Willingness to Contribute as a Component of the Social Cost of Water Pollution

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ABSTRACT *Individuals contribute significant sums to environmental organizations, such as water-related groups, whose goals are to preserve and improve local water quality. These groups also fundraise to support these goals. However, the social cost of water pollution lacks contributions to water groups and their fundraising expenditures. If contributions and fundraising respond to changes in local water quality, there is a willingness to contribute toward mitigation of water pollution. Social costs should count these values. We provide proof of concept for this argument, showing significant evidence of local water quality affecting contributions to environmental nonprofits, as well as fundraising expenditures.* (JEL H41, Q53)

1. Introduction

Environmental groups devote time, creativity, and other efforts to protect and conserve the environment, with goals that range from combatting pollution to preserving high-quality natural resources and beauty. Over 25,000 such groups are registered with the U.S. Internal Revenue Service.[1] Citizens donate large sums to these nonprofits, which reveals a significant value of the groups: personal donations to nonprofits rose to $11.83 billion in 2017 for the category of environment and animals (Giving USA 2018). Yet, these donations rarely count toward the costs of maintaining and improving the environment. In addition, variation occurs in giving year over year; the environmental sector appears to have lost ground in 2018, down 2.9% from the previous year (Blackbaud 2019). Some of the variation in donations likely stems from levels of and marginal changes in environmental quality, at a local scale, and can provide an implicit assessment of part of the social costs of pollution. At present, this variation of nonprofits' donations lacks an attributable cause and measured value, so we are underestimating the social cost of pollution. We fill in this conceptual area and research gap by assessing the responses of contributions and fundraising to levels of and changes in environmental quality.

We study watershed groups, a common form of environmental organization, which protect and restore rivers and other water bodies. We argue an important component of the cost of water pollution to society is the value the nearby community members place on safeguarding pristine waterbodies and cleaning up dirty ones. To the extent that residents value local water quality or improvements thereof, we should expect a willingness to contribute to this cause. We estimate this willingness to contribute as the effect of water quality on donations raised by water-related environmental groups operating in the watershed. Additionally, we measure the effects on fundraising, which also reflects value in resources and effort expended by these groups to attract donations. In this paper, we provide a proof of this concept, empirically analyzing the changes in donations due to the level of and changes in water pollution. We find that, on average, fundraising and contributions are higher when water quality is worse; our results are robust to two identification methods: instrumental variables (IVs) and matching.

This paper makes important contributions to several strands of literature. A small but

[1] Nonprofits are categorized into one of 12 sectors by the National Taxonomy of Exempt Entities.

Land Economics • November 2020 • 96 (4): 573–588
ISSN 0023-7639; E-ISSN 1543-8325

Appendix materials are freely available at http://le.uwpress.org and via the links in the electronic version of this article.

growing research area provides theory and anecdotal evidence that environmental groups are important in providing and protecting environmental amenities (Baik and Shogren 1994; Heyes 1997; Cronin and Kennedy 1999; Sundberg 2006; Albers, Ando, and Batz 2008). Grant and Langpap (2019) investigate the causal role that environmental groups play in mitigating environmental problems with an empirical analysis of the effect of water groups on water quality. There is also evidence that environmental groups affect the enforcement actions of environmental regulators, interacting with government agencies as watchdogs (Langpap and Shimshack 2010; Grant and Grooms 2013). We contribute to this literature by examining how changes in an environmental public good affect fundraising and contributions to environmental groups.

Additionally, this paper complements a large literature valuing water quality as an environmental public good (Booker et al. 2012; Griffin 2016; Young and Loomis 2014). This literature focuses on two general approaches: The first uses indirect measures, such as travel costs and the hedonics of home values, that approximate the water amenity values through related markets such as recreation and house prices (Muller 2009; Keeler et al. 2015; Mahan, Polasky, and Adams 2000; Phaneuf et al. 2008; Walsh and Milon 2016; Ward, Roach, and Henderson 1996). The second uses direct measures by surveying the preferences of constituents (Mitchell and Carson 1989; Brouwer et al. 1999) or by estimating the health effects, well-being, social damages, and defensive behaviors due to pollution (Keeler et al. 2012; Nelson et al. 2015; Ward 1987; Watts et al. 2001). Numerous papers compare and contrast the approaches or provide methods to transfer the estimate to other contexts (Adamowicz, Louviere, and Williams 1994; Hanley et al. 2006; Freeman, Herriges, and Kling 2014). Others discuss or implement methods to aggregate multiple values (Sanders, Walsh, and Loomis 1990; Huang, Haab, and Whitehead 1997; Nyborg 2000; Whitehead, Haab, and Huang 2000; Van Houtven et al. 2014). The literature is extensive and too voluminous to provide a complete review here, with many dimensions for valuing water quality changes.

Yet, these values are clearly at the heart of social cost measurements, which rely on understanding the economic harm from pollution, expressed as the dollar value of the total damages of a unit of pollution. The social costs can also be expressed as an inverse, the economic benefit of mitigation or improvement. Our primary aim is to take a step in demonstrating that variation in donations is part of the value. We hypothesize that places with lower water quality have greater needs for fundraising and larger giving from the community, even after controlling for water groups' tendency to locate in areas of worse water quality. Previous papers provide a basis for our study. Viscusi, Huber, and Bell (2008) measure willingness to pay for water quality improvements using a stated preference survey of over 4,000 people in the United States. They determine that households would incur a cost of living increase of $32 per year for a 1% increase in nearby streams and lakes that are ranked good, rather than not good. Their hypothetical scenario is similar to our watershed context: they frame the relevant water quality as a region that is "a 2-hour drive or so of your home" Champ et al. (1997), assess stated preferences for public land restoration, rather than water quality, and intentionally choose respondents far away (to measure passive use values), rather than nearby. However, they implement a novel method, asking some of the respondents to donate and comparing these actual outcomes to the stated values. They measure a large hypothetical bias, with stated values three time higher than donations. Taken together, we see a need to use empirical data on donations to better understand this aspect for local water quality. We believe this is the first paper to posit, and then estimate, that a revealed value of environmental amenities exists in local citizens' willingness to contribute to nonprofits.

