Social Efficiency in the Tax Deductibility of Charitable Donations

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Abstract

U.S. tax law allows deductibility of charitable donations. *Treasury* efficiency exists if donor responses exceed forgone government revenue, in elasticity. We improve the metric by introducing *social* efficiency, focusing on public benefits from changes in the tax price of giving. We derive our metric from changes in charities' public-good provision and the associated marginal value, benchmarking it against treasury efficiency, which allows comparison by researchers. A compelling empirical example estimates the elasticity of water quality and its value relative to tax price changes. Findings show that social efficiency can diverge significantly from treasury efficiency, implying differing policy recommendations.

Keywords: Public Goods, Tax Deduction, Charities, Nonprofits, Water Quality

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1 Introduction

Tax laws surrounding charitable donations have been a source of controversy since their introduction in 1917. Early proponents argued that preferential tax treatment would incentivize private donations from wealthy individuals, who were seen as essential for supporting causes that might otherwise go unfunded (Aprill, 2000). This debate persists today, with proposals ranging from imposing stricter caps on deductions to eliminating them altogether. Under current U.S. law, taxpayers can deduct donations made to nonprofit organizations, provided the organization is registered as a public charity with the IRS. These deductions effectively reduce the cost of giving, proportional to a donor's marginal tax rate. For example, for a taxpayer in the 35% tax bracket, a $100 donation to a nonprofit has an effective cost of $65, reducing the *price* of giving to 65 cents per dollar. However, this incentive comes at the cost of foregone tax revenue. Empirical research in this area often examines how tax rate changes influence charitable contributions, typically through the price elasticity of giving.[1] A charitable deduction is deemed *treasury efficient* if it generates as much or more in donations as the government loses in tax revenue. Most studies suggest the deduction achieves at least treasury neutrality, with a 1% decrease in the price of giving leading to at least a 1% increase in contributions (Bakija, 2013; Bakija and Heim, 2011; Duquette, 2016). In contrast, Han et al. (2024) use recent data from the Tax Cuts and Jobs Act and find an average elasticity of -0.6.

The concept of treasury efficiency, however, implicitly assumes that a 1% increase in donations results in at least a 1% increase in public good provision. This perspective overlooks the actual activities and impact of the nonprofits receiving these funds. The 1.5 million nonprofits operating in the U.S. do more than simply collect donations; they provide critical public goods and services, often addressing gaps left by markets, government agencies, and political institutions (National Center for Charitable Statistics, 2019). Thus, any assessment of the charitable deduction's efficiency must also account for the amount and value of public goods and services produced through these contributions. This research shifts the focus from treasury efficiency to a broader measure of *social efficiency*, which evaluates the societal value generated by donations.[2]

[1] Bakija (2024) provides a recent review with additional rationale for and research in charitable giving and its deductibility.

[2] Andreoni and Smith (2021) also coined the term *social efficiency* independently, in parallel with our use,

We reevaluate the efficiency of the tax deduction as *the change in the value of the public good* produced by nonprofits. Specifically, we define and calculate a broader criterion: the price elasticity of the public good's value, which measures the percentage change in the value of the public good induced by a 1% decrease in the price of giving. Building on previous theoretical frameworks, we derive a simple measure of social efficiency, benchmarked against the traditional metric of treasury efficiency and independent of government provision. This measure evaluates how one dollar of donations translates into changes in the value of public goods. Importantly, social efficiency neither implies nor is implied by treasury efficiency.

We provide an empirical illustration to contextualize this framework. Our focus is on environmental nonprofits, which number over 25,000 in the U.S. In 2021, donors contributed more than $16 billion to these organizations (Center on Philanthropy at Indiana University, 2022). We narrow our analysis to local environmental nonprofits whose activities affect water quality in rivers and streams. These organizations engage in various activities to address point-source pollution, such as litigation, permit evaluation, water quality sampling, and investigations of regulatory violations. For example, the Willamette Riverkeeper litigates state wastewater permit decisions. These groups also work toward mitigating non-point source pollution in a variety of ways. For instance, the James River Association and Shenandoah Riverkeeper create forest buffers and promote cost-sharing programs for landowners. Other organizations, such as the Genesee River Watch, reduce sediment and phosphorus loads by stabilizing unbuffered agricultural fields along riverbanks.

We focus on these groups for several reasons. They produce local public goods (Grant and Langpap, 2019), in contrast to other nonprofits that provide goods or services with private characteristics (Chang and Tuckman, 1996). Water-related nonprofits are numerous, homogeneous in mission, and geographically dispersed across the U.S., providing an ideal sample for robust empirical study.

We implement two sets of empirical models to examine these relationships. The first set estimates the price elasticity of giving, following seminal work on how tax incentives influence charitable contributions (Duquette, 2016). The second set expands on prior literature by estimating public good provision, using instrumental variable techniques to measure the effect of donations on nearby water quality. We then incorporate external

development of and metric for it.

estimates of the value of water quality improvements to calculate how changes in the price of giving affect both the quantity and value of the public good.

This paper makes two main contributions. First, we extend the existing framework of treasury efficiency to derive social efficiency, which explicitly includes the amount and value of public goods generated by nonprofits. Second, we provide an empirical example, demonstrating how environmental nonprofits improve water quality and estimating the associated value of these improvements. By moving beyond traditional measures of donation deductibility, we advance the analysis toward a social measure of efficiency.

Our work adds to two key literatures. It contributes to research on the tax deductibility of donations, expanding on the meta-analysis by Peloza and Steel (2005). Additionally, it enriches the growing body of literature on environmental nonprofits and their provision of public goods, as reviewed by Grant and Langpap (2024). Prior studies have examined the public goods provided by land trusts preserving open space (Albers et al., 2008; Parker and Thurman, 2011; Sundberg, 2006) and by nonprofits improving water quality (Grant and Langpap, 2019). We build on this work by explicitly calculating the value of water quality improvements generated through donations to environmental nonprofits.

Our first set of results challenges the findings of previous literature, showing that contributions to these environmental nonprofits are not treasury efficient: A 1% decrease in the price of giving results in only a 0.64% to 0.93% increase in contributions. However, the second set of results, our extension to a definition of social efficiency, demonstrates that conclusions about efficiency can reverse when accounting for changes in the public good and its value. We show that contributions lead to small but statistically and economically meaningful improvements in water quality. When these effects are combined with the value of the provision of public goods, we find that the charitable deduction may be justified on the grounds of public benefits.

Overall, we show that the impact of a change in tax deductibility, through its effect on the price of giving, depends on whether changes in the value of the public good are considered. The process we develop to compare treasury efficiency and social efficiency is broadly applicable. While our application focuses on environmental nonprofit groups and water quality, the approach can be extended to other types of nonprofits that provide public goods. For example, public and social benefit organizations aim to broaden citizen participation in

the political process. These groups may increase voter turnout in local referendums, resulting in measurable outcomes such as improved provision of local public goods like open spaces, or enhanced community services such as police and fire protection. Similarly, organizations focused on community improvement contribute to better neighborhood quality, which can be assessed through metrics like redevelopment rates or increases in homeownership. In these cases, the value of public good provision often reflects changes in real estate prices. Another example is consumer protection organizations, which provide information and assistance to mitigate harmful products and services. The benefits of such groups are typically health-related, including reduced lost wages, improved infant birth weights, and developmental outcomes in the targeted communities.

