the density of housing units. Specifically, these estimates divide treatment plants into ten deciles of the number of people in 2000 living within 25 miles of downstream river segments. They then use the regression estimates from column 4 of Table 5 to calculate the ratio of the change in the value of housing and grant costs, separately for each decile.[39] Finally, we average this ratio across all plants in each county. The map shows that the ratio of measured benefits to costs is much larger in more populated counties. The bottom decile of counties, for example, includes ratios of measured benefits to costs of below 0.01. The top decile of counties includes ratios between 0.31 and 0.45. Grants and population are both highly skewed—37 percent of grant costs and 54 percent of population are in the top decile.

We take three overall conclusions from this analysis of heterogeneity. First, we find suggestive evidence that ratios of measured benefits to costs follow sensible patterns, though not all estimates are precise. Second, none of these subsets of grants considered has a ratio of measured benefits to costs above one, though many of the confidence regions cannot reject a ratio of one. The largest ratios of estimated benefits to costs are for areas where outdoor fishing or swimming is common (ratio of 0.57), for high amenity urban areas (ratio of 0.63), and in the South (ratio of 0.74). Third, the predictable spatial variation in the net benefits of water quality variation suggests that allowing the stringency of regulation to vary over space might give it greater net benefits (see related arguments for air pollution in Muller and Mendelsohn (2009)). For example, U.S. regulators are actively considering cap-and-trade systems for water pollution, and the heterogeneity described here could give a reason to investigate non-uniform trading ratios which account for non-uniform spatial benefits of water pollution (see Fowlie and Muller (2013) for another air pollution application).

7.4 Interpreting Hedonic Estimates

The previous subsections obtained point estimates implying that Clean Water Act grants increased housing values, though the increase is generally smaller than the cost of the average grant. A natural question is how to interpret these estimates. We now discuss five reasons why these estimates may not reflect the full benefits of these grants. We believe these reasons provide support for interpreting the

[39] We also investigated estimates of equation (6) which allowed interaction terms for each of the ten deciles. These estimates of the effect of grants on housing and rents were not significantly different across the deciles. It is worth emphasizing that Appendix Figure 10 assumes the same hedonic price function in all regions but accounts for differences in the number of local residents; Appendix Table 7, by contrast, tests whether the hedonic price function varies across regions, and does not find statistically significant differences.

hedonic estimates as a lower bound on total benefits.[40]

First, people might have incomplete information about changes in water pollution and their welfare implications. Cross-sectional and time series analyses do find statistically significant though imperfect correlation between perceived local water pollution, as reported in surveys, and objectively measured local water pollution (Faulkner, Green, Pellaumail, and Weaver 2001; Poor, Boyle, Taylor, and Bouchard 2001; Jeon, Herriges, Kling, and Downing 2005; Steinwender, Gundacker, and Wittmann 2008; Artell, Ahtiainen, and Pouta 2013). Residents may observe indirect signals of polluted water, such as fish kills (dead fish floating on the water or sitting on the bank), algae blooms, sulfurous odors like rotten eggs, miscolored waters, and may learn about pollution directly from waterfront warning signs, news coverage, and publicity. People who go fishing value actually catching fish, so if pollution decreases the number of fish someone can catch, then water pollution may discourage fishing.

Incomplete information would be especially important if pollution abatement improves health. A direct analysis of the relationship between surface water quality and health would have more potential in recent years when more extensive health data with detailed geographic identifiers are available. Misperception would be less important if most benefits of surface water quality accrue through recreation or ambiance, since failing to perceive water pollution through any means (including the absence of fish) would mean its effects on recreational demand are limited. Most recent cost-benefit analyses of the Clean Water Act do estimate that a substantial share of benefits come from recreation and ambiance channels (Lyon and Farrow 1995; Freeman 2000; USEPA 2000a). Cropper and Oates (1992) in fact describe the Clean Water Act as the only major environmental regulation of the 1970s and 1980s which does not have health as its primary goal.

Second, these hedonic regressions may include some reasons for which people value water quality, including recreation and aesthetics, though not all. One category not counted in these estimates is "nonuse" or "existence" values. A person may value a clean river even if that person never visits or lives near that river. As mentioned in the introduction, the measurement of nonuse values has been controversial and faces severe challenges. The controversy is not over whether nonuse values exist; it is straightforward to explain their place in economic theory (Diamond and Hausman 1993). Instead, the controversy is over the extent to which stated preference or contingent valuation methods accurately reflect nonuse values. We recognize both the potential importance of nonuse values for clean surface waters and the severe challenges in accurately measuring these values.[41] Several other categories potentially not measured here include the value for commercial fisheries, industrial water supplies, lower treatment costs for drinking water, and safer drinking water.[42] Evidence on the existence and magnitude of the benefits

[40] Appendix F discusses several additional reasons which we believe have weaker support. These reasons include: changes in housing supply or resident characteristics; local taxes or fees; inattention to recreation; or homeowner advanced expectations about grants.

[41] The USEPA's (2000a) cost-benefit analysis of the Clean Water Act does estimate that nonuse values are about a sixth as large as use values. A meta-analysis of 131 estimates from 18 studies that compares use and nonuse values for water pollution also estimates that nonuse values are about a third as large as use values (Houtven, Powers, and Pattanayak 2007). These analyses, however, are subject to the same kinds of serious concerns about both use and non-use estimates in the underlying studies.

[42] Flint, Michigan, has recently had high lead levels in drinking water due to switching its water source from the Detroit River

from these other channels is limited, though as mentioned above, recreation and aesthetics are believed to account for a large majority of the benefits of clean surface waters.

Third, this analysis abstracts from general equilibrium changes. One possible channel is that wages change to reflect the improvement in amenities (Roback 1982). A second general equilibrium channel is that the hedonic price function may have shifted. In the presence of such general equilibrium changes, our estimates could be interpreted as a lower bound on willingness to pay (Banzhaf 2015).

Other possible general equilibrium channels describe reasons why the effects of cleaning up an entire river system could differ from summing up the effects of site-specific cleanups. One channel involves substitution. Rivers can be thought of as a differentiated product. Cleaning up part of a river in an area with many dirty rivers might have different value than cleaning up a river in an area with many clean rivers. Another possible channel involves ecology. The health of many aquatic species (so indirectly, the benefit people derive from a river) may depend nonlinearly on the area of clean water. Ecologists have well established that the growth rate of a population is an inverted U-shaped function of the population's size (Allee 1938), and the population size may depend on the area of clean river. Our approach focuses on the effects of cleaning up an individual site and is not as well suited to capture the potentially distinct effects of cleaning up entire river systems, though this is a potentially fruitful topic for future study.

Fourth, the 25 mile radius is only designed to capture 95 percent of recreational trips. The magnitude of benefits from the remaining 5 percent of trips is unclear; the last 5 percent of trips might account for more than 5 percent of the total surplus from recreational demand because they represent people willing to travel great distances for recreation. Alternatively, the most distant travelers might be the marginal participants in recreation, and the inframarginal people who derive the most surplus from water-based recreation may be those who choose to live nearer to recreational areas. Our recreation data also represent all trips, and water-based recreation trips might require different travel distances.

Finally, while our pass-through estimates suggest that an individual grant did not cause substantial crowd-out or crowd-in of municipal spending, we interpret this estimate cautiously since it reflects only 199 cities, does not use upstream waters as a comparison group, and reflects pass-through of marginal changes in investment, rather than the entire Clean Water Act.

Considering alternative pass-through values helps interpret these results. The point estimate in column (4) of Table 4 implies that each dollar of federal grants leads to 91 cents of additional municipal capital spending. In terms of Table 6, this point estimate of pass-through would imply that the ratio of the change in housing values to costs is 0.31. The 95 percent confidence interval of our pass-through estimate ranges from 0.50 to 1.32; in terms of Table 6, this implies the ratio of the change in housing values to costs ranges between 0.21 and 0.56. Alternatively, one way to assess the importance of crowdout is to ask: what value of pass-through would be needed to make the change in housing values exceed costs? Table 6 implies that for any pass-through rate above 0.28, costs exceed the change in housing values.

to the Flint River. The Flint River has high chloride levels due partly to natural salt levels and to road salt. The chloride causes service lines to leech lead. Flint potentially could have prevented these problems by adding corrosion inhibitors (e.g., orthophosphate), which are used in many cities including the Detroit water that Flint previously used, at cost of around \$100/day. Drinking water treatment falls under a separate set of regulations, the Safe Drinking Water Act.

8 Conclusions

The 1972 Clean Water Act is among the largest and most controversial regulations in U.S. history. The U.S. has spent more money abating water pollution than abating air pollution, even though economic research on the willingness to pay for air quality regulation is well-established and research on the value of water pollution regulation is more limited.

This paper assembles an array of new data to assess water pollution's trends, causes, and welfare consequences. We find that by most measures, U.S. water pollution has declined since 1972, though was declining at an even faster rate before 1972. The share of waters that are fishable has grown by over 10 percentage points since the Clean Water Act.

We study $680 billion in expenditure due to 35,000 grants the federal government gave cities to improve wastewater treatment plants. Each grant significantly decreased pollution for 25 miles downstream, and these benefits last for around 30 years. We find weak evidence that local residents value these grants, though estimates of increases in housing values are generally smaller than costs of grant projects.

These estimates may provide a lower bound on willingness to pay for water quality since they abstract from several other potential channels of demand for surface water quality, including nonuse ("existence") values, general equilibrium effects, and the roughly five percent longest recreational trips. The point estimates imply that the benefits of the Clean Water Act's municipal grants exceed their costs if these unmeasured components of willingness to pay are three or more times the components of willingness to pay that we measure. As mentioned in the introduction, other recent analyses estimate benefits of the Clean Water Act that are smaller than its costs, though these other estimates note that they may also provide a lower bound on benefits. For example, the U.S. Environmental Projection Agency (2000a; 2000c) suggests that the cost-benefit ratio of the Clean Water Act is below 1, though the EPA's preferred estimate of the cost-benefit ratio of the Clean Air Act is 42 (USEPA 1997).[43]

Our analysis does not directly explain such different findings for the Clean Water and Clean Air Acts. But it may be useful to highlight differences in how these laws answer four important questions about environmental regulation. These comparisons also highlight features of the Clean Water Act which are not widely recognized and could lead it to have lower net benefits than some other environmental regulation.

First is the choice of policy instrument. Market-based instruments are believed to be more cost-effective than alternatives. Parts of the Clean Air Act use cap-and-trade systems, but nearly none of the Clean Water Act does. The grants we study actually subsidize the adoption of pollution control equipment, which is a common policy globally that has undergone little empirical economic analysis.

A second question is scope. Cost-effective regulation equates marginal abatement costs across sources, which requires regulating all sources. The Clean Air Act covers essentially all major polluting sectors. The Clean Water Act, by contrast, mostly ignores "non-point" pollution sources like agriculture. Ignoring such a large source of pollution can make aggregate abatement more costly.

[43] Analyses of the Clean Air Act relying solely on hedonic estimates generally have smaller cost-benefit ratios; the EPA's cost-benefit numbers for air pollution rely heavily on estimated mortality impacts.

A third question involves substitution. Optimizing consumers should equate the marginal disutility of pollution to the marginal cost of protection from pollution. People breathe the air quality where they live, and relocating to another airshed or some other defenses against air pollution are costly (Deschenes, Greenstone, and Shapiro 2013). For water pollution, however, people can more easily substitute between nearby clean and dirty rivers for recreation.

A fourth question involves health. Air is typically unfiltered when it is inhaled, so air pollution is believed to have large mortality consequences that account for much of the benefits of air pollution regulation. Surface waters, by contrast, are typically filtered through a drinking water treatment plant before people drink them. Most analyses of recent U.S. water quality regulation count little or no direct benefit from improving human health (Lyon and Farrow 1995; Freeman 2000; USEPA 2000a; Olmstead 2010).[44]

Finally, we note one similarity between and air water pollution that may be relevant to policy design. We find some evidence that the net benefits of Clean Water Act grants vary over space in tandem with population density and the popularity of water-based recreation. Related patterns have been found for air pollution, and suggest that allowing the stringency of pollution regulation to vary over space might have potential to produce welfare gains.

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[44] This may contrast with the regulation of surface water quality in developing countries and in the historic U.S. (Ebenstein, 2012; Alsan and Goldin, 2015), both cases where drinking water was less well filtered, piped water access less widespread, and stringent regulatory standards for coliforms and other bacteria in drinking water were less common or less well enforced.

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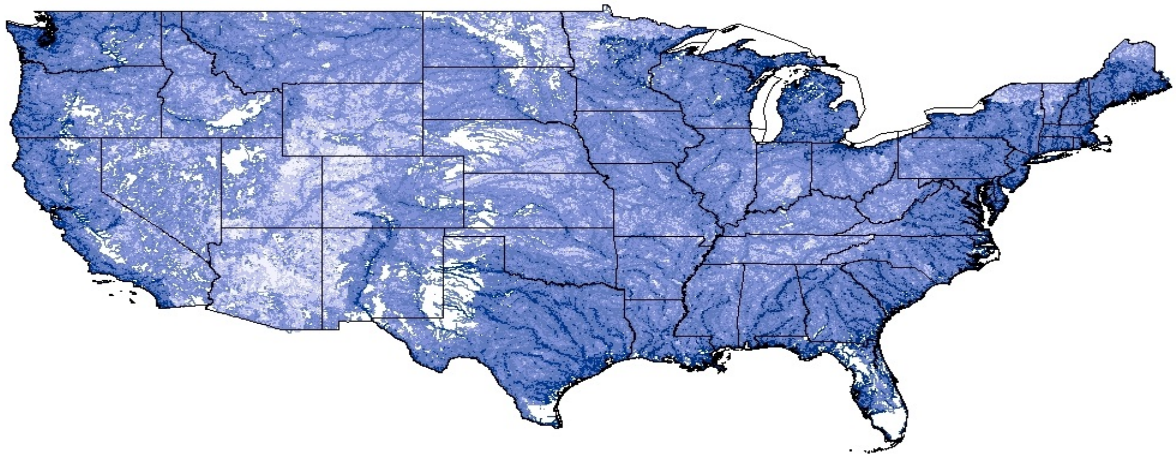
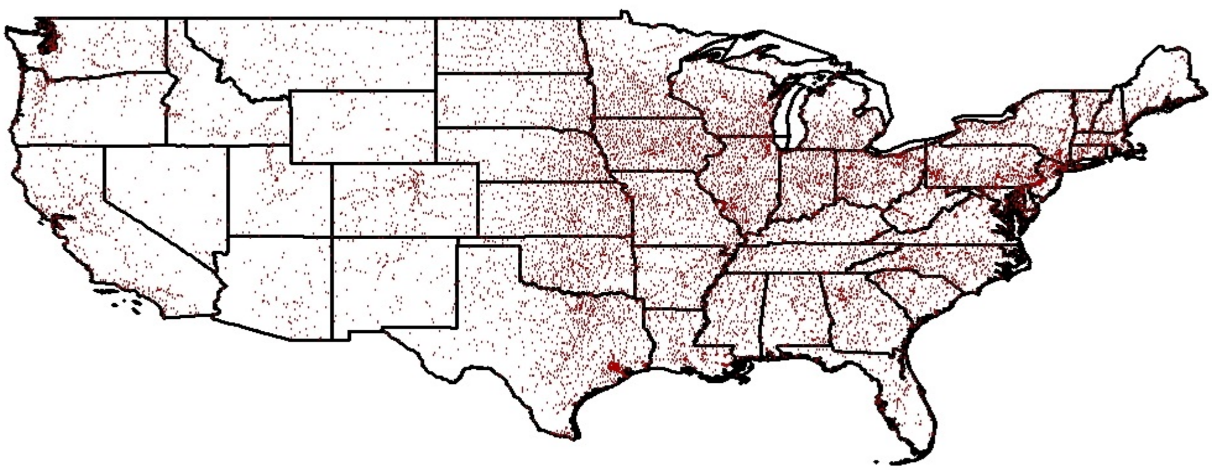
Figure 1. National Maps of Water Pollution Data

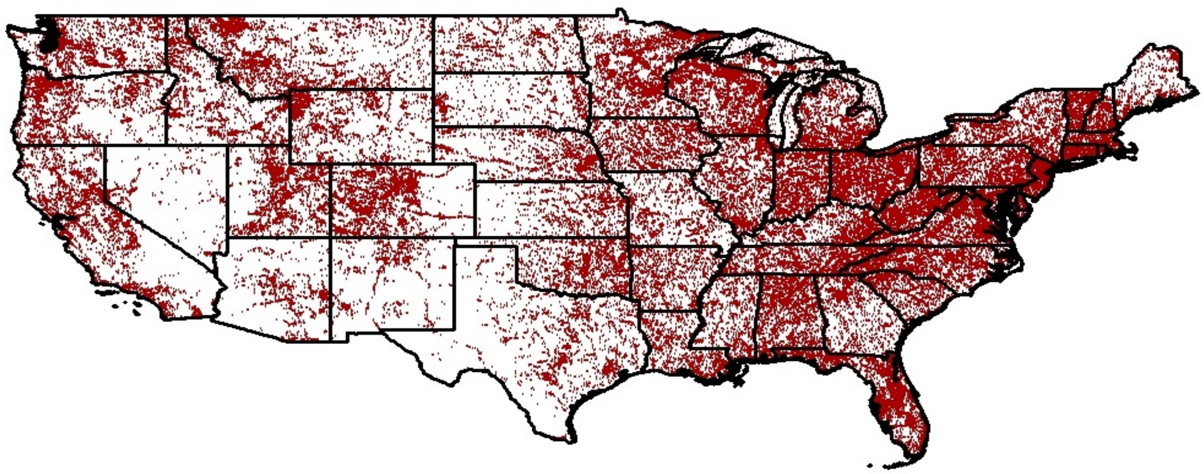
Panel A. The River and Stream Network



Panel B. Wastewater Treatment Plants



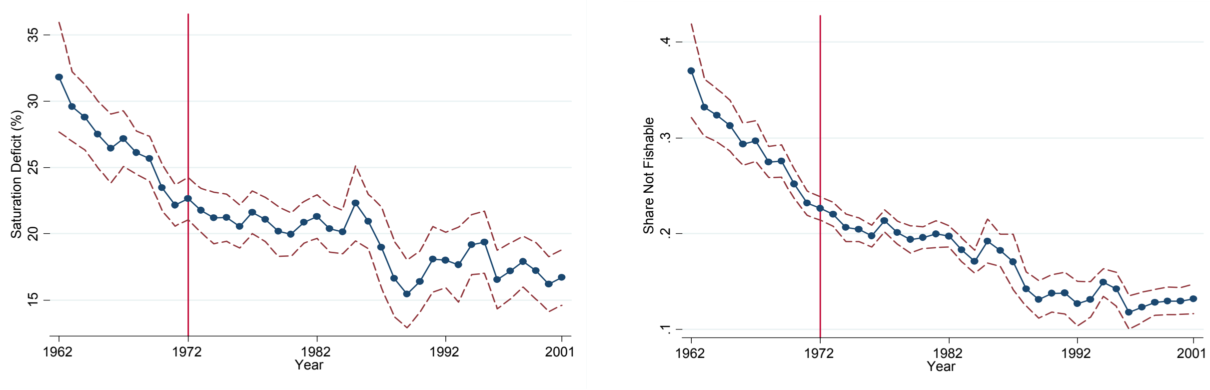
Panel C. Water Pollution Monitoring Sites



Notes: In Panel A, rivers are colored by Stream Level from the National Hydrography Dataset. Streams that flow into oceans, Great Lakes, Canada or Mexico and are the darkest. Streams that flow into these are lighter; streams that flow into these are still lighter, etc. Panel C shows monitoring sites appearing in years 1962-2001.