In order to inform water resources management properly, a full set of economic techniques is necessary. The techniques, collectively, provide a social cost of water pollution and attach a price tag for policies. Getting accurate values is critical in the face of environmental problems such as pollution, intensive land use in agriculture, and climate change. Our measure of willingness to contribute is one important component and complements the suite of valuation measures. We restrict our evaluation to watersheds; by focusing on regional water quality, we recover a value that likely encompasses a combination of indirect uses and option values for nearby households. However, our measure may be a lower bound, as free-riding can depress contributions (Champ et al. 1997). Whereas travel costs and recreation values obtain direct use measures. Stated preferences often obtain passive use values but can encompass potential use values; the values may have bias due to a hypothetical context and change in water quality. We assess contributions for the actual level of water quality, irrespective of the goal for the change in quality, and in addition to use value. Finding the social cost of water pollution requires many tools to obtain total economic valuation.

2. Data

The main hypothesis we test is that the water quality in a watershed affects fundraising and contributions received by water groups in that watershed. Specifically, we posit that groups located in watersheds with poorer water quality will attract more donations and have higher fundraising expenditures. To conduct this test, we control for a number of watershed characteristics that can also impact water group activity, including violations of the Clean Water Act (CWA), federal expenditures on water quality, land use, political preferences, and several demographic characteristics.

Data on water-focused nonprofit groups come from two main sources: listings of nonprofits and U.S. Internal Revenue Service 990 forms. We obtained a comprehensive list of groups working in the area of “water resource, wetlands conservation, and management” from GuideStar,[2] an organization that gathers information about nonprofits. We cross-referenced and supplemented this information with lists from the U.S. Environmental Protection Agency (EPA) and the River Network, a national group assisting regional and local organizations whose primary mission is protecting water resources. We excluded groups that operate in multiple states (which is indicated by the River Network data). The remaining groups cover a territory smaller than statewide; most groups focus on the river basin where they are located and are often named as such.[3] Because these nonprofit groups generally operate at a local scale, the appropriate unit of observation for our research is the eight-digit hydrologic unit code (HUC-8) watershed, which corresponds to the smallest area a single group will likely affect.[4] We determined the watershed for each watershed group by mapping their headquarters’ address using GIS software.[5]

For each organization, these data include type of watershed group, location, date of incorporation, and the employer identification number, which is the federal tax identifier. The employer identification number links this list to a database from the U.S. Internal Revenue Service with financial reporting data from 990 forms for each group. The 990-form data provide detailed yearly information on revenues and expenditures, including donations received and fundraising expenditures.[6] We aggregate yearly contributions and expenditures to the HUC-8 watershed level.[7] Contributions and expenditures are expressed in 2008 dollars.

We use two measures of water quality. When estimating the treatment values, we couple these water quality measures with state-level differences in stringency using fixed effects. To construct the first measure, we use information based on regulatory requirements: Section 303(d) of the CWA

[2] See www.guidestar.org.

[3] Personal communications with water group directors and researchers at the U.S. Geological Survey confirm that these groups carry out projects and engage the community within a relatively small area.

[4] Additionally, drainage basins correspond to the natural boundary for surface water flow.

[5] This process is not perfect, and some groups’ range of activity likely overlaps watersheds. We do not believe this affects our results because this would cause random measurement error only in the dependent variables and hence not bias our estimates.

[6] Fundraising expenditures reported on the 990 form include costs related to fundraising events, payments to professional or third-party fundraisers, and other general fundraising expenditures.

[7] There are 2,264 HUC-8 watersheds in the United States, averaging 700 mi^2 in land cover size.

mandates identification of water bodies (e.g., stream or river segments, lakes) for which current pollution controls are not sufficient to attain applicable water quality standards (impaired waters) or that have declining quality trends (threatened waters). The EPA requires each state to submit a list of all threatened and impaired waters, known as the "303(d) list," during even-numbered years (EPA 2009 and available at http://www.epa.gov/waters/ir/).[8] The treatment variable is the count of the number of listed water bodies in each HUC-8 watershed. We consider this a good measure of water quality in a watershed for several reasons. First, it is an intuitive measure, providing relative ease of discovery and comprehension by potential donors. Second, the 303(d) list is comprehensive, a review of all water bodies' current status relative to its designated use. Furthermore, the designation cannot be below the current designated use; although states designate the use of a water body, they cannot downgrade water bodies to avoid compliance (Houck 2014). Thus, the list establishes priority and reflects the degree of impairment.