In the next section we present a conceptual framework to motivate our research question. In Section 3 we discuss our empirical application. Then we provide details about the data in Section 4. Section 5 presents our results and sensitivity analysis. We conclude by discussing our results and further implications.

2 Conceptual Framework

Subsidizing charitable giving through tax incentives is considered treasury efficient if the resulting increase in donations outweighs the decrease in tax revenue (Roberts, 1987; Saez, 2004). In standard theory, g represents the gift or contribution to nonprofits, and tax denotes the marginal tax rate. When taxpayers can deduct their contributions, g becomes a function of tax, and their gifts reduce their tax obligation by $tax \cdot g(tax)$. Consequently, the price of giving is $1-tax$. The net value of deductibility for a given tax rate is expressed as $B(tax) = g(tax) - tax \cdot g(tax) = (1-tax) \cdot g(tax)$; dollars voluntarily given versus dollars lost to government.

The marginal benefit for a change in the tax rate is

$$\frac{\partial B(tax)}{\partial tax} = \frac{\partial g(tax)}{\partial tax} - \left[g(tax) + tax \cdot \frac{\partial g(tax)}{\partial tax} \right]$$

which measures the change in giving due to a tax change, minus the foregone revenue from

that tax change.[3] This is positive if and only if

$$\frac{\partial g(tax)}{\partial tax} > g(tax) + tax \cdot \frac{\partial g(tax)}{\partial tax}.$$

Or equivalently, noting that $\frac{\partial g(tax)}{\partial tax} = -\frac{\partial g(tax)}{\partial (1-tax)}$, the elasticity in the price of giving implies treasury efficiency if

$$\varepsilon_g = \frac{\partial g(tax)}{\partial (1-tax)} \left(\frac{1-tax}{g(tax)} \right) < -1. \tag{1}$$

A sizable literature examines the effect of tax changes on contributions. Peloza and Steel (2005) review 70 studies and provide a meta-analysis that finds elasticities ranging from -0.4 to -4, with a median of -1.2. The authors conclude that the tax deduction is treasury efficient — lowering the tax burden by one percent may raise donations by a percent or more. More recent literature finds mixed effects (Bakija, 2024; Bakija and Heim, 2011; Bradley et al., 2005; Duquette, 2016; Fack and Landais, 2010; Galle, 2017; Han et al., 2024).

2.1 Social Efficiency

One goal of the tax deduction for contributions is to support the provision of public goods (Almunia et al., 2020; Okten and Weisbrod, 2000). Yet, the implicit assumption that a one percent change in donations translates into at least an additional percent of public good provision may fail.[4] As many nonprofit organizations provide public goods beneficial for society, the value of these goods, with respect to the elasticity of tax rate *and* production of said goods, is of significant interest. The efficiency of the tax incentive needs to be evaluated relative to the value of public goods provided, i.e. whether a percent of revenue foregone generates more or less than an additional percent of public benefit.

We advance the current understanding by incorporating production of the public good

[3] The change in the marginal cost of public funds is negligible.

[4] Competition for donors increases fundraising costs, an opportunity cost for program spending (Aldashev and Verdier, 2010; Castaneda et al., 2008; Rose-Ackerman, 1982). The tax benefit can reduce donors' oversight of the uses of contributions (Castaneda et al., 2008; Glaeser and Shleifer, 2001; Rose-Ackerman, 1996; Werker and Ahmed, 2008). Nonprofit managers may engage in self-interested spending on perks as their objective is not profit maximization. Government provision, directly or through grants to nonprofits, may crowd-in or -out provision by nonprofits (Andreoni, 2006; Andreoni et al., 2014; Heutel, 2014).

by nonprofit organizations and by the government. For an evaluation that is tractable in applications, we assume that nonprofits and the government provide the same public good. Let the value of public goods generated by contributions be $G(tax)$ and those by tax revenue be $R(tax)$. The appropriate net benefit to assess is $B(tax) = G(tax) - R(tax)$, where $G(tax) = \nu \cdot f(g(tax))$, $R(tax) = \nu \cdot h(tax \cdot g(tax))$, and $\nu \geq 0$ is the per-unit dollar value of the public good. Thus, $B(tax) = \nu \cdot f(g(tax)) - \nu \cdot h(tax \cdot g(tax))$. The function $f(g(tax))$ denotes how nonprofits translate donations into the public good, whereas $h(tax \cdot g(tax))$ represents the public good provided publicly, as a function of tax revenue.

To determine whether changes in the price of giving increase net benefits, we derive the first-order condition for $B(tax)$ with respect to the price of giving, $1 - tax$. We find the necessary condition for social efficiency is

$$\varepsilon_G < \frac{h(tax \cdot g(tax))}{f(g(tax))} \varepsilon_R$$

where $\varepsilon_G = \frac{\partial G}{\partial(1-tax)} \frac{1-tax}{G}$ and $\varepsilon_R = \frac{\partial R}{\partial(1-tax)} \frac{1-tax}{R}$.[5] This condition indicates that tax deductibility of charitable contributions is socially efficient if the value of the public good provided by nonprofits is more responsive to changes in the price of giving than the value of the same public good provided by the government, weighted by the relative production of public good by the two sectors. Next, we decompose this expression into its component parts, aiming to provide analytical solutions for each component that are empirically measurable.

Elasticity of the Public Good's Value, as Produced by Nonprofits

We rewrite ε_G in terms of ε_g:

$$\varepsilon_G = f'(g(tax)) \cdot \frac{g(tax)}{f(g(tax))} \cdot \varepsilon_g.$$

Let $\varepsilon_{fg} = f'(g(tax)) \cdot \frac{g(tax)}{f(g(tax))}$. This term measures the responsiveness of the public good provision function $f(\cdot)$ with respect to changes in the level of contributions $g(tax)$, and hence is an elasticity-like measure of public good provision by groups. It tells us how the

[5] All algebraic derivations can be found in the Appendix.

marginal product of public good provision, given by $f'(g(tax))$, is scaled by the effectiveness of converting the contributions g into the public good $f(g(tax))$. If ε_{fg} is greater than one, it suggests that the public good provision is highly responsive to changes in g, whereas a value less than one indicates a lower responsiveness. In sum, $\varepsilon_G = \varepsilon_{f,g} \cdot \varepsilon_g$.[6]

Elasticity of the Public Good's Value, as Produced by Government

Noting that $\varepsilon_R = \frac{\partial R(tax)}{\partial(1-tax)} \cdot \frac{(1-tax)}{R(tax)}$, we find:

$$\varepsilon_R = h'(tax \cdot g(tax)) \cdot \frac{tax \cdot g(tax)}{h(tax \cdot g(tax))} \cdot \left(\varepsilon_g - \frac{1-tax}{tax}\right)$$

Let $\varepsilon_{h,g} = h'(\cdot)\frac{tax \cdot g(tax)}{h(\cdot)}$. This represents the responsiveness of the public good provision function by the government with respect to changes in the underlying level of tax revenue. Again, it is an an elasticity-like measure of public good provision, through government spending. It measures the proportional change in the government's provision of the public good $h(\cdot)$ in response to a proportional change in the underlying level of revenue, $tax \cdot g$. The final term, $\frac{1-tax}{tax}$, is the ratio of the price of giving to the tax rate. In short,

$$\varepsilon_R = \varepsilon_{h,g} \cdot \left(\varepsilon_g - \frac{1-tax}{tax}\right)$$

The Condition for Social Efficiency

By putting together the above components and simplifying, we rewrite the expression for social efficiency. This condition provides a threshold for determining when providing a tax deduction for giving to nonprofit groups yields a net social benefit. The above first order inequality for $B(tax)$ can be reformulated as

$$\varepsilon_{f,g} \cdot \varepsilon_g < \frac{h'(tax \cdot g(tax))}{f'(g(tax))} \varepsilon_{f,g} \cdot tax \left(\varepsilon_g - \frac{1-tax}{tax}\right).$$

[6]Note that the parameter ν cancels out and does not affect the elasticity relationship directly, in this condition.