Figure 2. Water Pollution Trends, 1962-2001

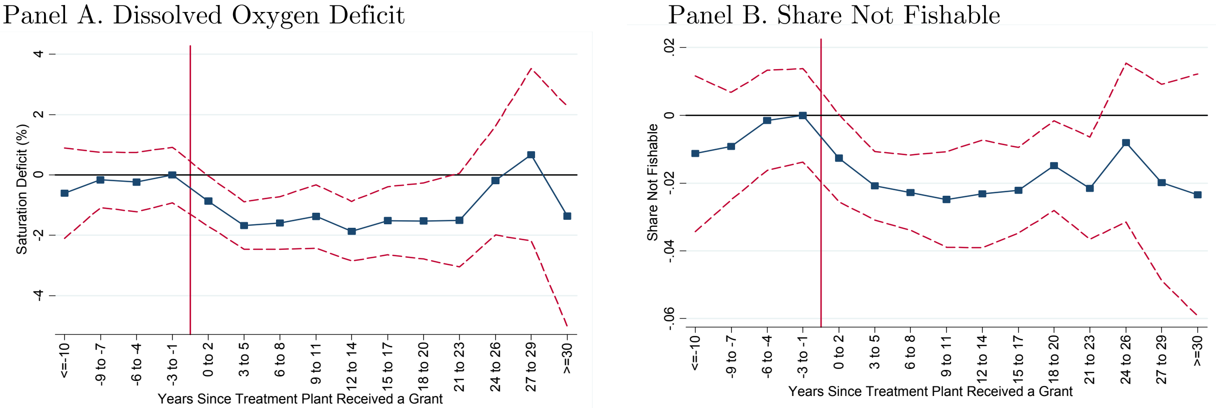
Panel A. Dissolved Oxygen Deficit Panel B. Share Not Fishable



Notes: Graphs show year fixed effects plus a constant from regressions which also control for monitoring site fixed effects, a day-of-year cubic polynomial, and an hour-of-day cubic polynomial, corresponding to equation (2) from the text. Connected dots show yearly values, dashed lines show 95% confidence interval, and 1962 is reference category. Standard errors are clustered by watershed.

Figure 3. Effects of Clean Water Act Grants on Water Pollution: Event Study Graphs

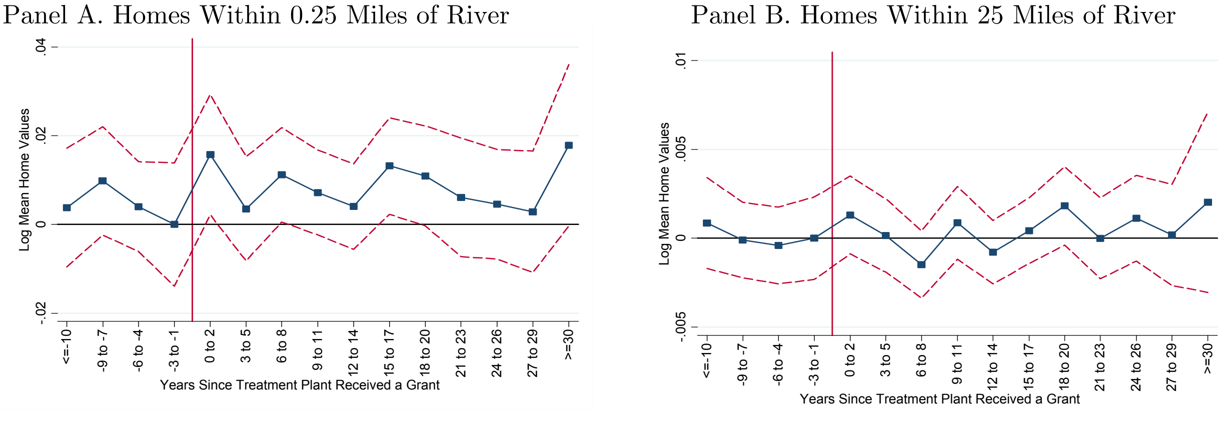
Panel A. Dissolved Oxygen Deficit Panel B. Share Not Fishable



Notes: Graphs show coefficients on downstream times year-since-grant indicators from regressions which correspond to the specification of Table 3. These regressions are described in equation (5) from the main text. Data cover years 1962-2001. Connected dots show yearly values, dashed lines show 95% confidence interval. Standard errors are clustered by watershed.

Figure 4. Effects of Clean Water Act Grants on Log Mean Home Values: Event Study Graphs

Panel A. Homes Within 0.25 Miles of River Panel B. Homes Within 25 Miles of River



Notes: Graphs show coefficients on year-since-grant indicators from regressions corresponding to the specification of Table 6, column (3). Connected dots show yearly values, dashed lines show 95% confidence interval. Standard errors are clustered by watershed. Panels A and B show different ranges of values on their y-axes. Data cover decennial census years 1970-2000.

Table 1. Water Pollution Trends, 1962-2001

	Main Pollution Measures		Other Pollution Measures			
	Dissolved Oxygen Deficit	Not Fishable	Biochemical Oxygen Demand	Fecal Coliforms	Not Swimmable	Total Suspended Solids
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Linear Trend						
Year	-0.234***	-0.004***	-0.064***	-83.716***	-0.004***	-0.831***
	(0.0298)	(0.0003)	(0.0052)	(8.6031)	(0.0003)	(0.1006)
Panel B. 1972 Trend Break						
Year	-0.866***	-0.013***	-0.132***	-274.358***	-0.015***	-0.448
	(0.132)	(0.001)	(0.020)	(81.556)	(0.002)	(0.494)
Year *	0.683***	0.009***	0.072***	198.346**	0.012***	-0.398
1[Year>=1972]	(0.143)	(0.002)	(0.021)	(80.537)	(0.002)	(0.507)
1972 to 2001 change	-5.297	-0.111	-1.724	-2204.347	-0.106	-24.532
	(0.933)	(0.009)	(0.155)	(240.044)	(0.010)	(2.994)
N	5,551,888	10,558,704	1,246,679	2,016,952	10,558,704	1,693,303
Dep. Var. Mean	17.83	0.25	4.04	2,994.39	0.50	49.64
Monitor Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Season Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time of Day Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each observation in the data is a pollution reading. Data includes years 1962-2001. Dissolved oxygen deficit equals 100 minus dissolved oxygen saturation, measured in percentage points. Season controls are a cubic polynomial in day of year. Time of Day controls are a cubic polynomial in hour of day. In Panel B, the year variables are recentered around the year 1972. The 1972 to 2001 change equals the fitted value Year*39 + Year*1[Year≥1972]*39. Dependent variable mean refers to years 1962-1971. Standard errors are clustered by watershed. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Table 2. Effect of Clean Water Act Grants on Water Pollution

	Main Pollution Measures		Other Pollution Measures			
	Dissolved Oxygen Deficit	Not Fishable	Biochemical Oxygen Demand	Fecal Coliforms	Not Swimmable	Total Suspended Solids
	(1)	(2)	(3)	(4)	(5)	(6)
Downstream	-0.770***	-0.007**	-0.113**	-189.389**	-0.004**	-0.410
* Cumul. # of Grants	(0.192)	(0.003)	(0.047)	(77.401)	(0.002)	(0.675)
N	55,240	59,490	28,270	33,884	59,490	29,992
Dep. Var. Mean	11.882	0.288	3.308	2202.363	0.559	43.942
Fixed Effects:						
Plant-Downstream	Yes	Yes	Yes	Yes	Yes	Yes
Plant-Year	Yes	Yes	Yes	Yes	Yes	Yes
Downst.-Basin-Year	Yes	Yes	Yes	Yes	Yes	Yes
Weather	Yes	Yes	Yes	Yes	Yes	Yes

Dissolved oxygen deficit equals 100 minus dissolved oxygen saturation, measured in percentage points. Dependent variable mean describes upstream mean. Standard errors are clustered by watershed. Asterisks

Table 3. Cost Effectiveness of Clean Water Act Grants ($2014 Mn)

	(1)	(2)	(3)
Annual Cost to Increase Dissolved Oxygen Saturation in a River-Mile by 10%	0.57	0.44	0.54
	[0.38 , 1.14]	[0.29 , 0.88]	[0.36 , 1.06]
Annual Cost to Make a River-Mile Fishable	1.82	1.40	1.51
	[1.29 , 3.08]	[1.00 , 2.37]	[1.00 , 3.07]
Total Costs	295,450	395,162	618,301
Federal Capital	87,551	117,222	184,306
Local Capital	37,167	49,773	77,118
Operation & Maintenance	170,733	228,167	356,878
River-Miles Made Fishable	5,409	9,377	16,385
River Miles * Pct. Saturation Increase / 10	17,353	30,084	45,756
Regression Sample	Yes		
All Plants		Yes	
Assumed Stream Lengths			Yes

Notes: All values in $2014 millions. Calculations include grants given in years 1962-2001. Brackets show 95% confidence intervals. Annual cost assumes benefits acccrue for 30 years. Assumed stream length means stream length is assumed to be 25 miles. "All plants" includes plants with latitude and longitude data.

Table 4. Pass-Through of Clean Water Act Grants to Municipal Sewerage Capital Spending

	(1)	(2)	(3)	(4)
Panel A. Federal Grant Funds				
Federal Grant Funds	1.53***	1.27***	1.15***	1.21***
	(0.27)	(0.21)	(0.25)	(0.29)
Panel B. Grant Project Costs				
Grant Project Costs	1.09***	0.94***	0.86***	0.91***
	(0.19)	(0.15)	(0.18)	(0.21)
N	6,368	6,368	6,368	6,368
City FE and Year FE	Yes	Yes	Yes	Yes
Real Costs		Yes	Yes	Yes
Basin-by-Year FE			Yes	Yes
Propensity Score Reweight				Yes

Notes: Dependent variable is municipal sewerage capital investment. All municipal and grant costs are cumulative since 1970. Sewerage capital expenditures include federal and non-federal funds. Cumulative grant project costs also include federal grant amount and required local capital expenditure. Municipal spending data from Annual Survey of Governments and Census of Governments. Data include balanced panel of cities over years 1970-2001, see text for details. Columns (1)-(2) use nominal dollars; column (3) uses real dollars deflated by the Engineering News Record Construction Price Index. Column (4) weights by inverse propensity score for appearing in the balanced panel of cities, which is estimated as a function of log city population, log city total municipal expenditure, city type (municipality or township), and census division fixed effects, where city population and expenditure are averaged over all years of the data. Standard errors are clustered by city. Asterisks denote p-value < 0.10 (*), <0.05 (**), or 0.01 (***).

Table 5. Effect of Clean Water Act Grants on Housing Demand

	(1)	(2)	(3)	(4)
Panel A. Log Mean Home Values				
Cumulative Grants	-0.00008	0.00090	0.002665**	0.00025
	(0.002503)	(0.001412)	(0.001286)	(0.000326)
Panel B. Log Mean Rental Values				
Cumulative Grants	0.00002	-0.00077	0.00004	-0.00011
	(0.001700)	(0.000833)	(0.000711)	(0.000158)
Panel C. Log Total Housing Units				
Cumulative Grants	-0.007003**	-0.00046	-0.00041	-0.00018
	(0.003202)	(0.001186)	(0.000942)	(0.000242)
Panel D. Log Total Value of Housing Stock				
Cumulative Grants	-0.006306*	0.00005	0.00145	-0.00017
	(0.003292)	(0.001878)	(0.001603)	(0.000461)
Plant FE, Basin-by-Year FE	Yes	Yes	Yes	Yes
Dwelling Characteristics		Yes	Yes	Yes
Baseline Covariates * Year		Yes	Yes	Yes
Max Distance Homes to River (Miles)	0.25	0.25	1	25

Notes: Analysis includes homes within a given distance of downstream river segments. Data include decennial census years 1970-2000. Cumulative grants include grants in all previous years, not only census years. See main text for description of dwelling and baseline covariates. Standard errors are clustered by watershed. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Table 6. Clean Water Act Grants: Costs and Effects on Home Values ($2014 Bn)

	(1)	(2)	(3)	(4)
Ratio: Change in Home Values / Costs	0.04	0.25	0.25	0.28
	(0.03)	(0.33)	(0.33)	(0.37)
p-value: Ratio = 0	[0.15]	[0.44]	[0.45]	[0.45]
p-Value: Ratio = 1	[0.00]	[0.02]	[0.02]	[0.05]
Change in Value of Housing ($Bn)	13.06	86.12	85.03	108.07
Costs ($Bn)				
Capital: Fed.	93.77	101.82	101.82	113.69
Capital: Local	38.56	41.64	41.64	47.81
Variable	180.53	196.45	196.45	221.82
Total	312.86	339.92	339.92	383.32
Max Distance Homes to River (Miles)	1	25	25	25
Include Rental Units			Yes	Yes
Include Non-Metro Areas				Yes

Notes: All values in billions ($2014). Calculations include grants given in years 1962-2000. Ninety-five percent confidence regions are in brackets. Estimates come from regression specifications corresponding to Table 5, column (5).

A Expenditure on Water Pollution Abatement

This Appendix reviews available data on expenditures for abating water pollution and air pollution. Measuring such expenditures is difficult. The first attempt by the Bureau of Economic Analysis (BEA) to measure pollution abatement costs describes five challenges (Cremeans and Segel 1975) including determining counterfactual pollution abatement; the problem that many abatement technologies also have valuable byproducts; the proper classification of capital goods used for abatement; the difficulty in recognizing business decisions as environmental or not; and the separation of pollution abatement expenditures from expenditures for industrial safety and related purposes. These are only accounting challenges; an additional challenge is that even correct accounting measures do not equal full economic costs. Our goal is simply to describe available estimates, recognizing these caveats.

We consider three sets of estimates: BEA annual accounts for the period 1972-1994; Census abatement cost surveys for manufacturing combined with EPA expenditure records for government; and EPA reports on the costs of the Clean Water Act and Clean Air Act. All three methods suggest that total expenditure on water pollution abatement since the Clean Water Act has exceeded \$1 trillion (\$2014), which is over \$100 per person-year, or equivalently, annual expenditure just over half a percent of GDP. All three methods also imply that expenditure on water pollution abatement has exceeded expenditure on air pollution abatement.

The first set of estimates comes from the Bureau of Economic Analysis (BEA) for the years 1972-1994 (Vogan 1996).[45] The BEA estimates aggregate expenditure on water pollution abatement in the period 1972-1994 of \$1.3 or \$1.4 trillion (\$2014) when deflated using quantity or price indices, respectively. Private business accounts for two-thirds of these expenditures, and government for the remaining one-third. The BEA data report total air pollution abatement expenditures at \$1.0 to \$1.4 trillion (\$2014) using quantity or price indices, respectively, including expenditures by private households (e.g., for vehicles). This indicates that water pollution abatement expenditures exceed air pollution abatement expenditures by 6 to 27 percent.

The second set of estimates comes from the Census Bureau for private industry and EPA for government sources. The Census conducted the Pollution Abatement Costs and Expenditures survey annually between 1972 and 1994. We sum capital and operating costs from this survey, and linearly interpolate for the year 1987 (which had no survey). These data indicate total 1973-1994 abatement expenditures of \$315 billion for water pollution abatement and \$338 billion for air pollution abatement (\$2014). These numbers include only the manufacturing sector. Our EPA data on the construction grants program indicate that local governments spent about \$190 billion in federal grant funds, supplemented by local expenditures, and a federal Revolving Loan fund. [46]

The third set of estimates is from EPA reports on the costs of the Clean Air and Clean Water Acts (USEPA 1997, 2000c). In 1990, the compliance cost of the Clean Air Act was about \$25 billion (\$1990). In 1994, the cost of water pollution abatement was \$44.6 billion (\$1997), though \$32 billion of this would have been spent even without the Clean Water Act. These reports provide no evidence on trends in these numbers. Under the strong assumption that they had been constant over the period 1972-2001, they imply costs of \$2.5 trillion for water pollution and \$1.8 trillion for air pollution (\$2014).

[45] The BEA reports both quantity and price deflators indexed to 1992. We deflate all BEA values to 1992. For comparability with the rest of the paper, which reports figures in 2014 dollars, we then deflate these values to the year 2014 using the 1992 and 2014 Construction Price Index of Engineering News Records.

[46] A study by national Mayor office estimates that local governments spent \$1.4 trillion (\$2008) on wastewater treatment between 1956 and 2008. Another estimate of these expenditures is a report by the Congressional Budget Office (CBO 1985) which reports that total annual wastewater spending by federal, state, and local governments was above \$7 billion (in 1983 dollars) in each year between 1972 and 1983. Extrapolating to the entire period 1972-2016 implies total expenditure was above \$753 billion (2014\$).

B Data Details

For each dataset, this section provides additional details on the data and on various tests we have undertaken to probe their accuracy.

B.1 Deflator

Published annually since 1908, the Construction Cost Index of the Engineering News Record (ENR) index reflects the cost of 200 hours of common labor including wages and fringe benefits, the cost of 2,500 pounds of fabricated structural steel, 1.128 tons of bulk portland cement, and 1,088 board feet of 2x4 lumber. To obtain the index, ENR averages the cost across 20 large cities. The closest series published by the federal government is the Census' construction price index for single-family homes.

B.2 National Hydrography Dataset (NHD)

EPA and USGS designed the general attributes of NHD, and a private contractor developed it. The first version of NHD appeared in 2006, while version 2 with more detail was released in 2012.[47] These data include physical features of every surface water in the U.S. including rivers, streams, ditches, canals, lakes, ponds, and others.

NHD includes a variety of identifying variables that the main text describes with more common language. We use the term "watershed" to describe what hydrologists and NHD call an 8-digit hydrologic unit code (HUC). We use the term "river" to describe what NHD calls a "levelpathi." We use the terms "river basin" or just "basin" to describe a 4-digit HUC. NHD classifies 1 million distinct rivers, though most are not conventional rivers (e.g., many "rivers" are seasonal streams less than one mile long) and only 70,000 levelpathis are named. We use the phrase "river segment" to describe what NHD calls a "comid." A comid is a unique identifier code for a specific line segment in NHD. On average a comid is 1.2 miles long. A comid connects a set of points, and we refer to these points as "stream nodes." NHD also includes a more coarse partition of rivers called reach codes which we do not utilize.

We use NHD's "flowline" features to describe upstream and downstream relationships of rivers and streams. In many cases, the "flowline" data include flows through lakes, ponds, and other types of water bodies.

B.3 Water Pollution Data

This section provides additional information on the data then explains how we extract and clean it. About 85 percent of the data come from rivers and the rest from lakes (Appendix Table 1).[48] The average monitoring site appears in 11 different years and has 25 to 40 total readings per pollutant. About 25 percent of monitoring sites are in metro areas but only 15 percent of the U.S. land area is in

[47] Since the 1970s, the EPA has developed increasingly detailed hydrologic data on U.S. water networks. This sequence of data includes Reach File 1 (created in 1975); Reach File 2 (created in 1987); and and Reach File 3 (available in 1993). Technically, the National Hydrography Dataset Plus is an application of the National Hydrography Dataset which also incorporates information from the 30-meter National Elevation Dataset and the National Watershed Boundary Dataset.

[48] The data include unique station identification codes. We describe "monitoring sites," and identify a unique monitoring site by latitude and longitude, for two reasons. First, some monitors appear with different codes in the different repositories; latitude and longitude let us link them. Second, calling them "monitors" suggests the presence of a single physical instrument. Water pollution data, unlike air pollution data, often requires a person on a bridge or in a boat to collect a water sample by hand, and some pollutants then require evaluation in a lab.

metro areas, so they sightly over-represent metro areas. Monitoring is evenly spread through the 1970s, 1980s, and 1990s, though much less common in the 1960s.

Plotting densities of the raw data helps illustrate some of their properties (Appendix Figure 1). Dissolved oxygen deficits follow a roughly normal distribution, while BOD, fecal coliforms, and TSS are more skewed. The dissolved oxygen deficit distribution is smoother than the others because its sample size is bigger. Some reports list pollution only out to two, one, or zero decimal points, which leads to heaping in the raw data and visible pileups, for example, at BOD of 0=ln(1) or 0.69=ln(2).