The second measure of water quality is dissolved oxygen (DO), which gives the amount of oxygen dissolved in the water. A high level of DO is critical for the aquatic life that uses oxygen in respiration, including fish, plants, invertebrates, and bacteria. We obtained DO measurements from two databases: STORET and the National Water Information System (NWIS).[9] STORET gathers water quality data collected by federal agencies, states, tribes, volunteer groups, and universities; it is managed by the EPA. The NWIS, which is administered by the U.S. Geological Survey, contains data from all 50 states, the District of Columbia, and U.S. territories. We use several steps to construct our measure from the data available, following previous research (Keiser and Shapiro 2019; Grant and Langpap 2019): We drop measurements from nonroutine hydrologic events (e.g., floods, storms, hurricanes) and keep only routine (as opposed to quality control) samples. We choose only total (not dissolved, particle, or suspended) measurements from rivers, streams, and lakes. We replace values greater than the 99th percentile of the measurement distribution with the 99th percentile value to minimize the impact of outliers. We keep only actual (as opposed to estimated or calculated) measurements and drop measurements with missing observation date. We convert all measures to a standard unit (milligrams per liter) and drop measurements with units that cannot be converted. Finally, we convert DO in milligrams per liter to dissolved oxygen saturation (percent) using a standard formula, and calculate dissolved oxygen deficit (DOD) as 100 – DO (in percent saturation). This process yields 2,276,913 measurements during our study period. We aggregate to the watershed-year by calculating annual averages of all measurements within each HUC-8.

We gather information on CWA violations and location of facilities from the EPA's Enforcement and Compliance History Online (ECHO) database[10] and aggregate to the HUC-8 level. The total number of discharge permit violations in a watershed in each period accounts for state and federal enforcement of the CWA.

In some model specifications, we control for federal expenditures in each state-year from three major programs: the Environmental Quality Incentives Program (EQUIP), the Conservation Reserve Program (CRP), and the EPA 319 Grant Program.[11] Data on payments made under EQUIP contracts are provided by the Environmental Working Group[12]; CRP payments come from the U.S. Department of Agriculture Farm Service Agency[13]; and data on payments made under the EPA 319 program are from the Grants Reporting and Tracking System.[14]

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[8] See https://www.epa.gov/ceam/303d-listed-impaired-waters.

[9] STORET is an online system for "STORage and RETrieval" of water quality monitoring data.

[10] See https://echo.epa.gov.

[11] While water quality was not a primary focus of the CRP, it could be indirectly affected by conservation measures taken under this program.

[12] See www.ewg.org.

[13] See www.fsa.usda.gov/programs-and-services/conservation-programs/reports-and-statistics/conservation-reserve-program-statistics/index.

[14] See iaspub.epa.gov/apex/grts/f?p=109:9118.

We control for land use in the watershed by including measures of urban and agricultural land cover from the Multi-resolution Land Characterization Consortium.[15] Using maps of the contiguous United States at a 30 by 30 meter resolution, we derive the proportion of each type of land in each HUC-8 for each year.

We also control for political preferences of the residents of a watershed, environmental and otherwise, using election outcomes: the proportion of votes for Republican candidates in U.S. Senate races. County-level data on election results are from the CQ Press Voting and Elections Collection.[16] We interpolate for years in which there were no Senate races in a state and aggregate to the HUC-8 level.[17]

Finally, we control for several demographic characteristics that can impact contributions and expenditures. We include population density, per capita income (in 2008 dollars), percentage of population with a high school degree, ethnic composition (proportion of white population), unemployment rate, and home ownership rate. This information is available at the county level from the Bureau of Economic Analysis and the U.S. Census. Population, unemployment, and income projections are available for every year. Education attainment, home ownership, and ethnicity information is available for 1990, 2000, and 2010, so we interpolate for intracensus years. We aggregate the data to the HUC-8 level based on the proportions of counties contained in a watershed.

We construct a panel dataset of these variables for 1,131 HUC-8 watersheds in the contiguous 48 states for the years 1996–2008 (even years only for impairment listings). Summary statistics are presented in Table 1. The number of water groups per watershed increases between 1996 and 2008. Donations to these groups and their fundraising expenditures generally increase over the study period, but not monotonically, as contributions and expenditures increase in some years but decrease in others. DOD shows a similar pattern, increasing in some years and decreasing in others, particularly at the end of the study period. In contrast, number of listings per watershed unambiguously grows through time, from around 8 to over 38. The relationship between water quality and water groups' contributions and fundraising is not clear from these trends. Furthermore, other watershed characteristics like the growth in population density and urban footprint may be driving both, and the direction of causality between water quality and fundraising or contributions is not clear. We overcome these confounds through IV estimation.

3. Estimation

Empirical Models

Contributions to water groups in watershed i in year t are a function of water quality and other covariates:

$$\ln(Contributions_{it}) = \alpha_1 \ln(Water\ Quality_{it}) + \mathbf{X}_{it}\boldsymbol{\alpha}_2 + \boldsymbol{\delta}_i + \boldsymbol{\tau}_t + \varepsilon_{it}. \quad [1]$$

For fundraising expenditures by water groups in watershed i in year t, the basic model is

$$\ln(Fundraising_{it}) = \beta_1 \ln(Water\ Quality_{it}) + \mathbf{X}_{it}\boldsymbol{\beta}_2 + \boldsymbol{\rho}_i + \boldsymbol{\sigma}_t + u_{it}. \quad [2]$$

We use the two measures of water quality separately: total number of water bodies listed as impaired and mean biological oxygen deficiency in watershed i and year t.[18] The matrix X_{it} contains the explanatory variables discussed above and, in addition, the number of water groups in the watershed to account for *scale*.[19] Year fixed effects, $\boldsymbol{\tau}$ and $\boldsymbol{\sigma}$, control

[15] See https://www.mrlc.gov/.

[16] See http://library.cqpress.com/elections/index.php.

[17] We find the linear fit for each pair of years available and use that slope to produce values between the pairs. For example, if we have Senate results for 2004 and 2008 for a state, we estimate the values for the intervening years. A similar process is followed for census data, filling in all nine years between decennial surveys.