Because $\varepsilon_{f,g}$ cancels out of both sides and we can isolate ε_g, this is equivalent to

$$\varepsilon_g < -\frac{1 - tax}{\frac{f'(g(tax))}{h'(tax \cdot g(tax))} - tax}. \tag{2}$$

Thus, we provide a simple measure of social efficiency, which is benchmarked against treasury efficiency. On the right-hand side, the ratio $\frac{f'(g(tax))}{h'(tax \cdot g(tax))}$ plays a central role in comparing the efficiency of private donations and government tax revenue in producing public goods. This ratio represents how effectively private donations, $g(tax)$, create public goods relative to how the government would use tax revenue, $tax \cdot g(tax)$, for provision. A high ratio indicates that private donations are more effective at generating public goods at the margin, while a low ratio suggests that government spending is more effective. With this in mind, the full expression describes the conditions under which a tax deduction for charitable giving is more efficient than directly collecting tax revenue.

When an additional dollar of contributions or revenues is assumed to generate an additional dollar of public goods, meaning $\frac{f'(g(tax))}{h'(tax \cdot g(tax))} = 1$, the right-hand side simplifies to -1, which gives the standard treasury-efficiency condition. This implies that private donations and government spending are equally effective, even though donations exceed the potential government spending, by a factor of $1/tax$. If this is true, donations are preferable if the elasticity of giving is larger than one in absolute value, as noted by previous literature.

In contrast, social efficiency requires the right-hand side to exceed the tax-price elasticity of giving, ε_g. As the ratio $\frac{f'(g(tax))}{h'(tax \cdot g(tax))}$ increases, the condition for social efficiency becomes easier to satisfy. This implies that, as private donations become more effective relative to government spending, the elasticity of giving, ε_g, can be smaller in absolute value for social efficiency to hold. In practical terms, when private donations are highly effective, encouraging charitable giving through tax deductions becomes more socially efficient. And more so if donations are also highly responsive to tax incentives.

This analysis informs policymakers on whether to rely more on taxation or to incentivize private donations for public good provision. Social efficiency reflects the balance between the marginal benefit of public goods from private donations and the forgone benefits of government provision relative to the responsiveness of charitable giving to changes in the tax rate. This framework represents a critical advancement in the field, offering a more

rigorous and comprehensive method for evaluating the efficiency of charitable giving deductions. The approach improves upon traditional approaches that rely solely on tax revenue impacts.

2.2 Implementation Conditional on Data Availability

Empirical evaluation of the social efficiency condition depends on data availability for the specific context of a given public good. Ideally, empirical researchers can estimate each component of Equation 2. The values of tax are publicly available from information on federal tax rates, and estimation methods for ε_g are well known from previous literature on treasury efficiency. In a second stage, the researcher must estimate $f'(g(tax))$ and $h'(tax \cdot g(tax))$, or alternatively their ratio. These are measures of marginal products of the public good from gifts to nonprofits and government tax revenue. This requires estimation of public good provision as a function of both private contributions to nonprofits and government expenditures on the same public good. The latter marginal product may be particularly hard to estimate given limited availability of government revenue data, disaggregated with respect to the use for specific purposes.

However, we can simplify our criterion further for empirical implementation: An implicit assumption, based on government reporting for public provision of public goods, is that every dollar the government spends is converted into an equivalent dollar of public goods.[7] This is common in national accounting, where the outputs of non-market sectors like government are not sold at market prices, and therefore cannot be valued based on market transactions. Instead, expenditures on wages, materials, and capital inputs are used as a proxy for the value of the services provided. With this assumption, the government's public good production function can be written as $R(tax) = \nu \cdot h(tax \cdot g(tax)) = tax \cdot g(tax)$ and the condition for social efficiency of the tax deduction becomes

$$\varepsilon_g < -\frac{(1 - tax)}{\nu \cdot f'(g(tax)) - tax} \tag{3}$$

[7] The U.S. Bureau of Economic Analysis (BEA) describes government consumption expenditures as "services (such as education and national defense) produced by government that are valued at their cost of production." See National Income and Product Accounts, Table 3.9.5., Government Consumption Expenditures and Gross Investment.

This assumption eliminates the need to estimate marginal production $h'(tax \cdot g(tax))$. However, it requires an estimate of the value of public good ν. A higher ν, all else equal, lowers the bar for the elasticity of giving — if goods provided privately are of high value, then the elasticity of the price of giving can be lower and still justify the deduction.

The next section provides the estimation approach for the price elasticity of giving and the provision of public goods by nonprofits. Section 4 provides specifics about the data for our application. Then Section 5 gives results for all estimations and brings in the value of the public good, providing our empirical measure of social efficiency.

3 Empirical Application to Water Quality

We now turn to our application: How does a change in the price of giving impact the value of the public good provided, and how does social efficiency compare with traditional treasury efficiency? Our conceptual framework provides guidance. We estimate contributions as a function of the price of giving. With the standard criterion, assessment of efficiency stops here. We add three further steps. First, we estimate public good provision attributable to the contributions. Second, we gather measures of values of the public good, which draw on external literature, such as non-market valuation studies. Third, we calculate the threshold for social efficiency and assess whether tax deductibility of contributions is socially efficient.

Our empirical application uses contributions to environmental nonprofits whose activities impact water. We estimate changes in water quality near environmental groups as a function of the contributions received by those groups. The two sets of econometric models follow, the specifications for treasury efficiency and for provision of water quality. In the results section, we provide the estimated outcomes. We then incorporate values for changes in water quality to calculate the metric for social efficiency.

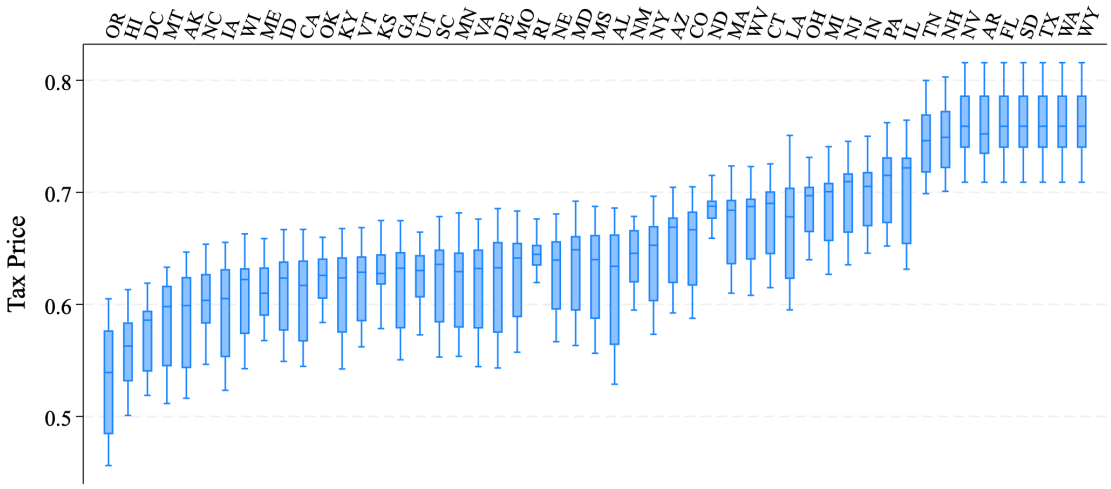
3.1 Price Elasticity of Giving

We estimate the following regression model to measure the price elasticity of giving:

$$\text{Contributions}_{ist} = \delta_0 \ + \delta_1 \ln \text{Price}_{st} + \mathbf{G}'_{ist}\Gamma + \mathbf{X}'_{st}\Psi + \eta_i + \tau_t + \varepsilon_{ist} \tag{4}$$

where giving is the dependent variable, measured as contributions received by environmental group i, located in state s, in year t.[8] We construct Price_{st}, the price of giving for state s in year t, using a nationwide representative sample of households' tax returns. State and federal tax rules for every state and year in our study period are applied to this sample of taxpayers to calculate their tax obligations with and without charitable contributions, while keeping taxpayer characteristics constant; details are in the next section.

Figure 1. Distribution of the Price of Giving, by State



Note: The panel data are balanced over the years 1998 to 2017. Box plots give the distribution of tax price, within state for all years: they mark median, p25, p75; whiskers are extreme values. Outlier values not plotted. States sorted by ascending median. FL, NV, SD, TX, WA, and WY do not have state income tax; their variation is due to federal-level changes.

We identify the coefficient of interest, δ_1, the price elasticity of giving, using the variation in tax price within state, over time, shown by the box and whisker plots in Figure 1. Numerous changes in federal and state tax rules occur over the study period. Between 1998 and 2017, seventy-one changes in the federal tax code impacted the price of giving, on average over three times per year. Some are significant changes, such as the Economic Growth and Tax Relief Reconciliation Act of 2001 and the American Recovery and Reinvestment Act of 2009. While these changes affect all taxpayers, preexisting differences in state tax rules

[8] A small number of groups have zero contributions in some years during the study period. We avoid issues associated with log-like transformations of zero-valued outcomes by using a Poisson regression, as suggested in Chen and Roth (2024). With the Poisson specification, the coefficient on a level-log model is interpreted as an elasticity.

and further state-level changes interact with the federal changes, generating considerable variation in the price of giving across states (Duquette, 2016).[9] For instance, Oregon made numerous and substantial changes to its tax code, with eighty-nine changes during the study period. Combined with federal changes, that is eight per year on average. Contributing to nonprofits is relatively cheap in Oregon, because their taxes are high. Donating is more expensive in Wyoming as they have no state income tax. Maryland has moderate state taxes and a deduction for giving, so the price of giving is in the middle of the pack.

$\mathbf{G}_{ist}$ is a matrix of environmental group characteristics (age, fundraising expenditures, assets and liabilities, program revenues); the matrix $\mathbf{X}_{st}$ contains state characteristics of gross state product, per-capita income, poverty rate, unemployment, population and population density, educational attainment, political inclination, proportion white; η_i and τ_t are group and year fixed effects. One specification includes state-level trends.

3.2 Public Good Provision

Next we estimate the impact of contributions on public good provision:

$$\text{Water Quality}_{it} = \beta_0 \ + \beta_1 \text{Contributions}_{it} + \mathbf{X}'_{ct}\psi + \sigma_s + \tau_t + \upsilon_{it}. \tag{5}$$

For the dependent variable, we interchange three characteristics of water quality: dissolved oxygen (DO), and nitrogen and phosphorus concentrations. DO is beneficial for aquatic life, and thus water quality. The latter two are pollutants that degrade water quality. Federal agencies monitor water quality at thousands of sites throughout the U.S. We aggregate the data from monitors near group i into metrics for each water quality characteristic specific to year t. We define nearby in two alternative ways, to address our uncertainty about the nonprofits' sphere of influence. One metric is the annual average of water-quality monitors most proximate to each group, up to 40 sites. We base proximity on the latitude-longitude Euclidean distance between groups and monitors and limit it to 150 miles. The distance is likely farther than a group's influence; however, this allows us to match nearly all groups to water quality and provides a conservative, lower-bound estimate. We then calculate

[9] Mean year-to-year within state variation over time ranges from -28% to 39%, with a median of -1.1%. Further, the interactions of changes in federal and state tax rules are potentially highly nonlinear. This means that much of the variation is not eliminated by state fixed effects.

annual, nearest-monitor average for each type of water quality. The second metric is the average of each water quality type for all monitors in the county where the group is located. In the sensitivity section we limit the sample to summer measurements, when water quality tends to worsen. The parameter of interest, β_1, is the change in water quality resulting from a one unit ($10,000) increase in contributions to the environmental group.

The matrix $\mathbf{X}_{ct}$ contains annual county characteristics for county c where group i is located: land use, per-capita income, educational attainment, population density, race, political inclination, unemployment, precipitation, and the number of Clean Water Act violations in a year. The use of county-level demographic regressors mitigates concerns about sub-state heterogeneity that could cause spurious correlation between contributions and water quality. For instance, county-level per capita income controls for within-state variation in wealth that could be correlated with both water quality and contributions to environmental groups. We also include state-level government expenditures on water quality. Vectors σ_s and τ_t are state and year fixed effects.[10]

We wish to identify causal effects of contributions on water quality. One requirement is that contributions to water groups are randomly located, conditional on covariates. This may fail for a couple of reasons. Contributions may be higher where water quality is poorer, due to a greater perceived need for the activity of these groups. Alternatively, people who care more about the environment give more and live in cleaner places. We address these concerns using an instrumental variables approach, building on evidence that changes in price of giving affect contributions to nonprofits. Since the price of giving only varies at the state level and impacts all nonprofit groups in a state, we use an instrument that scales the impact of state-wide changes to the individual environmental group level. We construct the instrument by interacting a group's baseline (1997) share of total contributions to all nonprofits in the state where the group is located with the state's price of giving in each year (Boustan et al., 2013; Nakamura and Steinsson, 2014; Nunn and Qian, 2014). The initial shares of contributions act as weights that determine how state-level tax changes likely affect contributions to each group.

The instrument exploits two sources of variation: plausibly exogenous, annual state-level variation in price of giving and group-level variation in initial share of total state con-

[10] State fixed effects are appropriate because each state makes water quality management decisions annually. Group fixed effects remove the signal we wish to measure in the data.

tributions. Contributions to environmental groups are orthogonal to changes in tax code because these represent a small subset of all donations to nonprofits. We check this by estimating a state-level regression of price of giving on mean contributions to environmental nonprofits, state-level covariates, and year and state-fixed effects. The results, shown in Table A.1, suggest there is no correlation. Additionally, fixing the initial share of contributions before the beginning of the study period mitigates concerns about contributions to groups depending on water quality. We evaluate this assumption by regressing the baseline share of contributions to environmental groups on five leads of each water quality measure, county covariates, and state fixed effects. The estimates, available in Table A.2, suggest no correlation between baseline shares and future dissolved oxygen, nitrogen, or phosphorus measures. Hence, the instrument is likely not affected by local water quality, as it isolates the part of change in contributions driven by state trends in taxes and, therefore, price of giving and incentives to contribute.[11]

4 Data

The two main datasets are a panel of financial metrics for environmental groups and a panel of water quality measures. We merge these and bring in additional, relevant covariates. Summary statistics are in Table 1.