We download the Storet Legacy data from U.S. EPA's Storet Legacy Data Center and Storet and NWIS data from the Water Quality Portal. Several decisions are required to extract data from the three repositories of water pollution data and to make them comparable. We describe steps for each issue in turn, and then steps taken to make the three repositories comparable.

Ambient Monitoring in Rivers and Lakes. Our analysis includes only rivers and lakes. This excludes estuaries, oceans, wells, pipes, canals, sampling inside industrial plants, and other sites, though these other types are uncommon in the pollution data. In Storet Legacy, we identify streams and lakes using the Storet Legacy station type field provided by the station files. We also remove measurements where the Primary Activity is Effluent Permit Condition, Effluent(Sample), Biological, or Tissue. We also exclude records where the Secondary Activity Category is Dredge, Core, Ground Water, or others that are clearly not river or lake samples, such as Standard Deviation or Sum of Squares. Additionally in all three repositories, we exclude records around dams since they are highly dependent on dam operations and often for dam monitoring; these are identified from the word, "Dam," in the station name or description.

In Modern Storet and NWIS, we limit the data to rivers/streams and lakes in a few steps. First, we restrict the sample media to surface water. We also restrict the media subtype to Surface Water, which removes typically less than 1 percent of records that are coded as other media subtype such as Effluent or Groundwater. For Modern Storet, the media subtype field is only populated for approximately 20 to 30 percent of observations. Of those coded, typically less than 1 percent of records are classified as something other than "Surface Water." Thus, for Modern Storet, we keep records where the media subtype is missing to preserve a large amount of data given that nearly all records that are coded are for surface water. Next, we limit the site type to lake, reservoir, impoundment, or stream. We distinguish streams and lakes in the NWIS station data using the provided monitoring location type name field in the station file. Streams are identified as "Stream," "Stream: Canal," "Stream: Ditch," or "Stream: Tidal stream." Lakes are identified as "Lake, Reservoir, Impoundment." For Modern Storet, we also identify streams and lakes using the monitoring location type name field. For Modern Storet, streams are identified as "River/Stream," "River/Stream Ephemeral," "River/Stream Intermittent," "River/Stream Perennial," "Riverine Impoundment," "River/stream Effluent-Dominated," "Canal Drainage," "Canal Irrigation," "Canal Transport," "Channelized Stream," "Floodwater," "Floodwater Urban," or "Floodwater non-Urban." Lakes are identified as "Lake," "Reservoir," "Great Lake," "Pond-Anchialine," or "Pond-Stormwater."

Measures of Water Pollution. Storet Legacy and NWIS classify each measure of water pollution according to a single parameter code. These parameter codes classify water quality parameters according to a broadly defined characteristic (e.g., biochemical oxygen demand) and the method for measuring the pollutant (e.g., the temperature at which the measurement is taken and the incubation time period). For example, the parameter code 00310 describes biochemical oxygen demand, measured at a temperature of twenty degrees Celsius, over a five day incubation period. The parameter code 00306 describes biochemical oxygen demand, also measured at twenty degrees Celsius, but only over a four day incubation period. For each measure of water pollution that we use, we start by choosing the parameter code which has the most observations in STORET Legacy. In nearly all cases, this parameter code corresponds to the parameter code given in the EPA's first major water pollution report after the Clean Water Act (USEPA 1974c).

We also include parameter codes which are comparable to this main code(s) (e.g., measured in different units or a different device) if they have at least 10,000 observations in Storet Legacy. We use this rule because Storet Legacy has the largest number of observations among the three repositories used in the study, and the largest share of observations concentrated around the early 1970s when the Clean Water Act began. For NWIS data, we use the same parameter codes as Storet Legacy to extract corresponding measures of water quality from the Water Quality Portal.

Modern Storet does not use a parameter code, but rather identifies water quality parameters according to characteristic names. We take several steps to match these characteristics in Storet to those pollutants in Storet Legacy and NWIS repositories. We utilize concordance tables provided by EPA and the Water Quality Portal that map Storet Legacy and NWIS parameter codes to Modern Storet "search names."[49]

A single characteristic name often corresponds to multiple parameter codes. The EPA concordance provides the meaning of parameter codes, including information on sample preparation (e.g., details regarding filter size), whether the measurement was in the field or laboratory, measurement units, result sample fraction (e.g., total versus dissolved), result temperature basis, result statistical basis (e.g., mean, median), additional comments, and additional measurement method details. We supplement this information with a similar table from the Water Quality Portal website that provides a few additional details for each parameter code including result time basis, result weight basis and result particle size basis.

Between these two files, we note which aspects distinguish certain parameter codes from others and use these to restrict and subsequently match Modern Storet pollution records to Storet Legacy and NWIS records by pollutant. In addition to the characteristic name, the main distinguishing aspect of a measure of water pollution is the result sample fraction field that often identifies total versus dissolved measurements. For biochemical oxygen demand and fecal coliforms, we also restrict based on the result temperature basis (20 degrees Celsius or missing and 45 degrees Celsius or missing respectively) and result time basis (5 day or missing and 24 hours or missing respectively). For dissolved oxygen, we convert dissolved oxygen in mg/L to dissolved oxygen saturation (%) using a standard formula (Lung 2001).[50]

Sample Exclusions. We impose several sample exclusions. We keep observations with non-missing observation date, latitude, and longitude. We also limit analysis to ambient monitoring. To limit the influence of outliers, for each reading above the 99th percentile of the distribution of readings, separately by pollutant, we recode the result to equal the 99th percentile. To ease interpretation, we define all pollution outcomes so that lower levels of the outcome represent cleaner water.

For NWIS, we exclude records of Spills, Hurricanes, and Storms by limiting to routine hydrologic events. Modern Storet and Storet Legacy, unlike NWIS, provide no information on hydrologic events. We convert all temperature readings to degrees Fahrenheit. For other pollutants, we keep all records with unit data that are easily converted to standard units. For Storet Legacy and NWIS, we keep observations with missing units since parameter codes are already assigned to specific units. For Modern Storet, we keep observations with missing units except for dissolved oxygen and temperature. We exclude observations with missing units for dissolved oxygen and temperature since we are unable to distinguish

[49]The U.S. EPA provides several crosswalks to identify measurements in Storet that are comparable to those in the Storet Legacy and NWIS repositories (ftp://ftp.epa.gov/storet/modern/reference_tables/Characteristic_Parameter_Code_Map/). In particular, we use the crosswalk STORET_Modern_vs_NWIS.xls. The water quality portal table links a parameter code to characteristic name, measurement unit code, result sample fraction, result temperature basis, result statistical basis, result time basis, result weight basis, result particle size basis, and medium. (http://waterqualitydata.us/public_srsnames/)

[50]The formula is $DO_{perc} = \frac{DO_{mgl}}{468/(31.5+T)}$ where T is the water temperature in Celsius. We only apply this conversion for observations which record both dissolved oxygen in mg/L and water temperature, and for station-days which do not already have dissolved oxygen saturation (%) defined. When applied to stations which do have dissolved oxygen saturation defined, regressing the reported level of dissolved oxygen saturation on the value obtained from this conversion obtains a coefficient of 0.996 with a standard error of 0.001.

between mg/l and percent saturation in the dissolved oxygen data and degrees C and degrees F in the temperature data. We restrict our data to samples collected in the continental U.S.

Definitions of Geographic Variables. We use a few steps to define geographic variables. Storet Legacy has separate files describing stations and describing actual pollution readings. Geographic identifiers like latitude, longitude, watershed, and county appear in both. We prioritize values of these variables from station files. When those are missing, we supplement them with values from the results files. For all repositories, when watershed and county are missing from both station and results files, we define them based on a monitoring site's latitude and longitude.

Types of Water Pollution. We use a few criteria to choose additional measures of pollution for sensitivity analysis in Appendix Table 4. We partly take this list of additional pollutants from the EPA's (1974a) first major assessment of water pollution after the Clean Water Act was passed. These additional pollutants include water temperature, ammonia-nitrogen (total as N), nitrates (total as N), total nitrite plus nitrate, orthophosphate (dissolved as P)[51] , phosphate (total as PO4), total phosphorus, total and dissolved chlorides, color, total phenols, total dissolved solids, total and dissolved sulfate, total coliforms, and turbidity.[52] Finally, we add total nitrogen as a key measure of nutrient pollution, and lead and mercury as important heavy metals.

Specific Monitor Networks. For NWIS, we identify stations that are a part of several networks specifically designed by USGS to examine long-term trends in water quality. These networks are NASQAN, NAWQA, and HBN. Station identifiers were obtained from USGS. We obtained NASQAN and HBN station identifiers through a request from USGS. NAWQA site identifiers were downloaded from a USGS website using filters on "stream" and "lake" for site types (http://cida.usgs.gov/nawqa_queries_public/jsp/sitemaster.jsp). Our NASQAN and HBN samples include only the original NASQAN and HBN networks, which spanned the years 1974-1995. Our NAWQA sample includes both the NAWQA networks focused on streams/rivers and on lakes. We add "USGS-" to the stationid field and match these station files to monitoring files provided by the Water Quality portal. In several cases, monitoring was performed at these stations even when they were not officially part of their designated networks. We include all monitoring results during the 1962-2001 time period that we study.

Station Definitions. Some stations change name slightly—for example, the same station may have similar names in Modern Storet and in Storet Legacy. In regressions that include station fixed effects or allow station-level autocorrelation, we define a station as a unique latitude and longitude pair.

In our data, the tuple of a station's name, the name of the agency that manages it, and the repository (Storet Legacy, Modern Storet, or NWIS) uniquely identifies a station. When we pool the three repositories, 5-10 percent of "stations" that appear unique by this definition have the same longitude and latitude as another "station." This is typically because a single station appears in both Storet Legacy and Modern Storet but with slightly different station codes. This motivates our use of longitude and latitude to define unique stations.

In a few cases, records appear in both Storet Legacy and Modern Storet. We identify and remove such duplicates based on station latitude and longitude, reading date and time, and reading value.

Monitoring Depth. We do not account for reading depth since many readings have missing units and our inspection suggests different monitors use different units.

Measurement Limits We capture special cases where the pollutant could not be measured or the measurement was outside of standard detection limits. For NWIS and Storet, we flag records with non-

[51]The 1974 report includes total soluble phosphate to determine reference levels. We choose to use orthophosphate (dissolved as P) instead. The number of records in Storet Legacy corresponding to total soluble phosphate (38,000) is far fewer than the 870,000 monitoring results for orthophosphate (dissolved as P).

[52]We add dissolved chlorides and dissolved sulfate to this list since the unique pollutant parameter codes listed in the NWQI Report for chlorides and sulfate refer to total chlorides and total sulfate in Storet Legacy, but dissolved chlorides and dissolved sulfate in the NWIS.

missing information in the detection type field. For example, this includes records coded with "Historical Lower Reporting Limit," "Upper Reporting Limit," or "Estimated Detection Level." For flagged records, we then let the result value equal the detection limit if the result value is missing and the detection limit is not missing. We also restrict the detection limit to be greater than zero except for temperature. For Storet Legacy, we use the "remarks" field to flag similar records. This includes remarks coded as "B," "C," "I," "J," "K," "L," "M," "N," "O," "P," "T," "U," "W," "Z," and "$," where the key is provided by the U.S. EPA (http://www.epa.gov/storet/legacy_remark.pdf). We make no changes to the reported measurement since the remarks suggest that the reported measurement equals the result value. In one sensitivity analysis, we take readings with the "Below Detection Limit" (BDL) field coded as "Lower Limit" or "Other," and replace them as half the listed value.

Measurement Time. For observations with missing information on the measurement time, we create a missing hour indicator. For Storet Legacy and Modern Storet, we also code this indicator for hour equal to 0 since there is a pileup of observations at this hour.

Test of Dissolved Oxygen Data Quality. This full dataset has not been used in research before, and so to ascertain the accuracy of our results it is useful to probe the quality of these data. The paper does report numerous sensitivity analyses that provide encouraging evidence that these data provide an accurate picture of U.S. water quality. Here we report one additional test of the data quality. Standard hydrology textbooks predict that dissolved oxygen deficits should increase with temperature, in summer (when flows are lower and temperatures higher), and in morning. The time-of-day patterns of dissolved oxygen are due to photosynthesis adding oxygen during the day and respiration removing oxygen at night. Appendix Figure 3 plots regressions of dissolved oxygen deficits on binned indicators for each of these physical factors, while including monitor fixed effects. The patterns closely follow standard chemistry predictions. We interpret this as one additional piece of evidence that these data provide good quality measures of water pollution.

B.4 Grants

The average government manages multiple plants, and the average plant receives multiple grants. Governments include cities, towns, sewage or water districts, and environmental agencies. After 1987, small grants to a few areas, mainly islands and Washington DC, continued through the year 2000. Two-thirds of U.S. wastewater treatment plants received at least one grant.

A local government could receive at least three grants for a single project. The first grant was for creating a facility plan, the second was for detailed engineering plans, and the third was for construction. Money was disbursed as it was spent and EPA reviewed projects after completion. The grants data used for analysis exclude the very few grants in the raw data that list either the federal or total (federal+local) cost as zero.

The microdata we obtain on grants are up to 50 years old, from an era when computers were rare. The machine which originally housed these data was decommissioned around the year 2000, so we sought to corroborate the accuracy of the data.

In order to test the accuracy of the microdata on 35,000 grants, we compare the grants against several published reports describing this program. A USEPA (2000b) report and associated book (Stoddard, Harcum, Simpson, Pagenkopf, and Bastian 2002) were based on detailed data describing these grants. Andy Stoddard and Jon Harcum generously shared the microdata underlying these reports. The grants data they analyze exactly mirror ours, with two exceptions. First, the aggregate nominal figure they report for grants ($61 billion) reflects both federal and municipal capital spending, though their publications and the associated EPA website describe it as federal money only. Second, they only obtained records of 10,000 grants. This appears to be because their data apply several exclusion criteria.

We also compared individual grants in the microdata we received against published reports we found that list individual grants given in early years (USEPA 1974a,b). The grants in our microdata also appear in these printed volumes, with the same plant and government authority listed. Grant dates are similar in the microdata and 1970s reports, though some differ by several months. The dollar amounts of individual grants have the same order of magnitude but the exact amounts differ. This may be because funds requested, approved, and disbursed can differ, and can take over a decade to finalize.

One sensitivity analysis in our paper looks only at grants given for construction rather than engineering plans. Following Stoddard, Harcum, Simpson, Pagenkopf, and Bastian (2002), we define a grant as for construction if the grants microdata list the grant "Step" as equal to three or four, and if the grant also lists the facility number of the plant receiving the grant.

Operating and Maintenance Costs. Clean Water Act grants involve three types of costs: federal grants for capital, local matching expenditures for capital, and expenditures for operating and maintenance (O&M). Our grants microdata report only the first two costs, so we estimate the third from other sources.

National data are consistent with the idea that the ratio of lifetime O&M costs to upfront capital costs increased almost linearly from 130 percent in 1972 to 259 percent in 1996. We linearly extrapolate these values to years before and after 1972-1996. These values reflect several sources. Two independent sources provide identical reports that concrete structures of treatment plants have a useful life of 50 years but mechanical and electrical components have a useful life of 15-25 years (American Society of Civil Engineers 2011 and USEPA 2002). We assume grants require O&M expenditures for 25.

We combine this 25 year statistic with the estimated ratio of O&M costs to capital stock in a typical year. This ratio grew almost linearly from 3.7 percent in 1972 to 7.4 percent in 1996 (USEPA 2002). These values reflect historic census records on O&M expenditures and perpetual inventory estimates of capital stocks (U.S. Army Corps of Engineers 1994), both for sewerage infrastructure.

These values represent the most accurate estimates of O&M costs that we can discern. Nonetheless, it is informative to compare these values against other estimates of these costs. One survey of 226 Clean Water Act projects found a ratio of annual O&M costs to upfront capital costs of 3.76% to 3.96% (Lake, Hanneman, and Oster 1979).[53] The ratio was similar across different community sizes and government types. These values are similar to the aforementioned numbers that we use, which report a ratio of 3.7% in 1972. A second source reports the prediction that for a typical city of 25,000 people, the total cost of building a treatment plant is about $4.6 million, and the expected real annual O&M cost is about $200,000 (USEPA 1979). The ratio of annual O&M costs to upfront capital costs in this second source is 4.3%, which is the value for the year 1976 implied by the data we use. A third source is an ex ante engineering prediction that lifetime O&M costs are 93 percent of upfront capital costs (Hitchcock and Giggey 1975).[54] The reason why the engineering predictions in this third study are smaller than the ex post realized costs we use is unclear, though engineering predictions have underestimated the costs of energy and environmental investments in other settings also.

B.5 Census Data from Geolytics

For each census tract, the Geolytics Neighborhood Change database reports mean or total values for the relevant housing and population variables we use. We measure the mean home value in a tract as the total value of specified owner-occupied housing divided by the total number of specified owner-occupied

[53] This study reports the ratio as 3.96% on p. 42 and 3.76% on p. 110. The reason for the discrepancy is unclear.

[54] This study reports O&M predicted costs for different categories of water pollution abatement expenditures. We obtain a national number by combining the category-specific O&M predictions from this study with category-specific capital expenditures under the Clean Water Act from Stoddard, Harcum, Simpson, Pagenkopf, and Bastian (2002).

housing units. In years 1970 and 1980, these data cover non-condominium housing units only. The housing data comes from the census "long form," which is given to 1 in 6 households. The actual census questionnaire has homeowners estimate the value of their property as falling into one of several bins.

We use a version of these data in which Geolytics has concorded all tract boundaries to the year 2010 boundaries. We use information on resident demographics, total population, physical features of housing (e.g., the number of rooms), home values, and rents. Some regressions control for housing structure characteristics. Because each observation is a census tract (which is subsequently aggregated to buffer a given distance from a river), we measure these structural characteristics as the share of homes with a given characteristic. The rental data for 1970 are "contract rents," which report the amount paid from renter to owner; the rental data for 1980-2000 are "gross rents," which include the contract rent plus utilities and fuels, if these are paid by the renter. As with home values, the actual census questionnaire has renters enter their contract rent as falling into one of several bins.

The census home values data reflect self-reported home values, rather than actual transaction values. The census data are also top-coded. Many studies find high correlation between self-reported home values and sales price indices, either in the cross-section, time-series, or panel (James R. Follain and Malpezzi 1981; Ihlanfeldt and Martinez-Vazquez 1986; John L. Goodman and Ittner 1992; DiPasquale and Somerville 1995; Kiel and Zabel 1999; Banzhaf and Farooque 2013; Benítez-Silva, Eren, Heiland, and Jiménez-Martín 2015), suggesting that self-reports are informative about market valuations. Banzhaf and Farooque (2013) actually find that community-mean rental values from the U.S. census are more strongly correlated with local amenities and with income than home sales value are. Because home values are the dependent variable in hedonic regressions, using self-reported home values in the presence of classical measurement error may decrease the precision of estimates but not create attenuation bias (Griliches and Hausman 1986; Bound and Krueger 1991).

Such self-reported home values may also suffer from inertia. Owner-occupants who have not purchased a home recently may be slow to update their beliefs about a home's value (Kuzmenko and Timmins 2011; Henriques 2013). This inertia appears to be consistent with a simple Bayesian updating model, specifically, a Kalman filter (Davis and Quintin 2016). But this means that homeowners may be slow to reflect changes in local amenities due to investments in surface water quality. Longstanding rental tenants often receive tenure discounts, though we are not aware of direct evidence on the speed with which such discounts adjust to changes in amenities. As one way to address these concerns, in analyzing home values and rents, we report specifications which allow homeowners and renters up to 10 years to reflect changes in water quality.