[18] Our results are robust to including watershed area (acreage) to control for the fact that larger watersheds may have more water bodies.

[19] We also estimated the model using the logarithm of the number of groups. The corresponding coefficient can be interpreted as an elasticity that indicates whether there are complementarity or substitution effects when additional groups form in a watershed. The coefficients are always larger than one, suggesting complementarity.

Table 1
Sample Means by HUC-8 Watershed

Variable	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Total donations to water groups (thousands of dollars)	746	886	1,040	865	1,211	1,503	1,336	1,340	1,356	1,561	1,522	1,702	1,223
Fundraising expenditures by water groups (thousands of dollars)	75.82	82.89	89.13	85.17	120.9	133.5	137.7	145.6	147.4	151.7	159.2	166.4	139.8
Number of water groups	0.372	0.412	0.434	0.328	0.517	0.564	0.580	0.605	0.603	0.646	0.670	0.674	0.294
Number of water groups conditional on at least one group	2.395	2.509	2.563	2.373	2.610	2.634	2.661	2.739	2.723	2.778	2.802	2.832	2.298
Dissolved oxygen deficiency	14.99	14.84	15.22	14.26	15.04	15.41	15.48	15.80	15.23	14.82	14.63	9.97	10.32
Number of listed water bodies[a]	7.88		14.85		15.87		24.93		29.63		33.94		38.27
Violations	0.061	0.071	0.070	0.076	0.085	0.090	0.095	0.171	0.177	0.180	0.195	0.203	0.170
Federal water quality expenditures (millions of dollars)	54.90	53.28	51.61	46.62	45.24	49.40	53.34	56.94	59.06	66.21	69.05	73.61	77.24
Percent agricultural land	0.292	0.285	0.277	0.270	0.263	0.255	0.246	0.238	0.228	20	0.211	0.202	0.183
Percent urban land	0.047	0.049	0.050	0.052	0.054	0.055	0.057	0.059	0.060	0.062	0.064	0.065	0.063
Population density (persons/mi^2)	47.89	48.43	48.96	49.49	50.00	50.44	51.05	51.44	51.77	52.13	52.58	52.90	50.75
Per capita income (thousands of dollars)	29.86	30.43	31.68	32.15	33.10	33.61	30.81	31.46	32.12	32.52	33.06	34.08	35.43
Percent population with high school degree	0.34	0.34	0.33	0.33	0.33	0.33	0.32	0.32	0.31	0.31	0.31	0.30	0.31
Mean precipitation (thousands of millimeters)	94.19	89.67	95.93	81.18	79.50	81.96	83.14	87.52	90.16	81.65	82.92	79.57	85.12
Percent Republican vote, U.S. Senate	0.536	0.536	0.529	0.529	0.557	0.557	0.549	0.549	0.535	0.535	0.513	0.513	0.516
Home ownership rate	0.596	0.598	0.600	0.602	0.604	0.601	0.598	0.596	0.593	0.591	0.591	0.589	0.586
Unemployment rate	0.068	0.068	0.067	0.067	0.066	0.067	0.068	0.069	0.070	0.071	0.072	0.073	0.079
Percent white population	0.880	0.880	0.878	0.877	0.873	0.872	0.871	0.870	0.868	0.867	0.866	0.863	0.840

[a] Impairment listings data are available only every other year.

for annual changes. State fixed effects, δ and ρ, provide baselines for each state responsible for impairment listing of water bodies in the watershed. The state is the appropriate level to introduce fixed effects because water body management and impairment listing decisions are made annually by each state. We avoid using watershed fixed effects because they remove the signal we wish to measure in the data;[20] water quality changes at a slow rate, which is confounded with a fixed effect. Watershed-level characteristics provide the necessary controls. Standard errors are clustered at the HUC-8 watershed level. We discuss the robustness of our results to alternative model specifications, below.

Identification

A possible concern when estimating models [1] and [2] is endogeneity of water quality. Water groups tend to locate where water bodies are impaired, which may also lead to more contributions and higher fundraising expenditures. As a result, ordinary least squares (OLS) estimates may be biased. Therefore, we use IV estimation to establish a causal connection between water quality and the water groups' contributions and expenditures.

We use the yearly mean of precipitation in a watershed to instrument for water quality. Precipitation is highly correlated with water quality. Even relatively small amounts of precipitation wash pollutants into water bodies through runoff. Conversely, relatively large amounts of precipitation will accelerate dilution of pollutants. For this reason, we include the square of mean precipitation as an additional instrument. Precipitation should not affect contributions to water groups or their expenditures, except through its effect on water quality. Thus, precipitation arguably satisfies exclusion restrictions. The data used to construct these instruments are from the PRISM Climate Group,[21] which provides point measurements of precipitation for the entire United States in a continuous 4 km grid. In Section 5, we check the robustness of our results to an alternative identification strategy in which we construct a balanced sample prior to estimation by matching on watershed characteristics.

[20] For example, see www.g-feed.com/2012/12/the-good-and-bad-of-fixed-effects.html.

[21] See http://www.prism.oregonstate.edu/.

4. Results

We examine the effect of water quality in a watershed on fundraising expenditures by water groups and on the contributions they receive. We use a two-stage least squares (2SLS) estimator with mean yearly precipitation and its square as instruments for water quality.