We obtain data on environmental groups from the National Center for Charitable Statistics (NCCS) (https://nccs-data.urban.org/index.php) for fiscal years from 1997 to 2017.[12] We use the annual NCCS Core files, which represent the entire population of active, reporting organizations filing tax forms. These data have, for each organization, contributions received, fundraising expenditures, year-end assets and liabilities, program revenue, government grants received, address and location (latitude-longitude), and date of incorporation. We select a subset of smaller, local groups by dropping all parent organizations and remaining organizations with large asset values. To assure our groups are water-focused nonprofits, we cross-reference three other sources. We obtain a comprehensive list of groups

[11] One potential concern is that, if baseline shares are correlated with baseline water quality and there are shocks to water quality that persist beyond one year, the baseline share may be endogenous during the first years of the sample. We address this concern in the sensitivity section.

[12] Data are available starting in 1987, but measurements for the water quality outcome variables are infrequent and noisy before 1997.

working in the area of "Water Resource, Wetlands Conservation, and Management" from GuideStar (www.guidestar.org), an organization that gathers information about nonprofits. We supplement this information with lists from the U.S. Environmental Protection Agency (EPA) and River Network, a national group assisting regional and local organizations whose primary mission is protecting water resources. The remaining groups in our sample are relatively small, located in one state, and focus on the region or river basin where they are located (often being named as such), operating at a local scale.[13] The mean contributions corroborate their size, with average giving at $225,000.

We calculate the annual state-level price of giving using TAXSIM and following Duquette (2016).[14] We use the 1984 IRS Public Use File, a nationally representative sample of 79,556 individual income-tax returns. This dataset captures heterogeneity in income and other factors influencing marginal tax rates, and thus the price of giving. It includes contributions by itemizers and non-itemizers, the latter observed due to a temporary tax code amendment in 1984. Including non-itemizers ensures accurate state-year averages by avoiding underestimation of the mean price of giving. Using TAXSIM, we compute the first-dollar marginal cost of a contribution for all state-years. The process assumes representative taxpayers in state s and year t and involves five steps: 1. Set charitable contributions to zero and calculate combined federal and state tax liabilities for each return under federal and state s tax rules in year t. 2. Adjust all dollar values for inflation. 3. Add a $10 contribution and recalculate combined tax liabilities. 4. Compute the marginal tax cost by dividing the change in combined tax liability by the $10 contribution. 5. Calculate the mean price of giving for state s and year t, weighted by reported contributions to account for variation in giving. This process is repeated for all states and years, yielding an average price of giving a dollar at $0.65.

[13] Personal communications with water group directors and researchers at the US Geological Service (USGS) confirm that these groups carry out projects and engage the community within a relatively small area. We test numerous other ways to limit the set of organizations to those which are regional in scale.

[14] TAXSIM is a program maintained at the National Bureau of Economic Research (NBER) (http://www.nber.org/taxsim/) and used to calculate federal and state income tax liabilities (Feenberg and Coutts, 1993).

Table 1. Summary Statistics; Fiscal Years 1998 – 2017

	Obs	Mean	SD	Min	Max
Contributions, USD	81,980	224,641.86	353,982.67	0	1,979,939
Age of Group, Years	81,625	15.12	12.16	0	53
Fundraising Expenditures, USD	74,164	24,314.90	48,356.18	208	405,680
Program Revenue, USD	77,156	255,120.30	5,349,676.52	0	456,848,128
Share of 1997 Total State Cont., %	88,676	0.08	0.03	0.00	1.19
Assets, USD	86,682	1,800,829.79	5,222,822.51	3,796	35,277,874
Liabilities, USD	86,682	168,538.68	634,213.82	0	4,703,507
Price of Giving, USD	86,682	0.65	0.07	0	1
Dissolved Oxygen, County, mg/l	65,099	8.86	1.64	0	15
Dissolved Oxygen, Nearest, mg/l	78,352	8.87	1.58	0	15
Nitrogen, County, mg/l	47,369	0.72	0.68	0	5
Nitrogen, Nearest, mg/l	72,061	0.68	0.46	0	5
Phosphorus, County, mg/l	56,449	0.14	0.18	0	2
Phosphorus, Nearest, mg/l	77,495	0.15	0.17	0	2
Gross State Product, USD	86,682	578,902.78	630,148.31	16,294	2,680,917
Per Capita Income, State, USD	86,682	46,979.37	7,806.11	29,714	77,475
Unemployment Rate, State, %	86,682	0.06	0.02	0	0
Poverty Rate, State, %	86,682	0.13	0.03	0	0
College, State, %	86,682	0.17	0.04	0	0
Republican, State, %	86,682	0.49	0.16	0	1
White, State, %	86,682	0.86	0.12	0	1
Population Density, County	84,438	1,338.95	5,096.54	0	48,577
Per Capita Income, County, USD	85,444	43,658.06	17,534.37	13,084	227,753
Unemployment Rate, County, %	86,306	0.06	0.02	0	0
College, County, %	86,323	0.22	0.08	0	1
Republican, County, %	83,007	0.43	0.17	0	1
White, County, %	86,325	0.82	0.15	0	1
Prop Ag Land, County, %	82,506	0.26	0.23	0	1
Prop Urban Land, County, %	82,506	0.24	0.23	0	1
Precipitation, County, 1,000 mm	84,729	1,035.09	452.19	12	3,732
CWA Violations, County	84,252	75.14	163.08	0	2,111
Government Expend., State, USD	86,682	35,527,045.29	43,897,922.67	0	322,013,792

Water quality measurements come from two databases in the Water Quality Portal (https://www.waterqualitydata.us/): STORET and NWIS. STORET is managed by the EPA and contains water quality data collected by federal agencies, states, tribes, volunteer groups, and universities. NWIS, which is administered by the USGS, contains data from all 50 states, the District of Columbia, and US territories. We obtained monitor-level measurements for dissolved oxygen (DO), nitrogen, and phosphorus. We follow previous research (Grant and Langpap, 2019; Keiser and Shapiro, 2019) to construct our variables from the data. We choose total measurements from only rivers and streams. We keep routine samples, dropping measurements from non-routine hydrologic events like floods, storms, and hurricanes. We also drop estimated or calculated measurements and those missing observation date. We winsorize at the 1^{st} and 99^{th} percentiles of the measurement distribution to minimize the impact of outliers. We aggregate water quality measures to two levels: county and nearest monitors; the distributions are similar between the two.

We obtain the other covariates from a variety of sources. Gross state product and state- and county-level per-capita income data are from the Bureau of Economic Analysis. State and county population and college graduation rates for population over age 25, which measures educational attainment, as well as state poverty rates, are from the US Census Bureau. State and county unemployment rates come from the Bureau of Labor Statistics. NBER provides race information, measured as percent of white population. We measure general political preferences using the proportion of votes for Republican candidates in US Senate races, with county and state-level data from the CQ Press. We interpolate for years without Senate races. Land use data come from the Natural Resources Conservation Service National Resources Inventory (NRI), which we use to calculate proportions of agricultural and urban land in a county. Precipitation data are from the PRISM Climate Group. We obtain information on Clean Water Act violations from the EPA's Enforcement and Compliance History Online (ECHO) database. Government expenditures on environmental projects include payments made under the Environmental Quality Incentives Program (EQUIP), the Conservation Reserve Program (CRP), and the EPA 319 Grant Program. EQUIP payments data are from the Environmental Working Group; CRP payments come from the USDA Farm Service Agency; and data on payments made under the EPA 319 program are from the Grants Reporting and Tracking System.