We define city centers for all Standard Metropolitan Statistical Areas (SMSAs) as follows. The definition of central business district locations used in most research comes from the 1982 Census of Retail Trade. This definition has two downsides in our setting—it is potentially endogenous to the Clean Water Act, since the definition was constructed ten years after the Act and since cleaning up rivers might shift the location of businesses; and it includes a limited number of cities. Instead, for each Standard Metropolitan Statistical Area (SMSA), we use the 1970 Population Census to construct an original definition of the city center as the latitude and longitude of the census block centroid which has the greatest population density. In cities with a central business district defined from the 1982 Census of Retail Trade, this typically ends up defining close but not identical definitions of city centers. For census tracts within an SMSA, we then define distance to the city center as distance to the city center of that SMSA. For census tracts outside an SMSA, we define the distance to the closest city center overall.

B.6 Municipal Expenditure Data

We impose a few sample restrictions to ensure that we accurately measure the response of municipal spending to federal grants. We restrict the sample to governments appearing in all years 1970-2001.[55] This is important since the data report capital expenditures but not capital stocks, and missing some years of municipal expenditures data could underestimate the response of municipal spending to federal grants. We also restrict the sample to municipalities and townships, which we collectively refer to as cities. This restriction excludes state governments, county governments, special districts, school districts, and the federal government. Finally, we exclude cities which have other governments with similar names in the same state, and cities that have sewer districts, counties, or other nearby related governments that may receive or spend grants. We make these exclusions because they help accurately measure sewerage capital and grant receipt. We identify such cities both using listings of sewer districts and local counties in the survey and census of governments, and using grants which list the authority receiving the grant as a sewer board, county agency, or other local government that is not a city. Many grants go to water boards, sewer districts, county agencies, or other local governments which have separate financial management from a city. Such grants would not appear in the city's financial records, but the grants data do not always distinguish which local government administered the grant. These restrictions leave a balanced panel of 199 cities. As noted in the main text, because this sample is relatively small, we report one specification using inverse propensity score reweighting to match the characteristics of a broader sample of cities.[56]

B.7 Additional Environmental Data[57]

We measure county-year-day air temperature and precipitation using data from the National Climate Data Center Summary of the Day files (file TD-3200). We use information on the daily maximum temperature, daily minimum temperature, and daily total precipitation. We use only weather stations reporting valid readings for every day in a year. To obtain county-level values, we take an inverse-distance weighted mean of data from stations within a 300 kilometer radius of the county centroid. Weights equal a monitoring site's squared distance to the county centroid, so more distant monitoring sites receive less weight.

As mentioned in the main text, we report one specification controlling for two separate counts of polluting industrial plants. The 1972 Census of Manufactures asked every U.S. manufacturing plant whether it used more than 20 million gallons of water per year, and the roughly 10,000 plants indicating that they used this much water appeared in the 1973 SWUM. For each wastewater treatment plant in our data, we count the number of manufacturing plants in the same county which use at least 20 million gallons of water in 1972. We control for these counts, interacted with a downstream indicator and interacted with year fixed effects. Although these data only directly measure total water use and

[55] The census has these data for the year 1967 and then annually beginning in 1970; our sample begins in 1970 since we need a balanced panel. All governments report data in years ending in 2 and 7 (1972, 1977, etc.). Other years contain a probabilistic sample of governments. In most years, the largest cities measured by population, total revenue, or expenditure are sampled with certainty. Among smaller cities, sampling probabilities vary by region, type of government, and size. The balanced panel is the main limiting factor in our data extract, since less than 1,000 cities appear in all years of the data 1970-2001.

[56] We estimate the propensity score from a probit using all cities. The estimated propensity score is a function of the city's log mean total expenditure across all years 1970-2001 when it appears in the census or survey of governments, the city's log mean population, an indicator for being a municipality (rather than township), and census division fixed effects. Cities with lower expenditure and in the West and South are significantly more likely to appear in the sample; conditional on the other variables, population does not significantly predict appearance in the sample.

[57] We thank Olivier Deschenes for providing the weather data and Michael Greenstone for providing the 1972-1977 nonattainment data.

not total water pollution emissions, the SWUM survey questions and resulting report both focus on water pollution,[58] and plants with extensive water use also emit large amounts of water pollution. For example, the industries that consume the most water in the 1978 version of these data (Becker 2015) – blast furnaces and steel mills, industrial organic chemicals, petroleum refining, and paper mills – are also the industries that emit the most water pollution.

The EPA does not have plant-level records from the 1970s. The current PCS data do list the first year a plant received a water pollution emissions permit. These data suffer from incomplete reporting, since not all states and plants uploaded data to the EPA's centralized database. They also suffer from sample selection, since plants which closed may not appear in the data.

Some sensitivity analyses control for county-by-year-by-pollutant nonattainment designations. For years after 1977, these data come from the EPA Green Book. Data for years 1972-1977 are constructed from raw monitors based on the reported nonattainment rule. We define ozone nonattainment to include all ozone or nitrogen oxides designations, and we define particulate matter nonattainment to include Total Suspended Particulates (TSPs), particulates smaller than 10 micrometers (PM_{10}), and particulates smaller than 2.5 micrometers ($PM_{2.5}$). Our binary measures of nonattainment include all partial, whole-county, and other types of nonattainment.

B.8 Data for Analyzing Heterogeneous Effects

Appendix Table 7 analyzes how the effects of grants on water pollution and housing values differs for certain subsets of grants. This subsection describes how we define these subsets.

Row 2 of Appendix Table 7 distinguishes grant projects which have a total cost (including federal and local contributions) above $1.2 million, measured in $2014. This is the median cost.

Row 3 of Appendix Table 7 describes grants to plants that have secondary or tertiary baseline abatement technology. These plant-level abatement technology data come from the Clean Watershed Needs Survey. Only available data for the 1978, 1984, and 1986 years of this survey cover all plants and include accurate plant identifier codes.[59]

These abatement technology data have several limitations. Only about 40 percent of grants or real grant dollars were given after 1978. Additionally, only having reports for the exact years 1976, 1984, and 1986 implies that without some kind of interpolation, abatement technologies are only directly reported for three years which together account for about 15 percent of grants or grant dollars. The CWNS data contain two possible measures of a plant's abatement technology: one is a field where the respondent writes in the level of treatment stringency (primary, advanced primary, secondary, advanced secondary, or tertiary). The other is a list of all the different abatement technologies the plant uses. The 1984 plant codebook classifies lists of abatement technologies into primary, secondary, and tertiary. Between these two reports, only 45 percent of plant-year observations have the same level of treatment (primary, secondary, or tertiary). In the self-reported level of treatment, a third of plants that report a change in the treatment level report a decrease in the level. In the lists of abatement technologies, large share of plants that report changes in an abatement technology reports its disappearance–for example, plants are almost as likely to report losing a trickling filter or activated sludge process (which are the two most common types of secondary treatment) as to report gaining one. We use secondary and tertiary classifications based on listed abatement technologies, which appear to have a lower level of gross reporting errors than

[58] The SWUM microdata were recently recovered from a historic Census Univac system. Unfortunately the water pollution data in that survey were not available. We thank Randy Becker for helping access and interpret the SWUM data.

[59] The available microdata from the 1976 survey exclude over half the plants, for reasons that are unclear. The 1980 and 1982 surveys have garbled plant identifier codes that can only be linked with substantial classification error to other years of the survey.

the handwritten secondary or tertiary entries.

Row 4 of Appendix Table 7 describes grants to plants with baseline pollution above the median. We measure baseline pollution as the mean pollution level for each watershed as measured in the years 1962-1971. Baseline pollution levels are calculated separately for dissolved oxygen and for the fishable standard.

Row 5 of Appendix Table 7 considers states that have decentralized authority to implement the Clean Water Act NPDES program.[60]

Row 6 of Appendix Table 7 considers counties that have above-median shares of people who report outdoor fishing in the previous year. We obtain these data from the confidential version of the National Survey on Recreation and the Environment (NSRE) years 1999-2009. Fishing is defined as coldwater or warmwater fishing in rivers, lakes, or streams. Swimming includes swimming in streams, lakes, ponds, or the ocean. (A separate question that we don't use asks about swimming in pools.) Our sample includes approximately 85,000 households. Earlier versions of the survey have been conducted intermittently since 1960; however, county and state participation shares are unavailable from earlier years. The NSRE is a partnership between the USDA Forest Service Southern Research Station, The National Oceanic and Atmospheric Administration, the University of Georgia, the University of Tennessee and other federal, state or private sponsors. The survey is a randomized telephone survey of households across the U.S. Unfortunately, state- or county-level rates of fishing participation for the entire U.S. are not available from years before the Clean Water Act.

Row 7 of Appendix Table 7 uses data on environmental views from the "Total Green Index" of Hall and Kerr (1991). States with Pro-Environmental Views are defined as those with above-median values of the total green index.

Finally, row 8 of Appendix Table 7 uses data on city growth and amenities. To identify declining urban areas, we follow Glaeser and Gyourko (2005) by taking 1970-2000 city population growth rate as reported in the 1972 and 2000 city data books (Haines and ICPSR 2010). We define declining urban areas as cities with population above 25,000 in the year 1970 which had a population decline by the year 2000. High amenity areas are defined as counties in an SMSA with above-median total amenity value, as reported in Albouy (2016), Appendix Table A1.

B.9 Tract Versus House-Level Data for Hedonic Models

Consider the following simplified regression model for home i in tract t

$$P_{it} = X_{it}'\beta + \epsilon_{it}$$

Let Ω_t denote the set of homes in tract t. Summing across homes within a tract and dividing by the number of housing units within a tract gives

$$\frac{\sum_{i\in\Omega_t} P_{it}}{N_t} = \frac{\sum_{i\in\Omega_t} X_{it}'}{N_t}\beta + \frac{\sum_{i\in\Omega_t} \epsilon_{it}}{N_t}$$

Letting $\tilde{P}_t$ denote the mean value of variable P of within tract t, we have

$$\tilde{P}_t = \tilde{X}_t\beta + \tilde{\epsilon}_t$$

This illustrates how the regression with grouped data (e.g., census tract), weighted by the number of housing units in the group, obtains the same parameter that house-level data would obtain.

[60] These data are obtained from https://www.epa.gov/npdes/npdes-state-program-information (accessed August 31, 2016).

C Spatial and Other Matching Across Datasets

Conducting the analysis of this paper requires linking several datasets. To link monitors and treatment plants to rivers, we use the fact that rivers in NHD are internally defined as 70 million distinct longitude and latitude points connected by straight lines. We refer to these points as stream nodes. We identify the location where each treatment plant discharges waste using longitude and latitude values from the 1984-1996 CWNS. For each monitor and treatment plant, we then find the nearest stream node. Written string descriptions included for some monitors suggest this link is very accurate. All treatment plants in the analysis sample are within 0.6 miles of a stream node.[61]

To measure distances upstream and downstream along rivers, we use files in NHD which list, for each stream node, the node(s) that are immediately upstream and/or downstream. We recursively construct a network tree that defines, for each treatment plant, all stream nodes that are upstream or downstream. We construct this algorithm to follow these flow relationships when one river flows into another, when rivers cross watersheds, or when the flow network passes through lakes, estuaries, and other types of water. Finally, we calculate distances between stream nodes and sum them to measure the distance along a river between a treatment plant and pollution monitor.

We also link treatment plants to upstream and downstream census tracts. For each treatment plant, we construct concentric buffers of 1 mile radius around river segments upstream and downstream of the plant. We define one buffer to include all homes within 1 mile of those rivers, a second buffer to include homes 1 to 2 miles from those rivers, etc. Many census tracts span multiple buffers. For each tract, we calculate the share of the tract's area which is in each buffer. For each tract, we measure population and housing characteristics within a buffer by multiplying the total within the tract by the share of the tract's area within the buffer. For example, if a tract has an aggregate home value of $10 million and has 100 homes, and a fourth of the area of this tract falls within a given 1-mile buffer, then we assume the section of the tract within the buffer has aggregate home value of $2.5 million and 25 homes.

Finally, we link each grant to the exact wastewater treatment plant receiving the grant. The Freedom of Information Act (FOIA) data we received list an identifier code for the facility receiving the grant. These same identifier codes appear in the Clean Watershed Needs Survey (CWNS), so let us precisely identify the wastewater treatment plant receiving the grant. In some cases where the facility identifier code is missing, CWNS itself lists the grant code which a plant used, and this grant code matches the grant codes used in the FOIA data. These two links unique identify the facility receiving a grant for about 76 percent of grants and 88 percent of grant dollars. This is the sample used in the main results. We experimented with fuzzy matching between the FOIA and CWNS data to link the unmatched grants. This matching used string fields such as county, city, zip code, and plant name. We do not focus on results using this fuzzy matching since the plant name and zip code are often missing or incorrect in the FOIA data and match quality is questionable.

[61] We explored estimating the effect of grants on water pollution using on treatment plants within 0.3 miles of a stream node, and obtained similar results.

D Cross-Sectional Water Pollution Around Wastewater Treatment Plants

Methodology

We use the following equation to estimate how water pollution changes as a river flows past a wastewater treatment plant:

$$Q_{pdy} = \beta d_d + \mu_{py} + \epsilon_{pdy}$$

Each observation in these data represents a plant-downstream-year tuple. Here Q_{pdy} measures pollution at plant p in year y and downstream location d. Location $d = 1$ includes areas downstream of the treatment plant, and location $d = 0$ includes areas upstream of the treatment plant. The plant-by-year fixed effects μ_{py} imply that these comparisons are made within a river×year, so they measure how water pollution changes as the river flows past the wastewater treatment plant. The coefficient β represents the mean difference in pollution between downstream and upstream waters near a treatment plant.

We also report the following variant in which the upstream/downstream indicator d is broken into several bins:

$$Q_{pdy} = \sum_{\delta=-25}^{\delta=20} \beta_\delta 1[d_d = \delta] + \mu_{py} + \epsilon_{pdy} \tag{7}$$

The data are grouped into distance bins of five miles along the river (20 to 25 miles upstream of the wastewater treatment plant, 15 to 20 miles upstream, ..., 20 to 25 miles downstream). We then regress pollution Q on indicators $1[\cdot]$ for the distance bin in which an observation is located. The bin just upstream of the treatment plant, 0 to 5 miles upstream, is excluded as a reference category.

These comparisons are cross-sectional and do not analyze changes in a river over time. Because wastewater treatment plants may locate near other pollution sources, such as urban runoff and industrial plants, these regressions do not identify the effect of wastewater treatment plants on water pollution. Area characteristics may also differ in the cross-section between upstream and downstream areas. Indeed, the average upstream and downstream monitoring sites are 20 miles apart. Compared to upstream areas, downstream areas have similar population density and share of families on welfare, though slightly lower share of adults with a college degree and slightly greater share population black.[62] These cross-sectional differences are another reason that our research design exploits the timing of grants across treatment plants. We view this analysis as a test of the accuracy of water pollution and plant data.

Results

As a river passes a wastewater treatment plant, data show large and statistically significant increases in pollution (Appendix Table 5). Dissolved oxygen deficits rise by 1.2 percent saturation, which is an increase of ten percent relative to the upstream pollution level. Fecal coliforms increase the most as a river passes a treatment plant, by about 40 percent. Other pollutants increase by smaller amounts. The probability that a river is not fishable rises by about 4 percentage points as a river passes a wastewater treatment plant.

Graphs of these pollutants by distance from the plant, corresponding to equation (7), show these patterns more flexibly (Appendix Figure 5). As a river approaches a treatment plant, dissolved oxygen

[62] The census tracts of downstream monitoring sites have population density of 835 persons per square mile; upstream areas have density of 862. Downstream areas have 4.88 percent of families on welfare, while upstream areas have 4.81 percent of families on welfare; downstream areas have 9.2 percent of adults with a college degree while upstream areas have 9.9 percent of adults with a college degree, and downstream areas have 8.5 percent of population black while upstream areas have 7.7 percent of population black. These values use 1970 census data.

deficits do not change at all, and the probability that it is not fishable increases gradually. The modest trend in fishability may occur because other pollution sources are located upstream of a treatment plant. In the miles just downstream of the treatment plant, dissolved oxygen deficits jump by 1-2 percentage points, and the probability the river violates fishing standards jumps by 3-4 percentage points. These increases in pollution levels persist for at least 25 miles downstream of the treatment plant. Similar patterns appear for other pollutants.[63] Some of this persistence may reflect other pollution sources near cities like industry or urban runoff, and later we directly estimate the length of distance downriver at which grants affect pollution. These patterns suggest the data behave as one might expect since water pollution concentrations rise as a river passes a pollution source.

E Sensitivity Analyses

E.1 Pollution Trends

This subsection reports sensitivity analyses for pollution trends using the linear trend specification of equation (2), noting the caveats mentioned earlier.

Rows 2-6 of Appendix Table 3 consider important subsamples. Row 2 only uses long-term stations, which begin operating by the year 1971 and report data through at least the year 1988. We choose these years since the Clean Water Act was passed in 1972, and since 1987 was the last year with the full grants program. Row 3 restricts the sample to the largely metro counties that had some home values data in all four decennial censuses 1970-2000; as mentioned earlier, the 1970-80 censuses excluded many non-metro areas. Rows 4-6 separately estimate results for the three pollution data repositories – NWIS, Storet Legacy, and Modern Storet – since each has different coverage and affiliated organizations which collect the data.

Rows 7-11 of Appendix Table 3 report sensitivity analyses prompted in part from discussing this analysis with hydrologists. Row 7 limits the sample to include only stations which have at least 25 readings, since these may have higher-quality data. Row 8 controls for the level of instantaneous stream flow, as measured at the same station and time as pollution, and so is limited to to "stream gauge" observations recording both streamflow and pollution. Row 9 uses data from only the months of July and August, since this is when streamflows are lowest, temperatures are greatest, and pollution concentrations are highest. Row 10 takes readings which indicate that they are below a monitor's detection limit ("BDL"), which are 5 percent of all readings, and replaces them with half the recorded value. (The main analysis uses the reported value for these BDL readings.) This is a standard sensitivity analyses for such readings in water quality research. Row 11 specifies the pollutants with a skewed distribution (BOD, fecal coliforms, and TSS) in logs rather than levels.

Rows 12-13 of Appendix Table 3 report alternative water pollution indices. Row 12 reports results where each observation describes mean values for a river-year. In this specification, a "river" is defined as a unique combination of a watershed and river code.[64] Row 13 defines the dependent variable as an indicator for whether more than 50 percent of pollution readings in the river-year are below the fishable or swimmable standard.

Rows 14-16 of Appendix Table 3 report results separately for three small and well-documented networks of high-quality monitoring sites, all managed by USGS. Row 14 shows estimates for the National

[63] Most pollutants, including BOD, fecal coliforms, and dissolved oxygen deficits, increase fairly abruptly in the 5 miles just before and after a treatment plant. TSS, which is the only exception, increases somewhat steadily in the 25 miles downstream of a treatment plant. These TSS patterns are consistent with the idea that urban runoff accounts for a large share of TSS emissions (Gianessi and Peskin 1981), and that urban runoff occurs in cities around treatment plants.

[64] A river here is defined as a "levelpathi" from NHD.

Stream Quality Accounting Network (NASQAN). Row 15 shows estimates for the National Water-Quality Assessment (NAWQA) (Smith, Alexander, and Wolman 1987; Alexander, Slack, Ludtke, Fitzgerald, and Schertz 1998; Rosen and Lapham 2008).[65] Row 16 shows estimates for the Hydrologic Benchmark Network (HBN), which includes 37 watersheds expected to have "minimal" effects from human activity (Alexander, Slack, Ludtke, Fitzgerald, and Schertz 1998). HBN shows smaller trends than the main sample for BOD, fecal coliforms, and TSS, which is consistent with anthropogenic causes of these pollutants in the national data.