Determinants of Water Quality: First-Stage Regressions

The results for the first-stage regressions, in Table 2, give the effects of the instruments and the exogenous variables on our treatments, the number of impaired waterbodies, and DOD. The estimated coefficients for precipitation are positive and significant, while the coefficients for precipitation squared are negative and significant. This confirms the hypothesized nonlinear relationship in which small amounts of precipitation have a negative impact on water quality through runoff, while larger amounts can mitigate this deterioration by diluting pollutants. The Stock-Yogo (2005) F-statistics on the excluded instruments are 56.65 and 13.76, indicating relevant instruments.

Effect of Water Quality on Fundraising Expenditures: OLS and Second-Stage Regressions

Table 3 presents our results for the effect of water quality on water group fundraising expenditures. For reference, we report OLS estimates in the first two columns of the table. The third and fourth columns show second-stage results for 2SLS.

The estimated coefficients for a number of impaired water bodies are positive and significant, but the 2SLS coefficient is more than twice the magnitude of the OLS coefficient, confirming the expected bias caused by the two-way causality of water quality and water group activity. The 2SLS coefficient suggests that, on average, a 1% increase in water body

Table 2
First-Stage Regressions: Determinants of Water Quality

Explanatory Variable	Dependent Variable: Number of Impaired Water Bodies	Dependent Variable: Dissolved Oxygen Deficiency
Precipitation	1.14E–05*** (1.52E–06)	1.02E–06*** (2.75E–07)
Precipitation2	–3.56E–11*** (5.47E–12)	–2.88E–12*** (9.70E–13)
Violations	0.138 (0.085)	0.022 (0.017)
Fraction agricultural land	–0.108 (0.111)	–0.020 (0.020)
Fraction urban land	3.805*** (0.728)	0.016 (0.062)
Population density (persons/mi^2)	–5.2E–04 (4.3E–04)	7.55E–05*** (2.86E–05)
Per capita income (thousands of dollars)	7.0E–04 (0.005)	2.56E–05 (4.74E–06)
High school education	0.061 (0.126)	–0.004 (0.015)
Unemployment rate	1.623 (1.053)	–0.427*** (0.165)
Number of water groups	0.034* (0.020)	–0.003** (0.001)
Home ownership	0.969 (0.308)	–0.158*** (0.044)
Percent white population	0.541** (0.215)	–0.173*** (0.038)
Percent Republican vote	–0.392** (0.165)	–0.031 (0.029)
Observations	10,990	14,974
R^2	0.53	0.17
F-statistic	128.00	21.06
Prob > F	0.000	0.000
Stock-Yogo F-statistic	56.65	13.76
Prob > F	0.000	0.000

Note: Includes year and state fixed effects. Standard errors clustered at the HUC-8 watershed level in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

impairment listings increases fundraising expenditures by 0.93%. To provide context for the magnitude of this effect, we note that the average watershed has roughly 24 impaired water bodies and almost $128,000 in fundraising expenditures. This implies that an additional listing, which is about a 4% increase in average listings, increases fundraising expenditures by about $5,000. The estimated coefficient for DOD is not significant for OLS, but the 2SLS result is positive, two orders of magnitude larger than for OLS, and significant. This coefficient indicates that a 1% increase in DOD increases fundraising expenditures by 19.63%, or roughly $25,000.[22]

We interpret estimated coefficients on the control variables as suggestive rather than causal relationships. Estimates from both of the water quality specifications show that watershed groups spend more on fundraising in watersheds with a higher proportion of urban land. Some coefficients are distinct for the impairment listing model: fundraising expenditures are higher in watersheds with higher income and high school graduation rates and lower in watersheds with more agricultural land, higher unemployment, higher home ownership, and higher percentage of Republican vote. Coefficients specific to the DOD model indicate that water groups spend less on fundraising in watersheds where there are more CWA violations.

Effect of Water Quality on Contributions to Water Groups: OLS and Second-Stage Regressions

Table 4 shows estimated coefficients for the effects of impairment listings and DOD on total contributions made to water groups in a watershed. As before, for reference we present both OLS and 2SLS estimates for each of the two models. Both the OLS and 2SLS coefficients for impairment listings are positive and significant, but the 2SLS coefficient is 2.7 times as large as the OLS coefficient. In the DOD model, the OLS coefficient is not statistically significant, whereas the 2SLS estimate shows DOD has a positive large and significant impact on contributions.

[22] Because we are estimating separate reduced-form models for fundraising and contributions, and given that the units of observation are watersheds rather than individual water groups, these estimates should not be interpreted to convey a rate of return of fundraising on contributions.

Table 3
Ordinary Least Squares (OLS) and Second-Stage Regressions: Effects of Water Quality on Fundraising Expenditures

		Dependent Variable: ln(Fundraising Expenditures)		
Explanatory Variable	OLS	OLS	2SLS	2SLS
ln(Number of impaired water bodies)	0.413***		0.932**	
	(0.071)		(0.372)	
ln(Dissolved oxygen deficiency)		0.084		19.628***
		(0.193)		(7.265)
Violations	–0.165	–0.656**	–0.257	–1.171**
	(0.211)	(0.243)	(0.224)	(0.484)
Fraction agricultural land	–0.574**	–0.258	–0.497*	0.238
	(0.240)	(0.279)	(0.255)	(0.502)
Fraction urban land	8.532***	12.112***	6.476***	11.628***
	(1.915)	(2.556)	(2.244)	(2.653)
Population density (persons/mi^2)	–0.002**	–3.93E–04	–0.002*	–0.002
	(0.001)	(9.37E–04)	(0.001)	(0.001)
Per capita income (thousands of dollars)	0.067***	6.15E–04	0.061***	–2.88E–05
	(0.022)	(0.001)	(0.021)	(0.001)
High school education	1.086**	0.418	1.068**	0.515
	(0.442)	(0.338)	(0.450)	(0.418)
Unemployment rate	–9.434**	–16.049***	–10.611***	–6.990
	(2.538)	(3.680)	(2.935)	(4.895)
Number of water groups	0.718***	0.691***	0.698***	0.738***
	(0.233)	(0.243)	(0.228)	(0.221)
Home ownership	–4.483***	–3.848***	–5.014***	–0.774
	(0.992)	(1.052)	(1.131)	(1.603)
Percent Republican vote	–1.455***	–2.132***	–1.182**	–1.332
	(0.509)	(0.694)	(0.477)	(0.825)
Percent white population	–0.421	–0.873	–0.727	2.485
	(0.584)	(0.697)	(0.623)	(1.606)
R^2	0.47	0.46	0.45	0.49
Observations	10,990	14,974	10,990	14,974