5 Results

5.1 Price Elasticity of Giving

Table 2 provides results for the price elasticity of giving, ε_g — the impacts of changes in tax price on charitable giving, for our case of water-related nonprofits. The estimates for our preferred specification are in Column (1), as itprovides a conservative reference point and follows from previous literature such as Duquette (2016). A notable exception is that, whereas he uses a natural log transform, $\ln(\text{contributions} + 1)$, we use contributions in levels as the dependent variable and estimate using Poisson quasi-maximum likelihood, as noted in Section 3. In the table, Column (2) adds state-specific trends to control for additional time-varying state heterogeneity that could affect contributions. Column (3) instead includes additional state-level demographic characteristics to make the specification consistent with those of the water quality models. Column (4) incorporates additional group characteristics.[15]

The estimated elasticity ranges from -0.93 to -0.64, indicating that the tax incentive for charitable giving lacks enough additional donations to justify lost revenue.[16] The findings indicate that the tax deductibility of donations to these nonprofits is not *treasury* efficient. These results underscore a critical need to reconsider how tax incentives align with promoting charitable giving to maximize public benefit rather than treasury income.

The effects of other covariates align with intuition. Several factors are positively associated with higher levels of giving, including higher gross state product, greater age of the charity, more active fundraising efforts, and higher levels of assets. Conversely, lower contributions are correlated with higher population, unemployment rates, and larger program revenue.

[15] Our preferred specification omits these group characteristics because some observations are unavailable, causing the sample size to decrease. However, using interpolated missing values yields similar results.

[16] Using a $\ln(\text{cont} + c)$ transform, which yields estimates that are sensitive to the scale of the transformation, gives estimated coefficients ranging from -1.32 to -2.39 for c between 0.001 and 1,000, further emphasizing the importance of using a robust estimation approach such as the Poisson (Chen and Roth, 2024).

Table 2. Price Elasticity of Giving Model - Poisson

	(1)	(2)	(3)	(4)	(5)
ln(Tax Price)	-0.930***	-0.772*	-0.889**	-0.701**	-0.639*
	(0.353)	(0.403)	(0.358)	(0.309)	(0.361)
ln(Grs State Product)	0.308	0.251	0.348	0.385**	0.554***
	(0.217)	(0.228)	(0.219)	(0.186)	(0.199)
ln(Per-cap Income)	-0.505	0.0798		-0.566*	-0.964***
	(0.365)	(0.362)		(0.311)	(0.340)
Population, State	-2.68e-08	-8.00e-08**		-2.41e-08	-4.70e-08***
	(1.66e-08)	(3.79e-08)		(1.50e-08)	(1.73e-08)
Unemployment Rate, State	-2.492**	-1.504		-2.164**	-1.394
	(1.052)	(1.019)		(0.952)	(1.052)
ln(Age)	0.141***	0.141***	0.146***	0.0398	0.0251
	(0.0266)	(0.0262)	(0.0272)	(0.0261)	(0.0310)
College, County (%)			-0.183		
			(0.391)		
Population Density, County			2.15e-05		
			(1.35e-05)		
White, County (%)			-0.00140		
			(0.265)		
ln(Fundraise)				0.0144***	0.0108***
				(0.00225)	(0.00224)
ln(Assets)				0.293***	0.243***
				(0.0164)	(0.0181)
ln(Prog Rev)				-0.0206***	-0.0205***
				(0.00203)	(0.00216)
Government Grants					0.0547***
					(0.00265)
State-specific Trends	No	Yes	No	No	No
Observations	52,592	52,592	51,827	50,649	33,382
Number of Groups	7,402	7,402	7,244	7,144	5,411

Note: All columns include State Poverty Rate, and group and year fixed effects. Robust standard errors in parentheses, clustered at group level. Significance indicated as *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5.2 Public Good Provision

Social efficiency evaluates the impact of tax changes on contributions, the resulting change in public good provision, and the marginal value of the additional public good. Here, we estimate the second component: the relationship between contributions and water quality, our measure of public good provision. We present two sets of results for each water quality metric in Tables 3 and 4. One set uses the mean of measurements from monitors nearest to each group's location, while the other uses the mean of all measurements within each county. Kleibergen-Paap F-statistics suggest the instrument is sufficiently strong to mitigate concerns about bias. Standard errors are clustered at the HUC8 watershed level, the appropriate scale for hydrological factors influencing water quality.[17]

Increases in contributions to environmental nonprofits improve water quality in U.S. streams and rivers. A \$10,000 increase in contributions leads to a $0.003 - 0.006\,\text{mg/L}$ rise in dissolved oxygen, benefiting aquatic life. It also results in a $0.0007 - 0.001\,\text{mg/L}$ decrease in nitrogen concentration and a $0.0003\,\text{mg/L}$ reduction in phosphorus concentration at county-level monitors. However, no statistically significant effect is observed for phosphorus at monitors near a group's location. While these changes are small in magnitude, they are economically significant.

Large improvements in water quality are constrained by its slow rate of change and substantial prior improvements (Keiser and Shapiro, 2019). Our estimates are meaningful relative to the mean annual changes in water quality during the study period. For dissolved oxygen, marginal effects represent 12.51% and 47.92% of annual changes at nearby and county-level monitors, respectively. For nitrogen, marginal effects account for 10.56% of annual change at nearby monitors and 61.56% at the county level. Finally, the marginal effect for phosphorus at the county level constitutes 28.7% of the mean annual change.

[17] First-stage regression results are in Tables A.3 and A.4. Robustness checks with clustering at the county and state levels show stable statistical significance. OLS estimates are small and insignificant except for county-level DO ($p = 0.06$), likely reflecting non-random group locations and spending. Results available upon request.

Table 3. Impact of Giving on Water Quality - Means for Nearest Monitors

	DO	Nitrogen	Phosphorus
Contributions (10,000 USD)	0.00284**	-0.000707***	-4.27e-05
	(0.00116)	(0.000250)	(8.33e-05)
Prop Ag Land, County	-0.246	0.535***	0.166***
	(0.192)	(0.0626)	(0.0206)
Prop Urban Land, County	0.0941	0.349***	0.163***
	(0.220)	(0.0738)	(0.0289)
Population Density, County	4.46e-06	5.79e-06***	4.83e-06***
	(4.12e-06)	(1.19e-06)	(4.66e-07)
Per Capita Income, County (USD)	-7.98e-06***	-8.08e-07	-1.19e-07
	(2.28e-06)	(6.87e-07)	(2.41e-07)
College, County (%)	0.354	0.0157	-0.0143
	(0.467)	(0.200)	(0.0616)
Republican, County (%)	-0.307*	-0.191***	-0.0348
	(0.181)	(0.0678)	(0.0311)
Unemployment Rate, County	-4.384***	1.077**	0.0105
	(1.436)	(0.535)	(0.234)
White, County (%)	1.681***	0.0467	0.107***
	(0.298)	(0.103)	(0.0388)
Mean Precipitation, County (1,000s mm)	-0.000132	-0.000262***	-9.94e-05***
	(0.000178)	(6.86e-05)	(3.58e-05)
Mean Precipitation^2, County	1.22e-07**	9.13e-08***	3.12e-08***
	(5.61e-08)	(2.09e-08)	(1.10e-08)
CWA Violations, County	-0.000142	0.000122*	3.03e-05
	(9.16e-05)	(6.64e-05)	(2.40e-05)
Government Expenditures, State (10,000 USD)	3.32e-05**	-1.80e-05***	-1.70e-06
	(1.34e-05)	(6.40e-06)	(2.43e-06)
Observations	63,717	58,347	62,505
Number of Clusters	1,217	1,203	1,215
Kleibergen-Paap F stat.	24.72	19.04	23.25
Prob > F	0.0000	0.0000	0.0000

Note: Second stage results. All models include state and year fixed effects. Robust standard errors in parentheses clustered at watershed level. *** p<0.01 ** p<0.05 * p<0.1.