Rows 17-25 of Appendix Table 3 report nine other important sensitivity analyses. Row 17 allows arbitrary autocorrelation within both watersheds and years. Row 18 limits the sample to lakes. An important paper by Smith and Wolloh (2012) finds that dissolved oxygen in lakes has not changed since the Clean Water Act, and Row 18 corroborates that finding. But the lake point estimate for dissolved oxygen deficits is negative, all other pollutants in lakes show downward trends, and nearly all of the roughly 20 other sensitivity analyses in Appendix Table 3 also show statistically significant downward trends. These results suggest that broader trends in water pollution differ from patterns evident in dissolved oxygen in lakes. Row 19 adds controls for temperature and precipitation. These are relevant since climate change is increasing air temperatures, but hotter temperatures can increase dissolved oxygen deficits. In row 20 each observation is the mean value in the county-year, and regressions are generalized least squares weighted by the population in the county-year. This may better reflect the trends experienced by the average person. Row 21 interacts the time-of-day and day-of-year controls with hydrologic region fixed effects, to capture the idea that seasonality and time patterns may differ across space. Rows 22-25 report estimates separately for each of the four census regions; all pollutants are declining in all regions, though declines were more rapid in the Northeast.

E.2 Effects of Clean Water Act Grants on Pollution

This subsection reports sensitivity analyses for effects of Clean Water Act grants on pollution, using variants of equation (3) from the main text. Rows 1-13 of Appendix Table 6 report the sensitivity analyses used for analyzing trends, and most of these give broadly similar results to the main specification. The alternative definitions of the "fishable" and "swimmable" standards do give more variable results—for example, defining fishable and swimmable as an indicator for whether 50% of readings are below the standard shows that each grant decreases the probability that waters violate the fishable standard by 2.4 percentage points, but does not significantly change the probability that waters are swimmable.

We also estimate about 15 sensitivity analyses which we do not report for trends regressions, and most also give similar results. Row 14 includes dummies for the range of distances from 0-25 miles, 25-50, 50-75, and 75-100 miles. These analyses show that the effect of grants on water pollution is concentrated within 25 miles. For BOD and dissolved oxygen, small and statistically insignificant effects may appear at further distances. Row 15 considers the subsample of plants with pollution monitoring sites at least 10 miles upstream and downstream.

Rows 16-20 of Appendix Table 6 describe other ways of measuring grants. Row 16 includes only grants that are for physical construction, and excludes grants for architectural or engineering plans. Row 17 includes separate indicators for each possible cumulative grant that a plant received. All grants appear to decrease pollution, though later grants may have had larger effects, and most pollutants show a positive dose-response function. Row 18 controls for the cumulative number of grants that all plants within 25

[65] We explored estimating the effect of Clean Water Act grants on water pollution using these networks, and we also explored estimating the change in water pollution downstream versus upstream of treatment plants. The networks are sparse enough that almost no treatment plants have monitoring sites in these networks that are both upstream and downstream, so they are not identified and we do not report them.

miles upstream had received, which hardly changes estimates. This control is designed to address the possible concern that facilities may be located near each other in rivers, and nearby plants may receive grants at similar times.[66] Row 19 includes controls for the number of grant projects of three different magnitudes (roughly terciles of the size distribution). The smallest grant projects have no clear effects on pollution, moderate-size projects lead to statistically insignificant decreases in pollution, and the largest projects produce the clearest decreases in pollution. Row 20 replaces the cumulative number of grants with a measure of the log of the cumulative real grant dollars provided, and indicates that a one percent increases in grant size increases the probability that downstream rivers are fishable by about 1 percent. As discussed earlier, one potential reason these estimates are less precise than estimates for the number of grants is that the distribution of grants is highly skewed, but also contains many zeros.

Rows 21-27 of Appendix Table 6 present several other important sensitivity analyses. Row 21 shows a differences-in-differences specification using data only from downstream waters. This specification includes plant fixed effects and water basin-by-year fixed effects, and reports the coefficient on a variable measuring the cumulative number of grants a plant has received. This finds slightly larger and more precise estimates than the main results do, though most of the main estimates and these estimates have overlapping confidence intervals. Row 22 allows arbitrary autocorrelation of confidence regions within year and within watershed. Row 23 includes monitoring sites on other rivers than the river where the wastewater treatment plant is directly located. Row 24 excludes small wastewater treatment plants that never received a grant. Row 25 shows unweighted OLS estimates. Finally, row 26 adds several potentially important control variables, each interacted with a downstream indicator: whether the county of the wastewater treatment plant was in nonattainment under the Clean Air Act, separately for each air pollutant; the total population in the county-year of the wastewater treatment plant; and two indicators for the number of polluting industrial plants in the county-year of the wastewater treatment plant, extracted from the databases SWUM and PCS as described earlier.[67]

Finally, we estimate the effect of these grants on other pollutants (Appendix Table 4, column 2). These results provide additional evidence in support of the identifying assumptions. We find no effect of a grant on any of the industrial pollutants (lead, mercury, or phenols), and perverse signs for two of the three. It is not impossible for a grant to affect these industrial pollutants, since some industrial waste can flow through treatment plants, but the lack of substantive effects on any of these three and incorrect signs are consistent with the idea that these grants are not correlated with unobserved variables like industrial activity or industrial water pollution regulations. We also detect no effects of grants on most measures of nutrients or more general water quality measures such as chlorides, stream flow, or temperature.

E.3 Hedonic Estimates

Appendix Table 8 reports a few sensitivity analyses. Columns (1)-(3) report effects of grants on log mean home values for different radii. Columns (4)-(6) analyze rental values. Columns (7)-(12) report estimates for residential characteristics like income, education, race, and age. If residents value characteristics of neighbors and grants change those characteristics, then looking only at price or quantity effects could misrepresent willingness to pay (Bayer, Ferreira, and McMillan 2007; Greenstone and Gallagher 2008).

Each row describes different analyses. Row 2 excludes all housing units within a 1-mile radius in any direction of the treatment plant, to address the possibility that grants change local disamenities

[66] Overall, 57 percent of the plants we analyze have at least one other plant within 25 miles upstream or 25 miles downstream, and the mean plant in our data has 1.7 other plants within 25 miles upstream or 25 miles downstream. The two additional controls included in Row 20 both have small and statistically insignificant coefficients.

[67] Because the Census RDC industrial water pollution data are only observed in 1972, they are interacted with a full set of year indicators, in addition to the interaction with downstream indicators.

like noise or odor. Row 3 allows two-way clustering of standard errors by watershed and also by year. The richest specifications of Table 5 include baseline controls interacted with year fixed effects; row 4 removes these baseline controls. Row 5 reports a differences-in-differences-in-differences regression comparing upstream versus downstream home values.[68] Row 6 reports unweighted OLS estimates. Row 7 replaces downstream-by-basin-by-year fixed effects with downstream-by-year fixed effects and basin-by-year trends. Row 8 reports estimates only for grants given in the year 1972. If communities in later years knew in advance a plant would receive a grant, then estimates for later years could be confounded by homeowner expectations. Row 9 reports the change in housing values around 1987 for plants that never received a grant. If homeowners had accurate expectations about future grants, these plants may have experienced a decrease in home values once the grants largely ceased. Row 10 restricts the sample to the 100 largest metropolitan areas as of 1970. Row 11 allows grants to affect outcomes after 10 years, which may be important if local public goods are only gradually incorporated into self-reported housing values.

Appendix Table 8 suggests little evidence that grants changed the composition of local residents (columns 7-12). All these point estimates are small, and most are statistically indistinguishable from zero. More broadly, these estimates do not change our qualitative conclusions about how grants affect housing values (columns 1-6), though point estimates do vary. There is modest evidence that home values (though not rents) increase within 0.25 or 1.0 miles of affected waters, though point estimates within 25 miles are uniformly small and indistinguishable from zero. The unweighted estimates for housing (though not rents) are more positive, which may suggest larger effects for less densely populated areas. Below we explore heterogeneity directly, and find some evidence of larger effects for (generally rural) areas where outdoor fishing or swimming is common.

F Interpreting Hedonic Estimates

Section 7.4 in the main text describes several reasons which have good empirical support for why the hedonic model might provide a lower bound on willingness to pay for Clean Water Act grants. This section describes several additional possible reasons which we believe have weaker empirical support.

First, the effects of these grants could have been reflected in changes in housing supply or in the characteristics of local residents (Greenstone and Gallagher 2008). As discussed earlier, Table 6 and Appendix Table 8 show little evidence of changes in either.

Second, these grants may require city taxes, sewer fees, or other local costs that depress home values. If this were widespread, one would expect smaller or negative benefits both upstream and downstream of a treatment plant, where residents are paying these costs. The data show no such pattern—in our broadest sample that includes homes up to 25 miles from the river, a triple-difference estimator which compares upstream and downstream values finds no evidence that grants increase home values (see column (3) in row 5 of Appendix Table 8). Moreover, because the 1980-2000 gross rent data reported in the census include utilities costs, if sewer taxes were particularly important, then one would expect home values to decline and gross rents to increase, whereas if anything the estimates of Table 6 suggest the opposite.

Third, people might not fully consider recreational demand or aesthetics when buying a home. Applications of the hedonic model generally assume that homeowners have complete information about the attributes of the home they are buying, not least because a home is typically a person's largest purchase. This common assumption seems plausible in this setting.

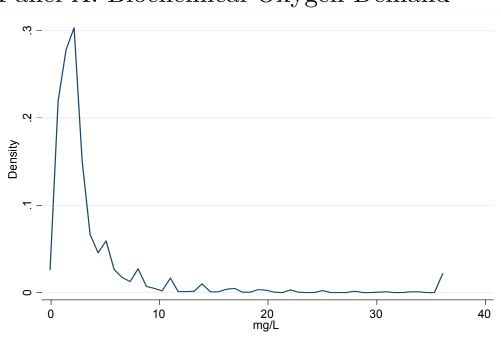
Fourth, if homeowners already expected a grant in a given year, then that grant might affect home prices before it was received. Qualitative evidence on such expectations is ambiguous. As Section 2.1

[68] In this sensitivity analysis, we draw a straight line through the treatment plant which is perpendicular to the river as it flows through the treatment plant. We put homes upstream of this line in the upstream group, and similarly for downstream homes. This avoids putting a home in both the upstream and downstream group for a given treatment plant.

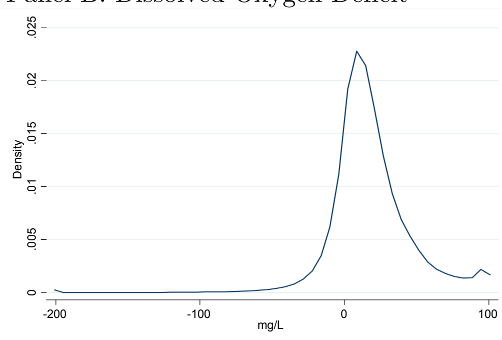
explains, states were supposed to discuss priority lists in public hearings, which could provide public knowledge about plants that might soon receive grants. The extent of such public knowledge is unclear, however, and both priority lists and the national budget of the grants program changed substantially between years. Available quantitative evidence does not show clear support for this idea. Homeowner expectations formed in the year(s) before a grant would create a positive pretrend in home values, but Figure 4 shows a flat pre-trend in the ten years before a grant. If expectations played a large role overall, then grants given in the first year of the program (1972) might have larger effects since these were largely unexpected. Row 8 of Appendix Table 8 estimates only the effect of grants given in the year 1972, and finds similar effects to the overall estimates of Row 1. Finally, we test for a change in home values in 1987, the year the grants largely concluded, for plants that failed to receive a grant. The point estimates for this are negative but not statistically distinguishable from either zero or the main estimates (Row 9).

Appendix Figure 1. Densities of Raw Pollution Readings

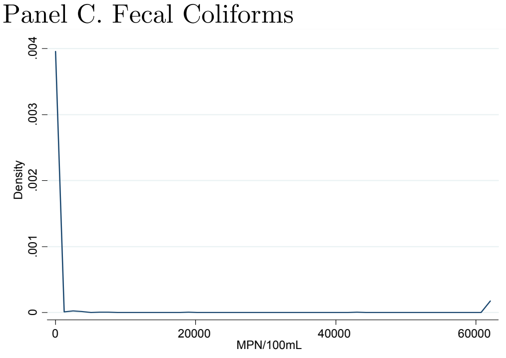
Panel A. Biochemical Oxygen Demand



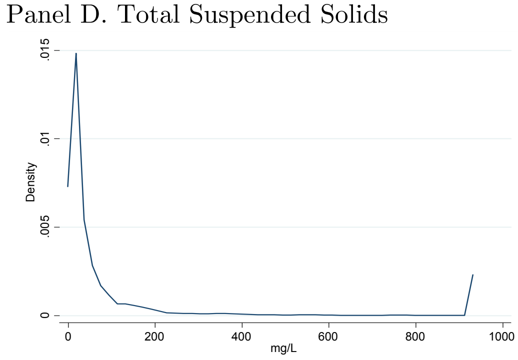
Panel B. Dissolved Oxygen Deficit



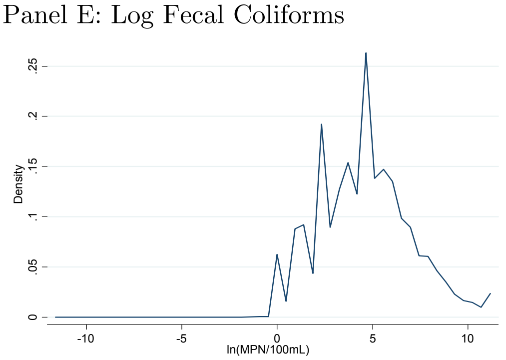
Panel C. Fecal Coliforms



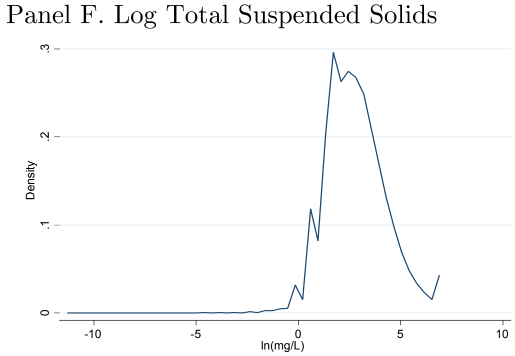
Panel D. Total Suspended Solids



Panel E: Log Fecal Coliforms



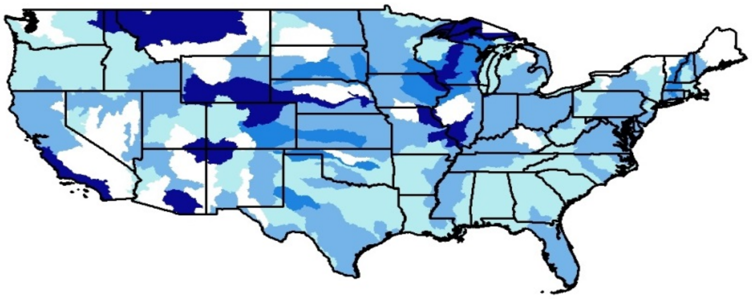
Panel F. Log Total Suspended Solids



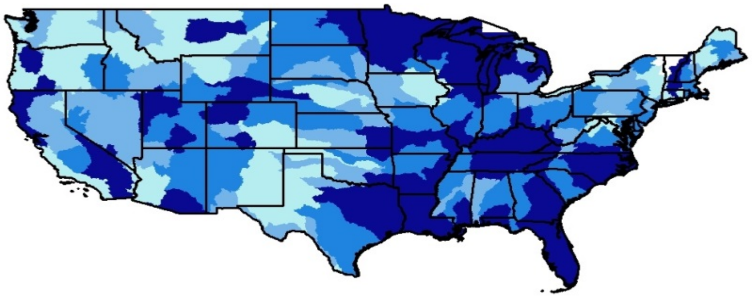
Notes: Data include years 1962-2001.

Appendix Figure 2a. Pollution by River Basin, 1992-2001

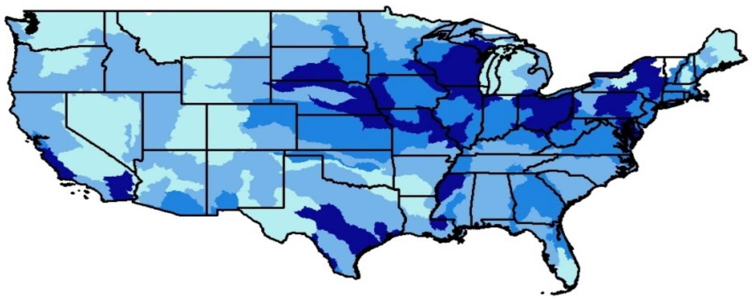
Panel A. Biochemical Oxygen Demand



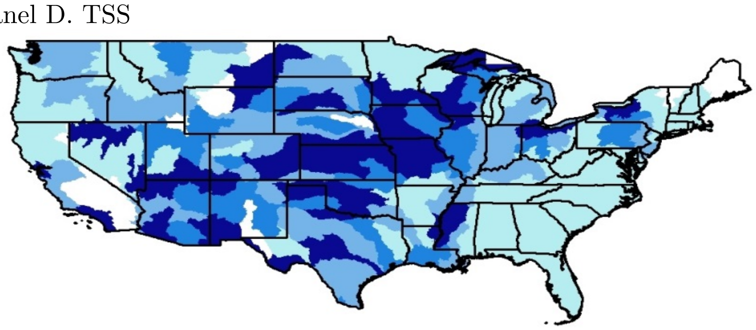
Panel B. Dissolved Oxygen Deficit



Panel C. Fecal Coliforms



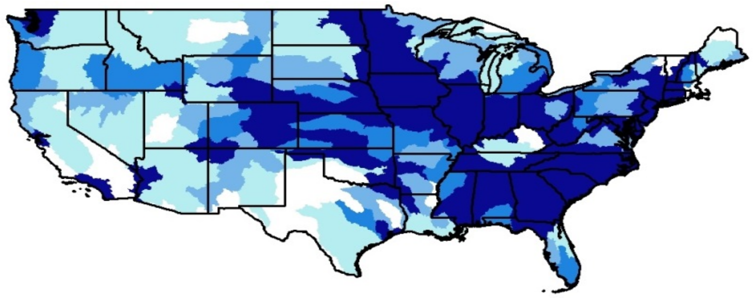
Panel D. TSS



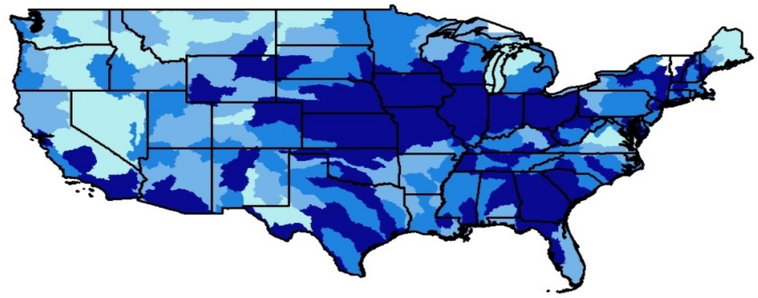
Notes: Data are mean by river basin. Darker colors represent worse pollution, white areas have no data. Categories are as follows. BOD: <2, 2 to 4, 4 to 6, >6. Dissolved oxygen deficit: <6, 6 to 12, 12 to 18, >18. Fecal coliforms: <250, 250 to 750, 750 to 1750, >1750. TSS: <25, 25 to 50, 50 to 75, >75.