Note: Includes year and state fixed effects. Standard errors clustered at the HUC-8 watershed level in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

The 2SLS coefficient for impairment listings indicates that a 1% increase in the number of impaired water bodies in a watershed leads to a 1.90% increase in contributions to water groups in that watershed. Given yearly contributions of about $1.2 million in the average watershed, this implies that an additional listing increases contributions by about $95,000 (about 8% relative to the mean).[23] The 2SLS coefficient for DOD suggests that a 1% increase in DOD in a watershed increases contributions to water groups by 33.1%, or roughly $397,000.

Coefficients for the control variables suggest that contributions to water groups are higher in watersheds with a larger proportion of urban land and high school graduation, and lower in watersheds that are more densely populated. Distinct coefficients from the impairment listing model suggest that contributions are higher in watersheds with higher income and lower in watersheds with more agricultural land, higher unemployment, and higher home ownership. Coefficients from the DOD model indicate that water groups receive more contributions in watersheds with higher percentage of white population and fewer CWA violations.

[23] If we separate impairment listings into two categories based on how observable the underlying causes are (e.g., turbidity vs. presence of biotoxins) we find that water groups spend more fundraising to bring attention to not-so-visible water quality issues, which in turn generates more contributions. Results are available upon request.

Table 4
Ordinary Least Squares (OLS) and Second-Stage Regressions: Effects of Water Quality on Contributions to Water Groups

	Dependent Variable: ln(Contributions)			
Explanatory Variable	OLS	OLS	2SLS	2SLS
ln(Number of impaired water bodies)	0.717***		1.903***	
	(0.097)		(0.536)	
ln(Dissolved oxygen deficiency)		0.237		33.131***
		(0.261)		(11.089)
Violations	0.083	–0.611*	–0.128	–1.478*
	(0.284)	(0.368)	(0.323)	(0.758)
Fraction agricultural land	–1.107***	–0.582	–0.931**	0.253
	(0.357)	(0.403)	(0.386)	(0.797)
Fraction urban land	14.532***	19.077***	9.833***	18.262***
	(2.395)	(3.344)	(2.904)	(3.807)
Population density (persons/mi^2)	–0.005***	–0.003*	–0.004***	–0.005**
	(0.001)	(0.001)	(0.001)	(0.002)
Per capita income (thousands of dollars)	0.097***	4.43E–04	0.085***	–0.002
	(0.029)	(0.002)	(0.026)	(0.002)
High school education	1.736***	0.895**	1.693***	1.057*
	(0.542)	(0.448)	(0.555)	(0.640)
Unemployment rate	–13.386***	–21.509***	–16.073***	–6.262
	(3.430)	(4.952)	(4.083)	(7.750)
Number of water groups	0.903***	0.850***	0.857***	0.930***
	(0.323)	(0.329)	(0.309)	(0.295)
Home ownership	–5.158***	–4.562***	–6.371***	0.610
	(1.306)	(1.397)	(1.506)	(2.472)
Percent Republican vote	–1.039	–1.776*	–0.416	–0.429
	(0.703)	(0.940)	(0.688)	(1.259)
Percent white population	0.453	0.485	–0.247	6.136**
	(0.791)	(0.961)	(0.873)	(2.500)
R^2	0.46	0.44	0.41	0.44
Observations	10,990	14,974	10,990	14,974

Note: Includes year and state fixed effects. Standard errors clustered at the HUC-8 watershed level in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

The negative impact of fraction of rural land in Tables 3 and 4 is not surprising, since water groups are more likely to locate in urban areas where there is a larger base of potential donors. The negative impacts of home ownership rate and population density (on contributions) are somewhat counterintuitive. One potential interpretation of these negative impacts stems from thinking of local nonprofits as coalitions of citizens seeking additional provision of a public good, namely, water quality. If home ownership and population density are proxies for the size of the coalition that will support local nonprofits, it is possible that as coalition size increases there may be less participation because of an incentive to free-ride (Andreoni 1988; McEvoy 2010) and also fewer contributions (Morrison 1978).