Table 4. Impact of Giving on Water Quality - County Means

	DO	Nitrogen	Phosphorus
Contributions (10,000 USD)	0.00556***	-0.00117***	-0.000316***
	(0.00112)	(0.000401)	(0.000109)
Prop Ag Land, County	-0.177	0.803***	0.231***
	(0.215)	(0.0977)	(0.0283)
Prop Urban Land, County	0.118	0.560***	0.136***
	(0.313)	(0.120)	(0.0329)
Population Density, County	-5.06e-05*	5.29e-07	9.83e-06***
	(2.76e-05)	(8.78e-06)	(1.82e-06)
Per Capita Income, County (USD)	-8.71e-06***	2.05e-07	-1.74e-07
	(2.32e-06)	(1.13e-06)	(2.94e-07)
College, County (%)	0.140	-0.427	-0.0565
	(0.542)	(0.354)	(0.0813)
Republican, County (%)	-0.205	-0.491***	-0.0733**
	(0.189)	(0.142)	(0.0324)
Unemployment Rate, County	-5.786***	0.620	-0.0485
	(1.783)	(0.855)	(0.274)
White, County (%)	1.675***	0.124	0.0749
	(0.332)	(0.157)	(0.0557)
Mean Precipitation, County (1,000s mm)	4.54e-05	-0.000540***	-6.70e-05
	(0.000171)	(0.000130)	(4.84e-05)
Mean Precipitation^2, County	9.87e-08*	2.09e-07***	2.17e-08
	(5.61e-08)	(4.79e-08)	(1.62e-08)
CWA Violations, County	-0.000291	0.000423***	3.25e-05*
	(0.000182)	(8.57e-05)	(1.92e-05)
Government Expenditures, State (10,000 USD)	9.65e-06	-8.84e-06	-5.39e-06
	(1.51e-05)	(8.03e-06)	(3.62e-06)
Observations	55,355	40,379	47,853
Number of Clusters	1,155	1,071	1,095
Kleibergen-Paap F stat.	22.67	43.14	26.70
Prob > F	0.0000	0.0000	0.0000

Note: Second stage results. All models include state and year fixed effects. Robust standard errors in parentheses clustered at watershed level. *** p<0.01 ** p<0.05 * p<0.1.

5.3 Total Effect of Contributions on Value of the Public Good

In this subsection, we calculate the social efficiency threshold for contributions to environmental nonprofit groups, considering water quality as the public good. We evaluate social efficiency using Equation 3. We cannot implement Equation 2 because we lack data on the marginal production of water quality from government expenditures at the same resolution as the environmental group data. The components for the threshold and the calculated thresholds are in Table 5.

Two components apply to all three metrics of water quality: For the price elasticity of giving, ε_g, we use the estimate from our preferred specification of the contributions model, shown in the first column of Table 2. We use the mean tax rate from our estimation sample for the *tax* variable.

For the marginal product of contributions in generating water quality, $f'(g)$, we use the estimated coefficients from the water quality model. We prefer results from Table 4, as they provide significant marginal effects for the three measures, dissolved oxygen, nitrogen, and phosphorus. Additionally, it is more tractable to calculate the value of the public good at the county level.

We derive the value of the public good, ν, from estimates of willingness to pay for water quality improvements found in the non-market valuation literature. The most comprehensive measure of this value is the *total* willingness to pay, obtained using survey-based stated preference approaches that capture both use and non-use values of water quality. To standardize these estimates, many studies rely on a water quality index (WQI), which aggregates various water quality criteria into a single index ranging from 0 to 100. Johnston and Bauer (2020) provide a meta-analysis of 51 stated preference studies, each estimating one or more willingness-to-pay values for hypothetical improvements in WQI. Using the meta-regression coefficients from this analysis, we calculate household willingness to pay for changes in dissolved oxygen, nitrogen, and phosphorus resulting from a marginal change in contributions ($10,000). All three measures of water quality are components of the WQI. Because willingness to pay is nonlinear with respect to changes in water quality and its components, we assess social efficiency separately for each pollutant. To calculate the total value of the public good, we aggregate household willingness-to-pay estimates to

the county level, using the average number of households per county in 2017.

Table 5. Social Efficiency, as Indicated by $\varepsilon_g <$ Threshold

Price Elasticity of Giving, ε_g	Tax Rate, ***tax***	Metric of Water Quality	Marginal Product of Contributions, $f'(g)$	Value of Public Good per \$10,000 in Contributions, ν	Social Efficiency Threshold
		Dissolved Ox.	0.0056	743.56	**-0.17**
-0.93	0.35	Nitrogen	0.0012	1,048.06	**-0.74**
		Phosphorus	0.0003	2,443.18	**-1.55**

Note: Value of the public good is in 2017\$ and includes use and non-use values, derived from stated preference studies of changes in the Water Quality Index (WQI).

Table 5 gives the social efficiency threshold in the last column. Social efficiency requires the price elasticity of giving (ε_g) to be lower than this threshold. The results indicate that, while the deductibility of contributions to environmental nonprofits is not treasury efficient, it is socially efficient when the public good is increased dissolved oxygen or reduced nitrogen.[18] For dissolved oxygen, the marginal product of contributions, at 0.0056 mg/L per \$10,000, is the highest among the three metrics and has a moderate public value, resulting in the lowest and easiest to achieve threshold ($\varepsilon_g < -0.17$). Nitrogen's higher value of the public good balances its lower marginal product, 0.0012 mg/L per \$10,000, leading to a moderately achievable threshold, $\varepsilon_g < -0.74$.

In contrast, phosphorus does not seem to meet the social efficiency threshold. The magnitude of the marginal product of contributions is low, at 0.0003, resulting in a high threshold, $\varepsilon_g < -1.55$, despite the high value of the public good. The discrepancy arises because average concentrations of phosphorus are much lower than those of other pollutants, so a marginal (1 mg/L) change constitutes a larger relative improvement in water quality, resulting in a higher perceived public good value. However, contributions have a significantly weaker effect on reducing phosphorus levels, which lowers the marginal product of contributions $f'(g)$ and, consequently, the marginal value of the public good, $\nu \times f'(g)$. This, in turn, raises the price elasticity threshold required for social efficiency, making it harder

[18] We repeat this analysis using 10,000 random draws from the 95% confidence intervals for price elasticity of giving, marginal products of contributions, and the value of water quality changes. These are used to calculate means and confidence intervals for social efficiency thresholds. Results, shown in Table A.5, confirm our conclusions about social efficiency.

to achieve. These results highlight that social efficiency depends critically on the interplay between the responsiveness of water quality to contributions and the perceived value of the resulting improvements.