Appendix Figure 2b. Fecal Coliforms, by River Basin and Decade, 1962-2001

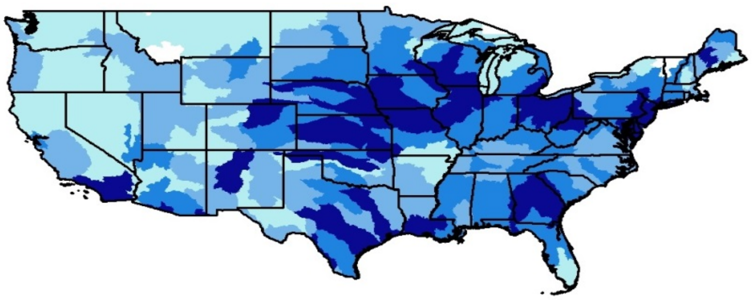
Panel A. 1962-1971



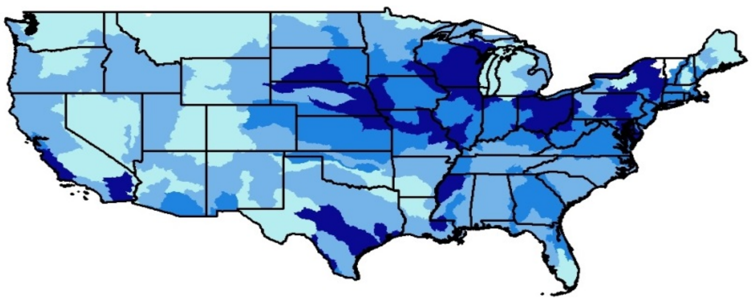
Panel B. 1972-1981



Panel C. 1982-1991



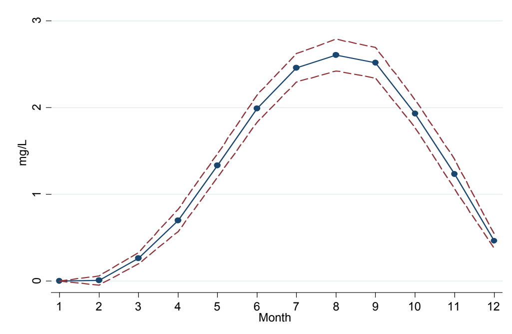
Panel D. 1992-2001



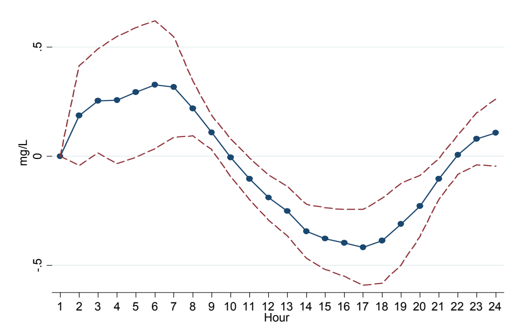
Notes: Data are mean by river basin. Darker colors represent worse pollution. Color cutoffs are same in each year. White areas have no data. Colors are as follows, with values in logs: No data (white), <250 (light blue), 250 to 750 (moderate blue), 750 to 1750 (darker blue), >1750 (darkest blue).

Appendix Figure 3. Patterns in Dissolved Oxygen Deficits

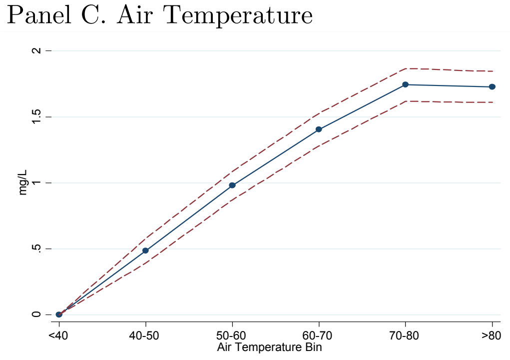
Panel A. Month



Panel B. Hour



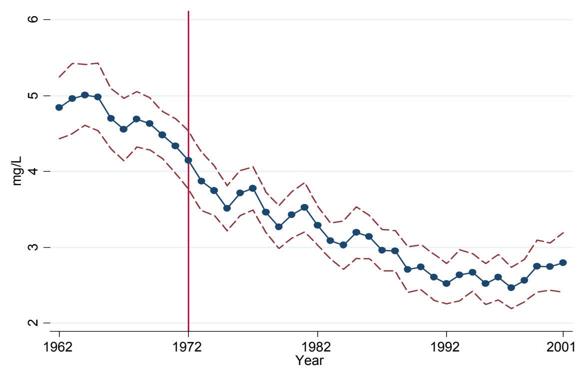
Panel C. Air Temperature



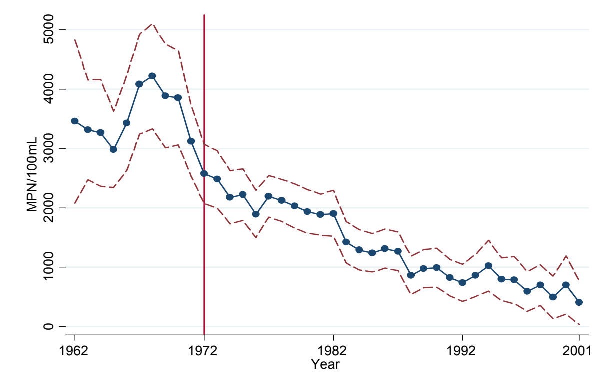
Notes: Figures show coefficients from a regression of dissolved oxygen deficit on monitoring station fixed effects and on dummy variables for the indicated controls. Data use only dissolved oxygen measured in mg/L. Dissolved oxygen deficit measured as 15 minus the reported level of dissolved oxygen in mg/L. Data cover years 1962-2001.

Appendix Figure 4. Water Pollution Trends, Other Pollution Measures, 1962-2001

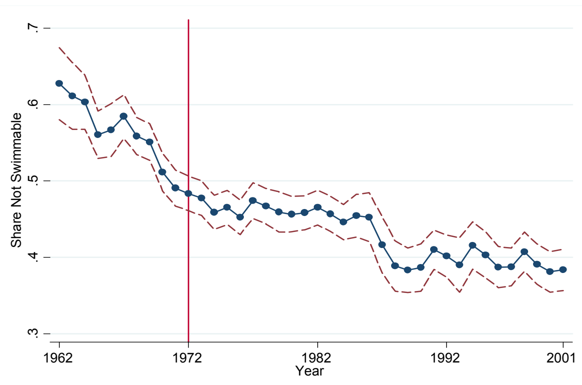
Panel A. Biochemical Oxygen Demand



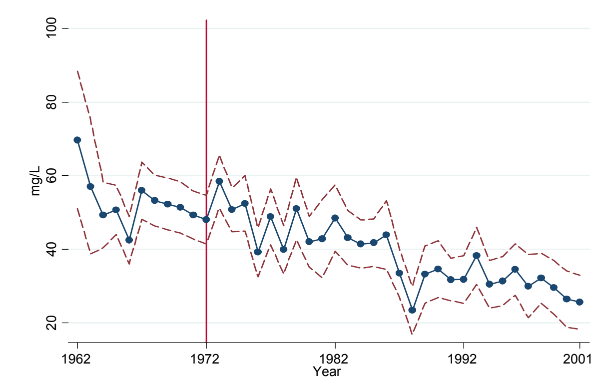
Panel B. Fecal Coliforms



Panel C. Not Swimmable



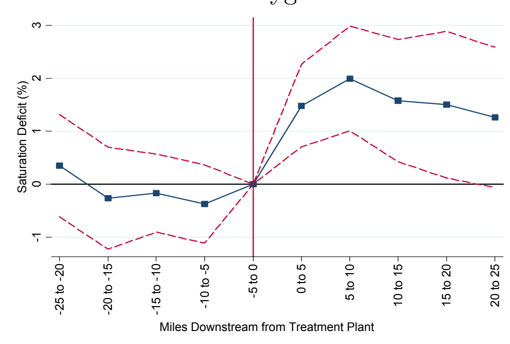
Panel D. Total Suspended Solids



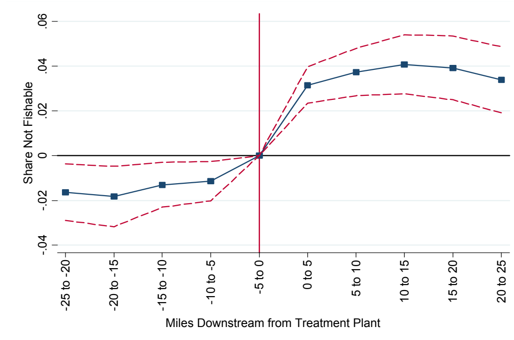
Notes: These graphs show year fixed effects plus the constant from regressions which control for station fixed effects, year fixed effects, day-of-year cubic polynomial, and hour-of-day cubic polynomial, corresponding to equation (2) in the text. Connected dots show yearly values, dashed lines show 95% confidence interval, and 1962 is reference category. Standard errors are clustered by watershed.

Appendix Figure 5. Water Pollution, by Distance Downstream from Treatment Plant, Other Pollution Measures

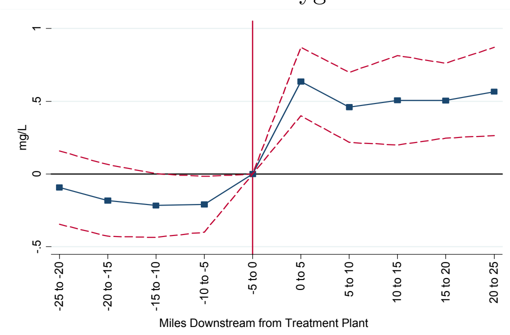
Panel A. Dissolved Oxygen Deficit



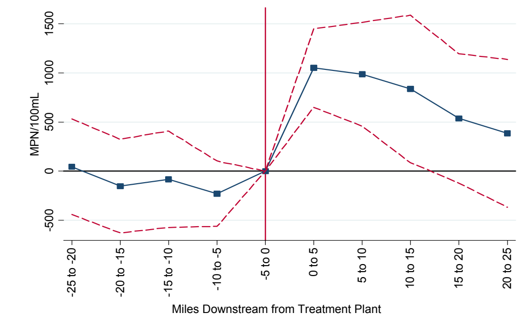
Panel B. Not Fishable



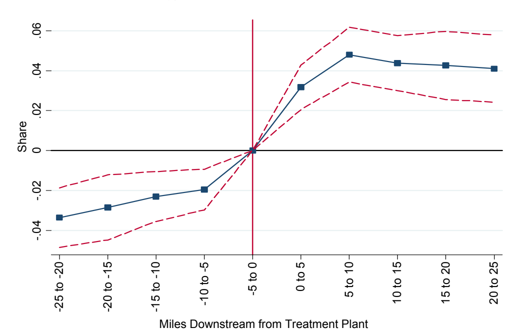
Panel C. Biochemical Oxygen Demand



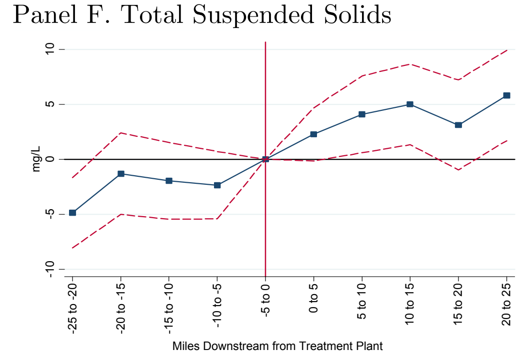
Panel D. Fecal Coliforms



Panel E. Not Swimmable



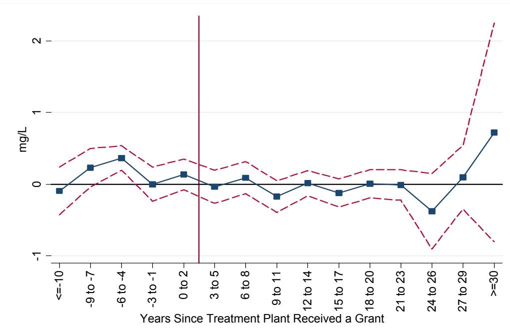
Panel F. Total Suspended Solids



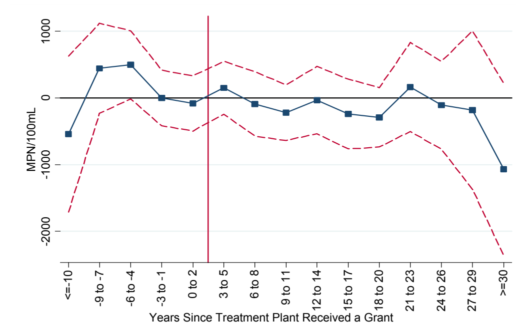
Notes: Graphs show coefficients on distance-from-plant indicators from regressions which also control for plant-by-year fixed effects, corresponding to equation (3) from the main text. Connected dots show yearly values, dashed lines show 95% confidence interval. Data cover years 1962-2001. Standard errors are clustered by watershed.

Appendix Figure 6. Effects of Clean Water Act Grants on Water Pollution, Event Study, Other Pollution Measures

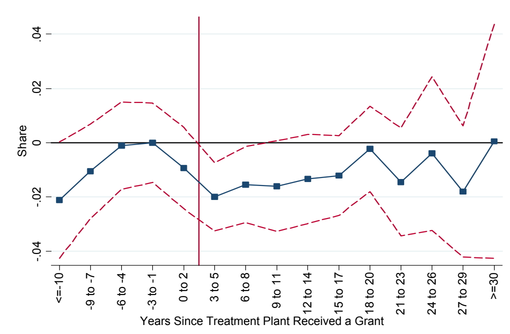
Panel A. Biochemical Oxygen Demand



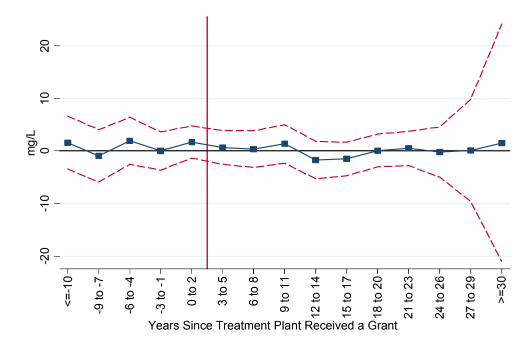
Panel B. Fecal Coliforms



Panel C. Share Not Swimmable



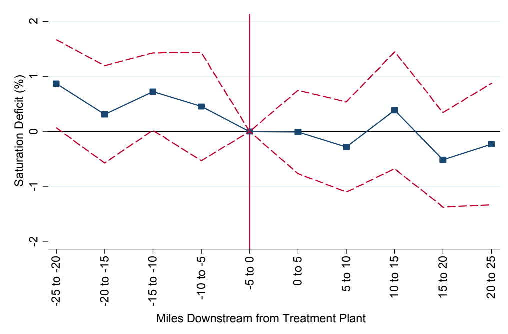
Panel D. Total Suspended Solids



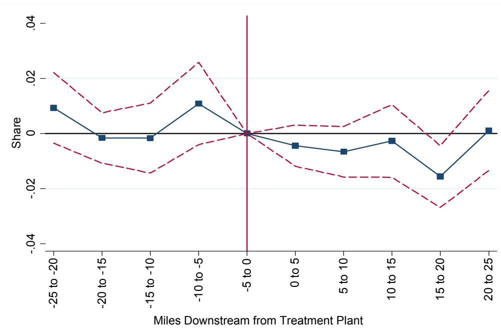
Notes: Graphs show coefficients on downstream times year-since-grant indicators from regressions which correspond to the specification of Table 3. These regressions are described in equation (5) from the main text. Connected dots show yearly values, dashed lines show 95% confidence interval. Data cover years 1962-2001. Standard errors are clustered by watershed.

Appendix Figure 7. Effects of Clean Water Act Grants on Water Pollution
by Distance Downstream from Treatment Plant

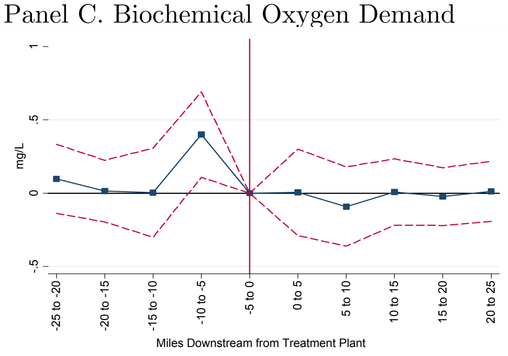
Panel A. Dissolved Oxygen Deficit



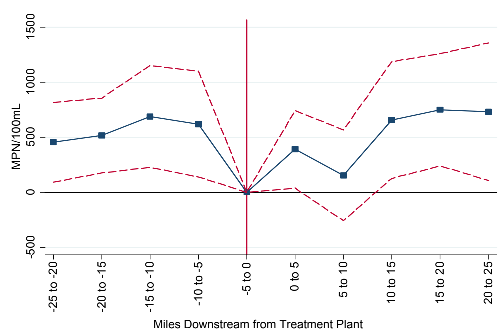
Panel B. Not Fishable



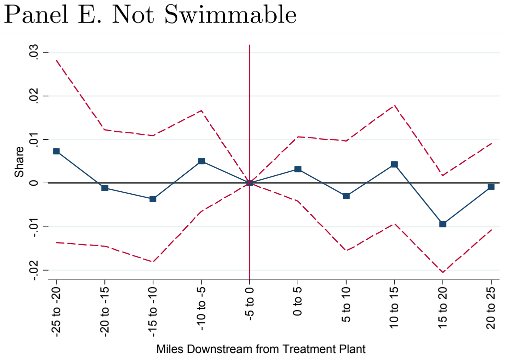
Panel C. Biochemical Oxygen Demand



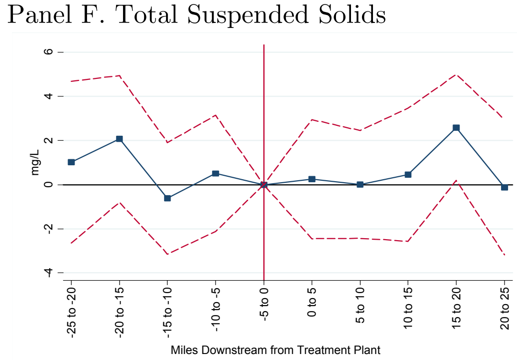
Panel D. Fecal Coliforms



Panel E. Not Swimmable

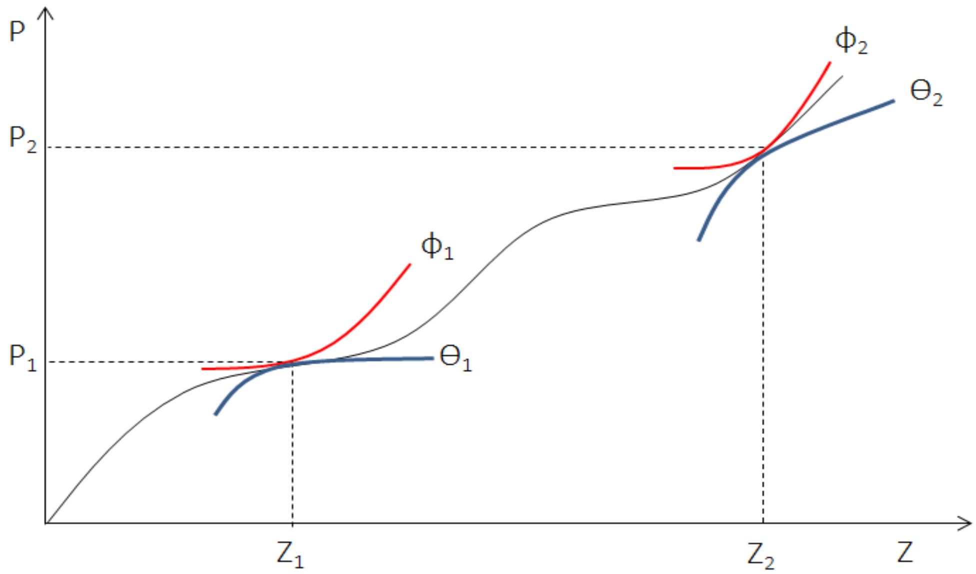


Panel F. Total Suspended Solids



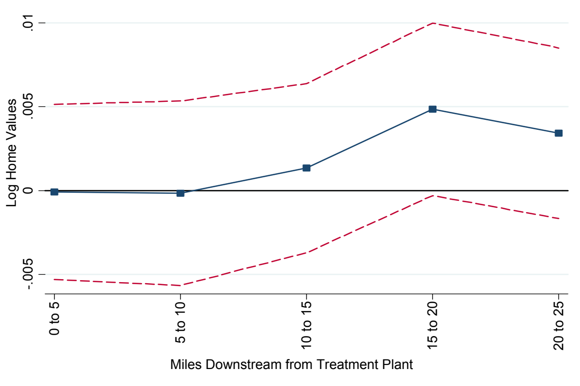
Notes: Graphs show distance-from-plant times cumulative grant indicators from regressions which also control for plant-by-distance, plant-by-year, and distance-by-water basin-by-year fixed effects. These regressions correspond to equation (6) in the text. Connected dots show yearly values, dashed lines show 95% confidence interval. Data cover years 1962-2001. Standard errors are clustered by watershed.