5. Sensitivity

Model Specification

We repeat our analysis using alternative model specifications to assess robustness of our results. First, we allow for the fact that water quality changes slowly by allowing for lagged effects of impairment listings and DOD, as well as all other variables, on fundraising and contributions. Second, we check whether controlling for federal government expenditures on water quality affects our results. We include total expenditures in the state where a watershed is located, for each year under the Conservation Reserve Program (CRP), the EPA 319 Grant Program, and the Environmental Quality Incentives Program

(EQUIP).[24] This variable is not included in our main specifications because it is potentially endogenous if private and public expenditures affect each other. Third, we estimate models for fundraising expenditures and contributions received per group in a watershed, rather than using total amounts for a watershed. Fourth, we estimate models with various subsets of watershed-level demographic characteristics that may all reflect urban-rural differences. Finally, we include transboundary fixed effects in addition to state fixed effects to account for watersheds that extend across state lines. Estimation results for these models are presented in Appendix Tables A1–A8. Tables A1–A4 show results for a number of impaired water bodies and DOD on fundraising expenditures, while Tables A5–A8 show results for contributions. Our results are robust to these alternative model specifications; all water quality coefficients remain positive and significant (see Appendix for more details).

Identification Check

We check the robustness of our results to the IV identification strategy by using an alternative identification approach: a combination of matching and fixed effects estimation (Imbens and Wooldridge 2009; Arriagada et al. 2012; Alix-Garcia, Sims, and Yañez-Pagans 2015). Estimates and inferences from this combination have been shown to replicate those in a randomized trial (Ferraro and Miranda 2014, 2017).

To carry out the matching procedure, we separately define treated watersheds for each of our two water quality measures. We define a watershed as treated with low water quality if the mean number of listed water bodies over the study period exceeds 45. This corresponds to roughly the 85th percentile of the distribution of number of impairment listings.[25] For DOD, we define a watershed as treated with low water quality if the mean DOD over the study period exceeds 40%. We choose this threshold because aquatic life is considered to be under stress due to algae growth and eutrophication for DO concentrations below 5 mg/l, which corresponds roughly to a 40% saturation deficiency.[26]

Based on these definitions of treatment, we preprocess the data to find treated and control watersheds that are observationally similar prior to the study period. We match on time-invariant or pretreatment observable characteristics that affect fundraising and contributions: 1995 values for the watershed characteristics included in our main specifications. Additionally, we match within state to account for state-level characteristics that may have an impact on fundraising and contributions. Finally, we match on fundraising or contributions (depending on the relevant outcome) in 1995. This helps mitigate the concern that water-focused groups may fundraise more actively and receive more contributions in watersheds with poorer water quality, since treated and control watersheds used in the estimation sample have similar fundraising expenditures or contributions at the beginning of the study period.

For the matching procedure, we use nearest neighbor one-to-one Mahalanobis covariate matching and propensity score matching, with and without calipers. The propensity score stems from a logit model with the dependent variable corresponding to a watershed's treatment status and explanatory variables given by the 1995 values of the watershed characteristics described above. We choose the matching procedure that yields the largest number of treated watersheds while achieving balance across all covariates. For the fundraising expenditures model with impairment listings as the measure of water quality, propensity score matching without a caliper is the best outcome. For fundraising and DOD, we use propensity score matching with a caliper set

[24] CRP payment data: U.S. Department of Agriculture Farm Service Agency (www.fsa.usda.gov/programs-and-services/conservation-programs/reports-and-statistics/conservation-reserve-program-statistics/index), payments made by EPA 319 program (iaspub.epa.gov/apex/grts/f?p=109:9118), and payments made under EQUIP contracts provided by the Environmental Working Group (www.ewg.org).

[25] We chose this percentile to achieve a balance between: (1) a sufficiently large number of impaired waterbodies to reflect relatively poorer water quality, and (2) a large enough number of treated watersheds (using the 90th percentile instead, for instance, would have meant roughly 600 fewer treated watersheds).

[26] Additionally, water quality is rated as "poor" for DO saturation levels below 50%.

to 0.03 times the standard deviation of the propensity score. For the contributions and impairment listings model, Mahalanobis covariate matching with no caliper provides the best balance. Finally, for contributions and DOD we choose propensity score matching with the caliper set to 0.05 times the standard deviation of the propensity score.

We also need to assess the effectiveness of the matching procedure in generating a balanced sample. Thus, we calculate the standardized difference in means (for 1995) between treated and control watersheds for each covariate. Current practice suggests that a standardized difference above 0.25 can cause bias in regression estimates (Imbens and Wooldridge 2009). The standardized differences and the corresponding percentage reduction (in absolute value) in bias achieved for the four models are shown in Appendix Tables A9–A12. The tables indicate that before matching, the samples were unbalanced across several covariates, with standardized differences close to or exceeding 0.25. Before matching, watersheds with a relatively high number of impairment listings tended to have somewhat higher per capita income and proportion of agricultural land. Watersheds with relatively high DOD deficiency were, on average, more densely populated and more urban and had higher proportions of white population, home ownership rate, precipitation, proportion of Republican vote, and more water groups and federal expenditures on water quality. After matching, all standardized differences are below 0.25, and the matching procedure generally achieves substantial reductions compared to before matching. Even in cases where the matching procedure increases the standardized difference, the difference after matching remains well below 0.25. The full samples are balanced in terms of fundraising expenditures and contributions, but the balance improves further after matching. This indicates that the matching procedure successfully breaks any preestimation link between water quality and fundraising or contributions, thereby mitigating joint causation concerns.

We estimate models [1] and [2] using the postmatching balanced samples and present estimates in Appendix Table A13. With the exception of the effect of DOD on contributions being positive but insignificant, water quality variables' impact on fundraising expenditures and contributions remains positive and statistically significant. Thus, our basic qualitative result is quite robust to this alternative identification approach. The magnitudes of the measured impacts are smaller than for the IV estimates, particularly for DOD. This discrepancy may be caused by the reduction in sample size resulting from the matching procedure, which implies that we are estimating the matching and IV models using relatively different samples.