Environmental characteristics and chemical processes also help explain the different outcomes for the three measures of water quality. DO responds directly to ecosystem interventions such as riparian restoration or aeration, which environmental groups often engage in. Nitrogen, while more dynamic, can also be effectively managed through contributions targeting wetland restoration or agricultural runoff, which have measurable impacts on reducing its concentration. In contrast, phosphorus binds to sediments and releases slowly, making immediate improvements harder to achieve. The slower cycling and higher cost of interventions targeting phosphorus reduce its marginal product and make it less responsive to contributions.

In addition, differences in nutrient inputs contribute to these disparities. Nitrogen often enters surface waters through diffuse sources like agricultural runoff, which can be managed cost-effectively, leading to significant reductions. Phosphorus, however, is frequently tied to point sources or sediment-bound reservoirs, requiring costly and large-scale interventions. Further, these point sources are governed by limits set at state and federal levels, which are largely outside the control of nonprofits. Nitrogen reductions are more feasible and impactful, while phosphorus improvements often have diminishing returns due to the system's slow response.

Contributions that affect dissolved oxygen and nitrogen meet social efficiency thresholds because they exhibit higher responsiveness to interventions and provide broader ecosystem benefits, such as improved aquatic health and reduced algal blooms. In contrast, the high cost and limited immediate impact of phosphorus interventions raise its social efficiency threshold, making it difficult to achieve. These results highlight the need for targeted strategies that account for pollutant-specific characteristics to maximize the cost-effectiveness of contributions and improve water quality outcomes.

5.4 Sensitivity

We conduct several sensitivity checks for the models in Table 4 and the results in Table 5, including sub-samples, alternative variable measurements, different model specifications, and identification checks. The results are presented in the Appendix (App. A) and Online Appendix (App. B.) The top half of each table reports the estimated coefficients for the effect of contributions on water quality. The bottom half includes the value of the public good, which varies when the estimation sample and thus the population change, the recalculated social efficiency threshold, and the (unchanged) price elasticity of giving for reference. The estimated impacts on water quality are consistent with those from the main specifications, with only minor deviations noted. Similarly, the conclusions about social efficiency remain unchanged, reinforcing the robustness of the main results.

5.4.1 Measurement of Variables

Our sample includes all local environmental groups that may influence water resources. However, some groups have broader focuses that extend beyond water quality. If contributions to these groups also support other environmental concerns, our measurement of contributions may contain error. Similarly, if environmental groups receive contributions from out-of-state donors, the price of giving variable may also be measured with error. To address these issues, we estimate the public good provision models using a sub-sample that excludes organizations focused on broader concerns, such as land resources, forest conservation, and environmental education. We also exclude groups likely to receive out-of-state contributions, identified by the presence of terms such as national, international, or global in their names. The results from this sensitivity analysis are presented in Table A.6.

Non-classical measurement error may arise when measuring average water quality at the county level. To address this, we estimate models that include controls for lagged contributions to other groups in the county and the total number of active groups in the county. The results of these sensitivity checks are presented in Table A.7.

We also estimate results using an alternative measure of water quality, calculated as the mean of summer measurements instead of annual averages. Water quality often worsens during the summer due to reduced water flows and lower precipitation levels. Environmen-

tal groups may direct more effort toward improving water quality during these periods of heightened concern. Results are in Table A.10.

5.4.2 Model Specification

Environmental groups engage in a variety of activities, some of which directly affect water quality, such as stream-bank restoration and river cleanups. Others, including education, outreach, and advocacy, have indirect impacts on water quality. If water quality improvements lag behind contributions, contemporaneous one-year regressions may fail to capture the full effects. To examine the timing of these effects, we estimate public good provision models using up to five-year lagged contributions.[19] The results, presented in Table A.11, confirm our conclusions, with the exception that nitrogen is marginally socially inefficient in the model with three-year lagged contributions.

The preferred model specifications include state and year fixed effects. To account for time-varying state-level unobservable heterogeneity, we also estimate models with an added linear trend for each state. The results of these models are shown in Table A.8.

5.4.3 Instrumental Variable

We construct the instrumental variable using an environmental group's baseline (1997) share of total contributions to nonprofits in the state where it is located. This share is expected to be unrelated to water quality in later years used for estimation. However, if baseline shares are correlated with baseline water quality, and shocks to water quality in 1997 persist beyond that year, the instrument may be correlated with these early shocks during the study period. To address this concern, we assess the robustness of our results by choosing later years as the start of our estimation sample, increasing the temporal separation between baseline shares and potential shocks to water quality. The results, presented in Table A.9, show that estimated coefficients, first-stage F-statistics, and social efficiency thresholds are very similar to those from our main analysis.

Although the exclusion restriction for the instrument cannot be directly tested, we further

[19] We instrument lagged contributions with interactions between baseline shares and lagged prices of giving.

examine the mechanism through which groups influence water quality. Specifically, we use environmental groups' instrumented expenditures rather than contributions in the main specifications. Groups receiving more contributions can allocate greater resources to their programs, which are expected to impact water quality. The results, shown in Table A.12, indicate that group expenditures have positive effects on water quality, providing additional evidence that changes in water quality are attributable to group activities.

6 Conclusions

The stated purpose of tax deductions for charitable giving is to elicit more contributions. Extensive economics literature evaluates this goal using treasury efficiency, typically measured by the price elasticity of giving. We argue that higher contributions alone should not be the ultimate objective and propose an alternative metric: the price elasticity of the public good's value as the appropriate measure for social efficiency. The proposed metric highlights the need to evaluate not just the amount of contributions but also how effectively they translate into public goods and the value generated by those goods.

This paper provides a framework to guide this shift in focus. In doing so, it makes two novel contributions to the literature. First, it offers a more comprehensive conceptual approach for evaluating the tradeoffs in public good provision generated by tax deductibility of charitable contributions. Second, it provides guidance for evaluating social efficiency empirically for specific public goods.

We apply this framework to environmental nonprofits that impact water resources, where the public good is improved water quality. While treasury inefficiency is evident in our sample, with the price elasticity of giving estimated between 0.6 and 0.9, our analysis shows that the treasury efficiency criterion alone provides an incomplete picture. When considering how contributions translate into public good provision and the associated value, we find that two of the three measures of public good provision (dissolved oxygen and nitrogen reduction) indicate that tax deductibility for contributions to environmental nonprofits is socially efficient. This result underscores our main point: accounting for both the provision of the public good and its value can yield different conclusions about efficiency compared to traditional metrics.

Our illustration of water-related environmental groups demonstrates the applicability of our criterion but is only one of many potential contexts to test this approach. The implications for other charitable sectors will vary depending on the price elasticity of giving, nonprofits' ability to effect change, measurable impacts, and the role of government in the same sector. Further research is needed to assess donation efficiency and tax deductibility in other areas of public good provision. In our context, contributions to environmental nonprofits have meaningful impacts on two measures of water quality, and the relatively high willingness to pay for water quality improvements lowers the threshold required for social efficiency. For phosphorus, where the threshold is not met, the marginal impact of contributions is small despite the high value of the public good, raising the threshold and making social efficiency harder to achieve.

Our model and analysis emphasize the importance of considering nonprofits' effectiveness in producing public goods and the value of those goods when evaluating the efficiency of tax deductibility. By incorporating these factors, our results show that conclusions about efficiency can differ significantly from traditional interpretations. This framework offers policymakers and researchers a more nuanced understanding of how to design and evaluate tax policies that support charitable giving while maximizing public good provision.

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