Appendix Figure 8. The Hedonic Model

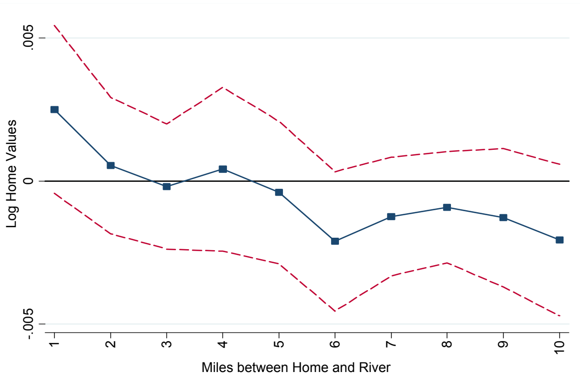


Appendix Figure 9. Effects of Clean Water Act Grants on Log Mean Home Values

Panel A. By Distance Downstream from Treatment Plant

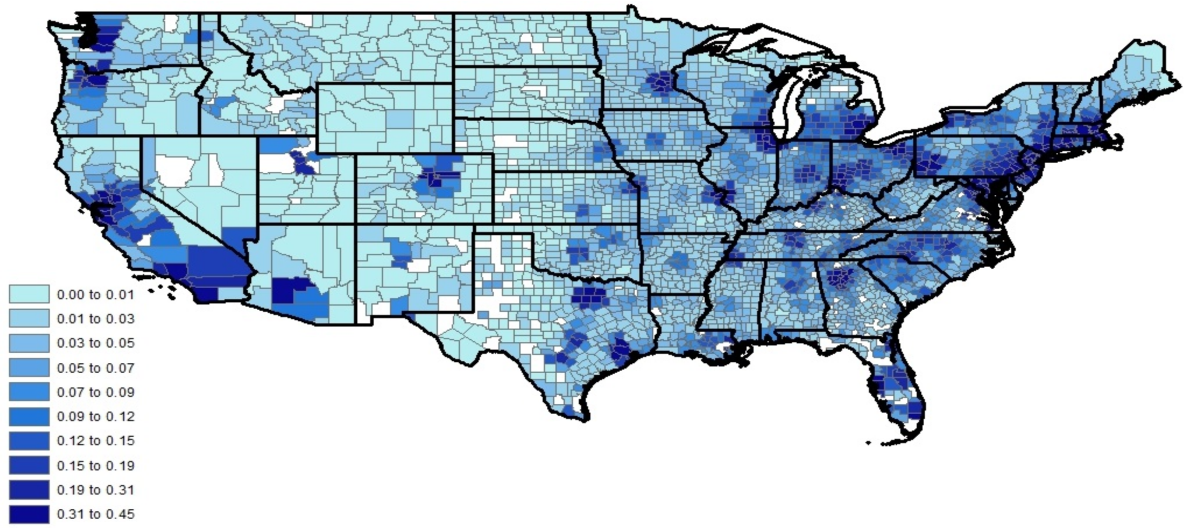


Panel B. Miles Between Home and River



Notes: Panel A includes homes within 1 mile of river. Data cover decennial census years 1970-2000.

Appendix Figure 10. Ratio of Change in Housing Values to Grant Costs, by County



Notes: We divide treatment plants into ten deciles based on the population in the year 2000 which is within a 25 mile radius in any direction of the river segments that are up to 25 miles downstream of the plant and on the same river as the plant. For each decile, we calculate the total value of owned homes and rentals satisfying the same criteria (within a 25 mile radius, etc.). To estimate the change in housing values, we apply the regression estimates from column (4) of Table 6, and assume improvements last 30 years. For each decile, we measure costs using the grants data. For each decile, we divide the total change in housing values by total costs. Finally, we calculate the unweighted average of this ratio across all plants in a county, and the map plots the result. Counties in white have no treatment plants or missing data. The share of total real grant project costs going to each decile, ordered from lowest-population to greatest-population, is as follows: 0.02, 0.02, 0.03, 0.04, 0.05, 0.06, 0.10, 0.13, 0.19, 0.37. The share of total population in each decile is as follows: 0.00, 0.01, 0.01, 0.02, 0.03, 0.04, 0.06, 0.10, 0.18, 0.54.

Appendix Table 1. Water Pollution Descriptive Statistics

	Pooled	Biochemical Oxygen Demand	Dissolved Oxygen Deficit	Fecal Coliforms	Total Suspended Solids
	(1)	(2)	(3)	(4)	(5)
Mean	---	3.19	19.28	1,688.54	51.32
	---	4.55	28.23	7,279.42	126.87
5th Percentile	---	0.50	-15.90	1.00	1.00
95th Percentile	---	10.00	79.60	6,000.00	211.00
Number of Distinct . . .					
Observations	10,581,253	1,258,312	5,582,228	2,032,112	1,708,601
Monitoring Sites	168,200	51,777	145,614	77,269	67,473
River Segments	96,775	35,434	87,222	49,928	44,581
Rivers	46,406	16,932	41,864	24,960	22,163
Mean Years per Monitoring Site	11	11	11	11	10
Mean Readings per Monitoring Site	63	24	38	26	25
Share in Metro Areas	0.27	0.29	0.27	0.26	0.27
Share from each repository:					
Storet Legacy	0.64	0.66	0.63	0.65	0.67
Storet	0.21	0.20	0.21	0.20	0.21
NWIS	0.15	0.14	0.16	0.15	0.12
Share from each type of surface water:					
Rivers	0.84	0.96	0.76	0.92	0.90
Lakes	0.16	0.04	0.24	0.08	0.10
Share from each Census Region:					
Northeast	0.07	0.06	0.08	0.06	0.05
Midwest	0.27	0.23	0.26	0.24	0.39
South	0.49	0.59	0.48	0.54	0.41
West	0.17	0.12	0.18	0.17	0.15
Share from each Decade:					
1962-1971	0.09	0.14	0.09	0.07	0.04
1972-1981	0.33	0.38	0.30	0.43	0.30
1982-1991	0.29	0.26	0.30	0.26	0.32
1992-2001	0.29	0.22	0.31	0.24	0.34
Share of Readings from Monitoring Sites in ...					
One Decade	0.26	0.26	0.28	0.26	0.31
Two Decades	0.30	0.31	0.31	0.29	0.31
Three Decades	0.29	0.25	0.28	0.33	0.28
Four Decades	0.16	0.18	0.13	0.12	0.10

Notes: Metro areas are defined as tracts from the 1970 census with non-missing home values data. Dissolved oxygen deficit equals 100 minus dissolved oxygen, measured in percent saturation. River segments are "comid"s, rivers are "levelpathi"s, as defined in the National Hydrography Dataset Plus, Version 2.1.Data cover years 1962-2001.

Appendix Table 2. Descriptive Statistics for Treatment Plants and Grants

Which Plants	All (1)	With Pollution Data (2)	River & Monitor on Same River (3)
Number of Plants	20,956	11,240	6,824
Number of Grants	24,271	14,378	9,483
Mean Number of Grants:			
All Plants	1.16	1.28	1.39
Plants with ≥1 Grant	2.75	2.80	2.90
Share of Plants Receiving Following Number of Grants:			
None	0.39	0.37	0.34
Exactly 1	0.30	0.27	0.27
Exactly 2	0.18	0.20	0.20
3 to 5	0.12	0.15	0.16
6 or More	0.01	0.01	0.02
Federal Contribution for a Grant ($2012 Millions)			
Mean	7.59	7.70	9.20
5th Percentile	0.03	0.03	0.04
50th Percentile	0.84	0.93	1.16
95th Percentile	29.99	32.44	39.73
Total Cost of a Grant Project ($2012 Millions)			
Mean	25.47	25.95	31.07
5th Percentile	0.09	0.10	0.12
50th Percentile	2.86	3.13	3.92
95th Percentile	101.32	109.84	135.76

Notes: Table counts multiple grants to the same plant in a single year as one grant. Column (1) includes only grants linked to treatment plants. Column (2) further restricts the sample to only plants that have BOD, dissolved oxygen, fecal coliforms, or TSS readings within 25 miles of the treatment plant, as measured along the river network. Column (3) further restricts the sample to plants which received at least one grant, and which are on the same river as the treatment plant, where a river is defined as a "levelpathi" from the value added attributes files of the National Hydrography Dataset Plus, version 2.1. Total cost of a grant project includes federal contribution, local capital cost, and operating and maintenance costs. Grant values are deflated using the Engineering News Record construction price index. Plants with zero grants, listed in columns (1) and (2), are plants that appear in in 1976, 1978, 1984, 1986, or 1988 Clean Watershed Needs Surveys (CWNS) with strictly positive population served, and which do not appear in the federal grants data. These are the only five years of the CWNS which were collected during the years of the grants program and which have accurate identifier codes for treatment plants. Data cover years 1962-2001.

Appendix Table 3. Water Pollution Trends, Sensitivity Analysis

	Main Pollution Measures		Other Pollution Measures			
	Dissolved Oxygen Deficit (1)	Not Fishable (2)	Biochemical Oxygen Demand (3)	Fecal Coliforms (4)	Not Swimmable (5)	Total Suspended Solids (6)
1. Main Estimates	-0.244***	-0.005***	-0.064***	-85.261***	-0.004***	-0.830***
	(0.030)	(0.000)	(0.005)	(8.850)	(0.000)	(0.101)
Important Subsamples						
2. Long-Term Stations	-0.246***	-0.005***	-0.054***	-100.509***	-0.006***	-0.903***
(≤1971 to ≥1988)	(0.035)	(0.000)	(0.008)	(14.930)	(0.000)	(0.156)
3. Counties in Balanced Panel	-0.335***	-0.006***	-0.098***	-96.007***	-0.005***	-0.923***
of Home Values Data	(0.047)	(0.000)	(0.009)	(12.432)	(0.000)	(0.124)
4. USGS NWIS Repository	-0.297***	-0.004***	-0.056***	-106.574***	-0.006***	-0.733***
	(0.022)	(0.000)	(0.010)	(17.706)	(0.000)	(0.184)
5. Storet Legacy Repository	-0.279***	-0.005***	-0.070***	-72.607***	-0.005***	-0.799***
	(0.044)	(0.000)	(0.007)	(8.850)	(0.000)	(0.105)
6. Modern Storet Repository	-0.106***	-0.003***	-0.048***	-104.168***	-0.003***	-0.968***
	(0.033)	(0.000)	(0.009)	(13.323)	(0.000)	(0.204)
Standard Water Quality Tests						
7. Exclude Stations with Less	-0.244***	-0.005***	-0.064***	-84.472***	-0.004***	-0.835***
than 25 Readings	(0.031)	(0.000)	(0.005)	(8.950)	(0.000)	(0.106)
8. Stream Gauge Observations,	-0.288***	-0.005***	-0.068***	-99.182***	-0.006***	-0.937***
Control for Flow	(0.023)	(0.000)	(0.010)	(15.292)	(0.000)	(0.212)
9. July-August Only	-0.252***	-0.005***	-0.067***	-91.698***	-0.004***	-0.795***
	(0.046)	(0.000)	(0.007)	(9.127)	(0.000)	(0.110)
10. Readings Below Limit ("BDL")	-0.244***	-0.005***	-0.068***	-85.244***	-0.005***	-0.833***
Equal Half Listed Value	(0.030)	(0.000)	(0.005)	(8.843)	(0.000)	(0.101)
11. Logs, Not Levels	---	---	-0.014***	-0.031***	---	-0.016***
	---	---	(0.002)	(0.002)	---	(0.001)
Other Fishable and Swimmable Definitions						
12. River-Year Means	---	-0.003***	---	---	-0.003***	---
	---	(0.000)	---	---	(0.000)	---
13. River-Year Means,	---	-0.004***	---	---	-0.005***	---
50% Fish/Swim Defn.	---	(0.000)	---	---	(0.000)	---

Appendix Table 3. Water Pollution Trends, Sensitivity Analysis (Continued)

	Standards		Constituent Pollutants			
	Dissolved Oxygen Deficit	Not Fishable	Biochemical Oxygen Demand	Fecal Coliforms	Not Swimmable	Total Suspended Solids
	(1)	(2)	(3)	(4)	(5)	(6)
Well-Documented USGS Networks						
14. NASQAN Network	-0.242***	-0.004***	-0.035***	-55.170***	-0.007***	-1.558***
	(0.027)	(0.000)	(0.014)	(8.267)	(0.001)	(0.426)
15. NAWQA Network	-0.322***	-0.005***	-0.079***	-92.195***	-0.007***	-0.863***
	(0.038)	(0.001)	(0.022)	(18.760)	(0.001)	(0.302)
16. HBN Network	-0.352***	-0.002***	0.018	0.825	-0.006***	-0.153
(Isolated, Natural Areas)	(0.080)	(0.001)	(0.016)	(1.938)	(0.001)	(0.325)
Other Important Sensitivity Analyses						
17. Cluster by Watershed And	-0.244***	-0.005***	-0.064***	-85.261***	-0.004***	-0.830***
and Year	(0.034)	(0.000)	(0.006)	(11.103)	(0.000)	(0.145)
18. Lakes	-0.078*	-0.001	-0.033***	-3.882*	-0.002***	-0.409**
	(0.042)	(0.000)	(0.011)	(2.156)	(0.001)	(0.166)
19. Weather Controls	-0.243***	-0.005***	-0.065***	-85.889***	-0.005***	-0.897***
	(0.030)	(0.000)	(0.005)	(8.812)	(0.000)	(0.099)
20. County-Year Means,	-0.243***	-0.004***	-0.097***	-104.834***	-0.004***	-1.283***
Population-Weighted	(0.055)	(0.000)	(0.017)	(14.171)	(0.000)	(0.316)
21. Flexible Seasonality and Time	-0.246***	-0.001***	-0.065***	-85.139***	-0.002***	-0.842***
	(0.030)	(0.000)	(0.005)	(8.603)	(0.000)	(0.102)
22. Census Region: Northeast	-0.473***	-0.006***	-0.067***	-77.046**	-0.007***	-0.719***
	(0.125)	(0.001)	(0.012)	(33.889)	(0.001)	(0.176)
23. Census Region: Midwest	-0.275***	-0.004***	-0.059***	-82.040***	-0.004***	-0.634***
	(0.035)	(0.000)	(0.008)	(14.610)	(0.000)	(0.201)
24. Census Region: South	-0.191***	-0.005***	-0.063***	-94.000***	-0.005***	-0.796***
	(0.048)	(0.000)	(0.007)	(13.118)	(0.001)	(0.078)
25. Census Region: West	-0.237***	-0.004***	-0.095***	-58.125***	-0.004***	-1.599***
	(0.056)	(0.000)	(0.022)	(11.715)	(0.001)	(0.278)

Notes: Standard errors are clustered by watershed. Regressions include Station FE and Season, Hour Controls except where otherwise noted. See text for details. Data cover years 1962-2001. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Appendix Table 4. Results for Other Measures of Water Pollution

	Trend (1)	Downstream * Cumulative # of Grants (2)
Industrial Pollutants		
1. Lead (μg/L)	-0.114***	-0.386
	(0.004)	(0.711)
Dependent Variable Mean	2.348	27.095
N	522,826	19,290
2. Mercury (μg/L)	-0.014***	0.017
	(0.001)	(0.016)
Dependent Variable Mean	0.339	0.382
N	388,432	14,470
3. Phenols (μg/L)	-1.793**	8.141*
	(0.729)	(4.487)
Dependent Variable Mean	58.695	10.767
N	145,894	6,758
Nutrients		
4. Ammonia (mg/L)	-0.039***	-0.030**
	(0.002)	(0.013)
Dependent Variable Mean	-2.408	0.456
N	1,667,380	34,354
5. Nitrates (mg/L)	0.000	0.024
	(0.002)	(0.035)
Dependent Variable Mean	-1.180	1.182
N	708,850	15,216
6. Nitrite Nitrate (mg/L)	0.003**	0.066**
	(0.001)	(0.032)
Dependent Variable Mean	-1.086	1.341
N	1,463,435	26,284
7. Nitrogen (mg/L)	-0.005***	28.803
	(0.001)	(50.019)
Dependent Variable Mean	3.389	2104.464
N	789,447	7,476
8. Orthophosphate (mg/L)	-0.024***	-0.015*
	(0.003)	(0.008)
Dependent Variable Mean	-3.559	0.226
N	879,991	11,512
9. Phosphorus (mg/L)	-0.006***	0.001
	(0.000)	(0.009)
Dependent Variable Mean	0.250	0.348
N	2,356,531	34,828

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Appendix Table 4. Results for Other Measures of Water Pollution (Continued)

	Trend (1)	Downstream * Cumulative # of Grants (2)
General Water Quality Measures		
10. Dissolved Chlorides (mg/L)	0.001	-8.181
	(0.001)	(7.764)
Dependent Variable Mean	3.037	106.949
N	1,006,375	16,054
11. Total Chlorides (mg/L)	-0.002	-16.816
	(0.002)	(11.824)
Dependent Variable Mean	3.694	147.111
N	1,525,148	19,272
12. Total Coliforms (count/100mL)	-0.049***	-2379.510
	(0.007)	(2089.800)
Dependent Variable Mean	6.440	34052.700
N	688,154	12,406
13. Color (PCU)	0.001	1.275
	(0.001)	(1.005)
Dependent Variable Mean	3.325	32.161
N	633,443	11,264
14. pH (pH units)	0.007***	-0.005
	(0.001)	(0.004)
Dependent Variable Mean	7.425	7.509
N	6,402,885	64,434
15. Total Dissolved Solids (mg/L)	0.000	-23.609*
	(0.001)	(13.693)
Dependent Variable Mean	5.399	445.416
N	1,845,578	27,766
16. Dissolved Sulfate (mg/L)	-0.001	-2.015
	(0.001)	(2.483)
Dependent Variable Mean	3.66	103.69
N	810,541	15,698
17. Stream Flow (Instanganeous, CFS)	0.001	-15.416
	(0.001)	(62.481)
Dependent Variable Mean	4.135	2225.705
N	1,960,480	23,994
18. Temperature (F)	0.025***	-0.035
	(0.005)	(0.049)
Dependent Variable Mean	60.140	58.995
N	10,693,062	70,874
19. Turbidity (NTU)	-0.489***	-0.614
	(0.049)	(0.433)
Dependent Variable Mean	21.233	26.053
N	2,381,622	29,988

Notes: Standard errors are clustered by watershed. Data cover years 1962-2001. All pollutants except mercury, phenols, phosphorus, pH, temperature, and turbidity are in logs. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Appendix Table 5. Water Pollution Upstream Versus Downstream of Treatment Plants