Threshold Effects

It is possible that there are threshold effects for the impact of water quality on contributions and fundraising. For instance, water groups may fundraise more actively and receive more contributions when water quality is relatively poor than when water quality is better. We can use our model to test for evidence of such thresholds by interacting the water quality measures with indicator variables for various percentiles of the corresponding water quality distribution. If there are threshold effects, we would expect to see the estimated positive impacts hold only at higher percentiles (when water quality is worse). We cannot introduce these interaction effects in our preferred IV specification because this would create additional endogenous variables, so we use the matching and fixed effects models. We include interaction terms for the 50th, 70th, and 90th percentiles. Results are shown in Appendix Table A14.[27] The effect of impairment listings on fundraising is significant only for the 90th percentile, while the effect on contributions is significant for the 70th and 90th percentiles, and larger for the 90th percentile. The effect of DOD on fundraising is significant only for the 90th percentile. As in the model without interactions, there is no effect of DOD on contributions.

[27] The models are estimated with all the control variables included in all other specifications, but we present estimated coefficients only for the relevant water quality–percentile interaction terms.

6. Discussion

Our results suggest that local water quality has an impact on contributions to watershed groups and on their fundraising expenditures. This demonstrates the proof of concept that the value placed by nearby community members on local water quality is an important component of the social cost of water pollution, as are water groups' expenditures to translate those values into donations.

Our estimates indicate that contributions and fundraising expenditures increase as water quality deteriorates. An additional water body listed as impaired in a watershed increases contributions by roughly $95,000 per year and fundraising expenditures by about $5,000 per year. Additionally, a 1% increase in DOD in a watershed leads to $397,000 in additional contributions in the watershed and $25,000 in additional fundraising expenditures. These effects are relatively large, particularly for DOD. Information on impairment listings is easy to understand, but not directly observable without explicit effort to seek out the information. On the other hand, while DOD is not an intuitive measure of water quality, it is associated with excessive algae growth and eutrophication, which often lead to declining fish populations. These consequences are destructive; watershed groups highlight them and because the effects are highly noticeable, donors can readily observe them. Hence, substantial impacts on willingness to contribute and fundraising expenditures are not surprising.

The impacts of changes in impairment listings and in DOD on contributions and fundraising indicate that there is a substantial willingness by local residents to contribute to groups focused on improving water quality. An important caveat is that, because these are private contributions toward provision of an environmental public good, they likely reflect a degree of free-riding. Hence, they are not intended to fully quantify a social value of water quality. Rather, our argument is that these contributions and expenditures respond to changes in water quality and thus reflect a significant part of the costs of poor water quality. Therefore, they should be counted as an important component of the social cost of water pollution.

While this paper represents an initial step in measuring the impacts of local water quality on contributions and fundraising as a relevant component of the social cost of water pollution, several caveats should be considered. While our results identify a causal relationship between water quality and water group activity, we are not able to say anything about the underlying mechanisms. For instance, we do not have information on what donors know about local water quality, or what relevant information water groups may be providing to elicit donations. A field experiment in which the information about local water quality provided by water groups is randomized would be a relevant next step in this line of research to gain a better understanding of the underlying mechanisms.

Additionally, we do not have enough information about the activities carried out by water groups to differentiate between types of organizations. For instance, it would be relevant to assess whether there are different impacts from water groups that mainly engage in cleanups and restorations, those that focus on outreach or lobbying, and those that emphasize litigation.

Finally, our analysis has focused on the effects of current or lagged levels of water quality on water groups' fundraising expenditures and the contributions they receive. These estimates capture the year-to-year variation in water quality and donors' values. Arguably, trends in water quality over a longer time period may be relevant, as well, if donors care about how long-run water quality is changing in addition to, or instead of, water quality at a given point in time. We conducted some preliminary analysis of the impacts of changes in our water quality measures over the preceding one to four years, as well as mean changes over the same periods, but have not found consistent evidence that they affect contributions or fundraising. An important caveat is that it is difficult to instrument for trends in water quality. We have used changes in mean precipitation and the standard variation of precipitation, but these do not appear to be adequate instruments, particularly for trends in DOD. Hence further analysis of the impact of long-run water quality trends, with more convincing identification, is left for future research.

7. Summary and Conclusions

Environmental groups can play an important role in providing public goods, and individuals contribute significant sums to these organizations with the intent of preserving and improving water quality. These contributions and related fundraising expenditures are lacking from the costs of mitigating water pollution. If variation in contributions responds to water quality, then failing to account for marginal changes in contributions results in underestimation of the social cost of pollution. In this paper, we suggest that there is a willingness to contribute to improving water quality through the activities of local environmental nonprofits, and that these contributions are part of the social cost of water pollution. We seek proof of concept for this idea by empirically estimating how changes in water quality affect donations to water groups and their fundraising expenditures.

We use watershed-level data and an IV estimator to identify the causal effect of two distinct water quality measures—waterbody impairment listings and dissolved oxygen deficiency (DOD) levels—on contributions to water groups and their fundraising expenditures. Our results reveal that when water quality is poorer, measured as additional impairment listings or larger DOD, water groups exhibit higher fundraising expenses and citizens increase contributions to these groups. The impacts are relatively large, particularly for DOD, which is likely due to the highly noticeable associated effects on water bodies. These results, therefore, provide evidence that contributions are at least partly driven by changes in water quality. Hence, our results support the argument that willingness to contribute is an important and unaccounted for component of the social cost of water pollution.

Acknowledgments

The authors would like to thank two anonymous reviewers for helpful insights that improved the clarity, and that added related literature and robustness to the paper. Any errors are our own.

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