	Main Pollution Measures		Other Pollution Measures			
	Dissolved Oxygen Deficit	Not Fishable	Biochemical Oxygen Demand	Fecal Coliforms	Not Swimmable	Total Suspended Solids
	(1)	(2)	(3)	(4)	(5)	(6)
Downstream	1.202***	0.041***	0.623***	914.524***	0.051***	5.416***
	(0.373)	(0.004)	(0.093)	(224.581)	(0.005)	(1.146)
N	58,444	62,814	30,784	36,810	62,814	32,802
Dep. Var. Mean	11.98	0.19	3.33	2,201.70	0.46	45.36
Plant-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each observation in a regression is a plant-downstream-year tuple. Data cover years 1962-2001. Dissolved oxygen deficit equals 100 minus dissolved oxygen saturation, measured in percentage points. Dependent variable mean is for upstream pollution. Standard errors are clustered by watershed. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Appendix Table 6. Sensitivity Analysis: Effects of Clean Water Act Grants on Water Pollution

	Main Pollution Measures		Other Pollution Measures			
	Dissolved Oxygen Deficit	Not Fishable	Biochemical Oxygen Demand	Fecal Coliforms	Not Swimmable	Total Suspended Solids
	(1)	(2)	(3)	(4)	(5)	(6)
1. Main Estimates	-0.768***	-0.007***	-0.114***	-196.183**	-0.004**	-0.404
	(0.197)	(0.003)	(0.042)	(95.860)	(0.002)	(0.591)
Important Subsamples						
2. Long-Term Stations (≤1971 to ≥1988)	-1.276***	-0.030***	-0.211*	-326.610	-0.008**	-2.194
	(0.334)	(0.010)	(0.125)	(387.461)	(0.003)	(1.959)
3. Facilities with Balanced Panel of Home Values	-0.712***	-0.007**	-0.100**	-156.264	-0.004*	-0.450
	(0.214)	(0.003)	(0.045)	(99.209)	(0.002)	(0.628)
4. USGS NWIS Repository	-0.641	-0.014***	0.188	-9.801	-0.020**	4.253**
	(0.868)	(0.005)	(0.233)	(198.404)	(0.010)	(1.761)
5. Storet Legacy Repository	-0.516*	-0.008*	-0.153**	-231.683**	-0.001	-0.714
	(0.263)	(0.005)	(0.065)	(114.240)	(0.003)	(0.534)
6. Modern Storet Repository	-0.943***	-0.007	-0.152**	-435.751***	-0.012***	-0.374
	(0.357)	(0.005)	(0.074)	(153.076)	(0.004)	(0.436)
7. Only Years ≥1972	-0.787***	-0.010***	-0.127**	-119.061	-0.003	-0.319
	(0.200)	(0.003)	(0.060)	(88.459)	(0.002)	(0.632)
Standard Water Quality Tests						
8. Exclude Stations with Less than 25 Readings	-0.817***	-0.008**	-0.113**	-156.773	-0.004**	-0.069
	(0.217)	(0.003)	(0.053)	(130.027)	(0.002)	(0.644)
9. Stream Gauge Observations, Control for Flow	-0.791*	-0.012**	-0.152	-91.499	-0.006	2.511
	(0.444)	(0.006)	(0.130)	(105.586)	(0.006)	(1.903)
10. July-August Only	-1.424***	-0.015***	-0.141**	-85.959	-0.011***	-0.003
	(0.375)	(0.004)	(0.066)	(160.404)	(0.004)	(0.886)
11. Readings Below Limit Equal Half Listed Value	-0.766***	-0.007***	-0.113***	-203.251**	-0.004**	-0.411
	(0.198)	(0.003)	(0.041)	(96.067)	(0.002)	(0.591)
12. Logs, Not Levels	---	---	-0.012*	-0.013	---	-0.003
	---	---	(0.006)	(0.024)	---	(0.009)
Other Fishable and Swimmable Definitions						
13. 50% Fishable-Swimmable Definition	---	-0.023***	---	---	0.003	---
	---	(0.005)	---	---	(0.006)	---

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Appendix Table 6: Sensitivity Analysis: Effects of Clean Water Act Grants on Water Pollution (Continued)

	Main Pollution Measures		Other Pollution Measures			
	Dissolved Oxygen Deficit	Not Fishable	Biochemical Oxygen Demand	Fecal Coliforms	Not Swimmable	Total Suspended Solids
	(1)	(2)	(3)	(4)	(5)	(6)
Other Distances Upstream and Downstream of Treatment Plant						
14. Separate by Downstream Dist.						
0 to 25 Miles Downstream	-0.655***	-0.009***	-0.094**	-240.926***	-0.002	-1.063**
	(0.188)	(0.002)	(0.039)	(75.691)	(0.002)	(0.489)
25 to 50 Miles Downstream	-0.096	0.007	-0.070*	143.268	0.004	-0.018
	(0.303)	(0.005)	(0.037)	(106.276)	(0.004)	(1.126)
50 to 75 Miles Downstream	0.027	0.002	-0.039	142.204	0.001	-0.207
	(0.251)	(0.004)	(0.051)	(101.642)	(0.003)	(0.905)
75 to 100 Miles Downstream	0.806	0.000	-0.196	-105.046	0.006	-0.197
	(0.647)	(0.005)	(0.128)	(124.609)	(0.008)	(1.060)
15. Plants with Monitors > 10 Mi.	-0.845***	-0.008***	-0.130***	-222.592**	-0.005**	-0.125
Upstream and Downstream	(0.204)	(0.003)	(0.039)	(109.611)	(0.002)	(0.521)
Other Specifications for Measuring Grants						
16. Grants for Construction	-1.206***	-0.010***	-0.132**	-93.551	-0.006**	-0.268
	(0.219)	(0.004)	(0.052)	(128.303)	(0.003)	(0.728)
17. Cumulative number of grants						
One	-0.958*	-0.010	0.016	-550.196*	-0.013	1.028
	(0.521)	(0.007)	(0.127)	(296.743)	(0.008)	(1.993)
Two	-1.217*	-0.023**	-0.256	-590.492*	-0.017	0.851
	(0.674)	(0.010)	(0.166)	(355.680)	(0.011)	(2.573)
Three	-1.302	-0.012	-0.371**	-425.735	-0.019	0.981
	(0.938)	(0.012)	(0.187)	(409.562)	(0.014)	(3.319)
Four	-2.498**	-0.029**	-0.349	-779.259	-0.023	-5.884*
	(1.022)	(0.013)	(0.268)	(522.423)	(0.015)	(3.554)
Five or More	-4.684***	-0.046***	-0.573	-1078.684	-0.029*	-5.462
18. Control for Cumulative	-0.857***	-0.008***	-0.109**	-276.040***	-0.003	-0.608
Upstream Grants	(0.207)	(0.003)	(0.050)	(84.427)	(0.003)	(0.623)
19. Cumulative Grants by Grant Project Amount						
\$0 to \$0.4 million	1.020*	0.012	-0.144	-83.383	0.014*	2.026
	(0.610)	(0.008)	(0.184)	(396.401)	(0.008)	(2.848)
\$0.4 to \$3.5 million	-0.695	-0.007	-0.187*	-131.536	-0.005	0.139
	(0.526)	(0.006)	(0.108)	(239.581)	(0.006)	(1.384)
> \$3.5 Million	-0.988***	-0.009***	-0.093**	-220.709	-0.006**	-0.609
	(0.211)	(0.003)	(0.045)	(138.789)	(0.003)	(0.650)
20. Log Cumulative Real Grant	-0.984***	-0.010***	-0.065	-255.290	-0.008*	-1.127
Dollars (\$Bn)	(0.302)	(0.004)	(0.079)	(170.719)	(0.005)	(1.136)

(Continued next page)

Appendix Table 6: Sensitivity Analysis: Effects of Clean Water Act Grants on Water Pollution (Continued)

	Main Pollution Measures		Other Pollution Measures			
	Dissolved Oxygen Deficit	Not Fishable	Biochemical Oxygen Demand	Fecal Coliforms	Not Swimmable	Total Suspended Solids
	(1)	(2)	(3)	(4)	(5)	(6)
Other Important Sensitivity Analyses						
21. Differences-in-Differences	-0.635***	-0.009***	-0.093	-284.175***	-0.003*	-0.874**
Downstream Areas Only	(0.158)	(0.002)	(0.058)	(71.707)	(0.002)	(0.401)
22. Cluster by Watershed	-0.768***	-0.007**	-0.114***	-196.183**	-0.004**	-0.404
and Year	(0.193)	(0.003)	(0.041)	(82.042)	(0.002)	(0.568)
23. Include Monitors on	-0.303	-0.004**	-0.001	-196.549*	0.001	0.210
Other Rivers	(0.190)	(0.002)	(0.050)	(104.364)	(0.003)	(0.716)
24. Exclude Plants with No Grant:	-0.673***	-0.007**	-0.080	-246.457*	-0.004	-0.160
	(0.244)	(0.003)	(0.057)	(142.479)	(0.003)	(0.730)
25. Unweighted	-0.808***	-0.004**	-0.128**	-317.536**	-0.003	-0.588
	(0.190)	(0.002)	(0.059)	(128.612)	(0.003)	(1.198)
26. Control for Downstream *. . .	-0.814***	-0.009***	-0.110***	-219.371***	-0.007***	-0.369
Nonattainment, Industrial	(0.180)	(0.003)	(0.036)	(70.975)	(0.002)	(0.607)
Sources, Population						

Notes: "Long Term Stations" includes only stations which begin operating by 1971 and continue through at least 1988. "Control for Stream Gauge Flow" includes only stations which report instantaneous stream flow at the same time they report pollution, and it controls for streamflow. "Include Monitors on Other Rivers" includes monitors on rivers different than the treatment plant, but that eventually flow into or out of the treatment plant s river. Decennial sample includes averaged periods 1965-1974, 1975-1984, 1985-1994, 1995-2004. "Cumulative Grants" rows use trends sample. Data cover years 1962-2001. Standard errors are clustered by watershed. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Appendix Table 7. Heterogeneity of Clean Water Act Grants on Water Pollution and Home Values

	Regressions				Fitted Values		
Dependent Variable	Dissolved Oxygen Deficit (1)	Not Fishable (2)	Log Mean Home Values (3)	Log Mean Rents (4)	Cost Per Unit Dissolved Oxygen (5)	Cost Per River-Mile Fishable (6)	Change in Housing Values / Costs (7)
1. Cumulative Grants	-0.770***	-0.024***	0.00025	-0.00011	0.53	1.70	0.25
	(0.197)	(0.005)	(0.00033)	(0.00016)	[0.35 , 1.08]	[1.21 , 2.87]	(0.34)
2. Cumulative Grants	0.214	-0.006	-0.00006	-0.00059	---	---	---
	(0.441)	(0.011)	(0.00082)	(0.00045)	---	---	---
... * Grant Projects	-1.153**	-0.020	0.00037	0.00058	0.57	2.02	0.23
Above $1.2 Million	(0.473)	(0.012)	(0.00083)	(0.00044)	[0.40 , 0.98]	[1.43 , 3.45]	(0.24)
3. Cumulative Grants	-0.656	-0.045***	0.00106	-0.00058	---	---	---
	(0.519)	(0.012)	(0.00113)	(0.00048)	---	---	---
... * Baseline Treatment:	-0.206	0.022*	-0.00136	0.00045	0.51	1.87	-0.39
Secondary	(0.592)	(0.013)	(0.00116)	(0.00051)	[0.30 , 1.63]	[1.22 , 4.00]	(0.63)
... * Baseline Treatment:	-1.077	-0.005	-0.00102	-0.00018	0.16	0.56	0.02
Tertiary	(0.928)	(0.033)	(0.00137)	(0.00054)	[0.09 , 0.60]	[0.26, ∞)	(0.95)
4. Cumulative Grants	-0.784***	-0.008	0.00080	0.00001	---	---	---
	(0.294)	(0.009)	(0.00079)	(0.00029)	---	---	---
... * Baseline Pollution	-0.002	-0.019*	-0.00094	-0.00030	0.46	1.36	-0.16
Above Median	(0.390)	(0.011)	(0.00087)	(0.00037)	[0.28 , 1.27]	[0.95 , 2.41]	(0.34)
5. Cumulative Grants	-0.431	-0.014	0.00005	0.00017	---	---	---
	(0.314)	(0.012)	(0.00077)	(0.00037)	---	---	---
... * State Authority to	-0.379	-0.010	0.00027	-0.00047	0.40	1.34	0.35
Administer NPDES	(0.308)	(0.010)	(0.00090)	(0.00044)	[0.27 , 0.76]	[0.96 , 2.22]	(0.43)
6. Cumulative Grants	-0.674***	-0.020***	0.00037	-0.00012	---	---	---
	(0.214)	(0.006)	(0.00039)	(0.00018)	---	---	---
... * Outdoor Fishing or	-0.793*	-0.020	0.00014	0.00013	0.21	0.77	0.57
Swimming is Common	(0.416)	(0.012)	(0.00093)	(0.00040)	[0.14 , 0.40]	[0.51 , 1.55]	(0.93)
7. Cumulative Grants	-0.950***	-0.025***	0.00032	-0.00012	---	---	---
	(0.261)	(0.007)	(0.00054)	(0.00023)	---	---	---
... * States with Pro-	0.197	-0.001	0.00021	0.00010	0.39	1.14	0.42
Environmental Views	(0.371)	(0.010)	(0.00067)	(0.00028)	[0.23 , 1.38]	[0.72 , 2.81]	(0.31)
8. Cumulative Grants	-0.254	-0.004	0.00101	-0.00014	---	---	---
	(0.415)	(0.008)	(0.00097)	(0.00056)	---	---	---
... * Declining Urban	0.201	0.000	-0.00125*	-0.00008	1.35	38.27	-0.26
Areas	(0.520)	(0.011)	(0.00075)	(0.00040)	[0.62, ∞)	[4.02, ∞)	(1.23)
... * High Amenity Areas	-0.571	-0.021**	-0.00052	0.00011	0.85	2.12	0.50
	(0.491)	(0.010)	(0.00106)	(0.00059)	[0.52 , 2.34]	[1.39 , 4.45]	(0.44)
9. Cumulative Grants	-0.928*	-0.016	0.00004	-0.00026	0.44	2.55	0.03
(Reference: Northeast)	(0.479)	(0.014)	(0.00067)	(0.00025)	[0.22 , ∞]	[0.93 , ∞]	(0.70)
... * Midwest	-0.379	-0.015	0.00038	0.00029	0.31	1.34	0.43
	(0.533)	(0.016)	(0.00082)	(0.00032)	[0.23 , 0.48]	[0.91 , 2.50]	(0.47)
... * South	0.465	-0.008	0.00069	-0.00032	0.88	1.70	0.74
	(0.599)	(0.019)	(0.00095)	(0.00036)	[0.35 , ∞]	[0.82 , ∞]	(0.70)
... * West	0.645	-0.029	-0.00028	-0.00006	1.44	0.92	-0.26
	(0.796)	(0.033)	(0.00103)	(0.00056)	[0.27 , ∞]	[0.39 , ∞]	(0.80)

Notes: Each row 1-9 comes from a separate regression. Rows 3-8 also control for downstream*year indicators interacted with the variable examined in each row. The median grant project is $1.2 million. Data cover 1962-2001. Dollars are in $2014 Columns (5) and (6) are in million dollars. Asterisks in columns (1)-(4) denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***). Brackets in columns (5)-(6) show 95% confidence regions.

Appendix Table 8. Sensitivity Analysis, Home Values

	Log Home Values			Log Rents			Mean Family Income	Families on Public Assistance	College Graduates (%)	Black (%)	Population Under Age 6 (%)	Population Age 65 or Older (%)
	0.25 Mi.	1 Mi.	25 Mi.	0.25 Mi.	1 Mi.	25 Mi.						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1. Main Estimates	0.0009	0.0027**	0.0002	-0.0008	0.0000	-0.0001	-0.0002	0.0000	0.0000	-0.0001	0.0000	0.0000
	(0.0014)	(0.0013)	(0.0003)	(0.0008)	(0.0007)	(0.0002)	(0.0003)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
2. Exclude 1-Mile Radius	---	0.0025*	0.0002	---	0.0000	-0.0001	-0.0002	0.0000	0.0000	-0.0001	0.0000	0.0000
Around Treatment Plant	---	(0.0013)	(0.0003)	---	(0.0007)	(0.0002)	(0.0003)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
3. Cluster by Watershed	0.0009	0.0027	0.0002	-0.0008	0.0000	-0.0001	-0.0002	0.0000	0.0000	-0.0001	0.0000	0.0000
and Year	(0.0035)	(0.0026)	(0.0006)	(0.0013)	(0.0011)	(0.0002)	(0.0004)	(0.0001)	(0.0002)	(0.0002)	(0.0000)	(0.0000)
4. No baseline controls	-0.0001	0.0018	0.0000	0.0000	0.0004	-0.0003	-0.0013**	0.0001	-0.0002	0.0003	0.0000	0.0000
	(0.0025)	(0.0023)	(0.0006)	(0.0017)	(0.0013)	(0.0003)	(0.0005)	(0.0001)	(0.0002)	(0.0002)	(0.0000)	(0.0001)
5. Triple-Difference	0.0058*	0.0046	0.0010	0.0026*	0.0018	0.0000	-0.0007	0.0000	0.0000	0.0003	0.0000	0.0000
Regression	(0.0033)	(0.0032)	(0.0012)	(0.0015)	(0.0015)	(0.0006)	(0.0006)	(0.0001)	(0.0003)	(0.0005)	(0.0000)	(0.0001)
6. OLS	0.0053***	0.0045***	0.0011	0.0016	0.0011	-0.0002	0.0000	-0.0001	0.0001	-0.0002	0.0000	0.0001
	(0.0017)	(0.0016)	(0.0008)	(0.0012)	(0.0012)	(0.0007)	(0.0004)	(0.0001)	(0.0002)	(0.0002)	(0.0000)	(0.0001)
7. Downstream-by-year FE	0.0010	0.0031**	-0.0002	-0.0005	0.0005	-0.0002	-0.0004	0.0000	0.0000	0.0000	0.0000	0.0000
and Basin-by-year trends	(0.0017)	(0.0015)	(0.0003)	(0.0009)	(0.0008)	(0.0002)	(0.0002)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
8. Grants Given in 1972	-0.0106	-0.0026	0.0018	0.0036	0.0042	0.0009	0.0012	-0.0008***	0.0005	-0.0001	-0.0001	0.0001
	(0.0083)	(0.0079)	(0.0026)	(0.0052)	(0.0051)	(0.0014)	(0.0017)	(0.0002)	(0.0006)	(0.0006)	(0.0001)	(0.0002)
9. Plants Without Grants,	-0.0042	-0.0041	-0.0009	0.0011	-0.0004	0.0000	0.0005	-0.0001	-0.0001	-0.0001	0.0000	0.0001
1987 Effect	(0.0044)	(0.0044)	(0.0012)	(0.0026)	(0.0022)	(0.0006)	(0.0009)	(0.0001)	(0.0003)	(0.0004)	(0.0000)	(0.0001)
10. Large Cities	0.0008	0.0024	0.0003	-0.0006	0.0005	0.0000	0.0001	0.0000	0.0001	-0.0002*	-0.0000*	0.0000
	(0.0016)	(0.0016)	(0.0003)	(0.0007)	(0.0007)	(0.0001)	(0.0002)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
11. Effect 10+ Years	0.0018	0.0016	0.0001	0.0002	0.0002	0.0001	0.0001	0.0000	0.0001**	0.0000	0.0000	0.0000
After a Grant	(0.0018)	(0.0015)	(0.0003)	(0.0006)	(0.0005)	(0.0001)	(0.0002)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)

Notes: Unless otherwise noted, all regressions include homes within 25 miles of the river of interest. Regression specification corresponds to column (6) of Table 5. Regressions weighted by denominator of response variable Row 5 includes treatment plants in the half of counties with above-median shares of people who fish in lakes and rivers, as measured in 1990 surveys. Row 6 includes treatment plants in the half of counties with above-median shares of people who swim in lakes and rivers, as measured in 1990 surveys. Data includes decennial census years 1970-2000. Standard errors clustered by watershed. Asterisks denote p-value $<$ 0.10 (*), $<$ 0.05 (**), or $<$ 0.01 (***).