Impact of Upstream Plant Level Pollution on Downstream Water Quality: Evidence from the Clean Water Act

Chakraborti, Lopamudra

CIDE

10 December 2019

Impact of Upstream Plant Level Pollution on Downstream Water Quality: Evidence from the Clean Water Act

Lopamudra Chakraborti

Associate Professor
Department of Economics, CIDE
Circuito Tecnopolo Norte No. 117
Fraccionamiento Tecnopolo Pocitos II
Aguascalientes, Ags. Mexico, 20313
Tel: 524499945150 ext. 5258
Email: lopamudra.chakraborti@cide.edu

December 10, 2019

ABSTRACT: This is the first study to find empirical evidence that pollutant inputs from major point sources worsens downstream water quality, net of upstream pollution levels, and controlling for location-specific factors. We utilize a panel data on monthly biochemical oxygen demand (BOD) concentration for a sample of 87 municipal and industrial plants located in the states of Maryland, Pennsylvania, and Virginia, for the period 1990-2003. We define water quality as monthly dissolved oxygen (DO) from 67 locations within 25 miles downstream. We find that upon an increase in aggregate BOD (by one or more plant) downstream DO net of ambient levels before their effluent outfalls declines by 0.001 mg/L. Despite the small magnitude (due to natural attenuation), the results are robust to distance traveled by pollutant and seasonal considerations of high temperature or low stream flow. From our results, we infer that self-reported pollution does not exhibit underreporting biases.

Keywords: U.S. Clean Water Act, Ambient Water Quality Model, Self-Reported Pollution, Total Maximum Daily Loads, Over-compliance

1. Introduction

Ambient water quality has not been studied extensively in the water pollution regulation literature primarily due to lack of reasonably good time series data for water bodies across the U.S. McConnell and Schwartz (1992) mention that consistent water quality data within even 20-50 miles of the plant locations were not available during the early 1980s. With the availability of data, most studies include conventional measures of water quality, namely ambient biochemical oxygen demand (Sigman, 2002, 2004), dissolved oxygen, fecal coliform, total suspended solids, phosphorus, and nitrogen (Sigman, 2005). However, none of the studies that model ambient water quality estimate the impact of upstream pollutant inputs on in-stream water quality. Most include proxies for pollution by point sources such as streamflow and temperature (Sigman, 2005).

More recently, water quality has taken the spotlight based on concerns of increasing non-point source pollution leading to stagnation in ambient water quality trends. Concurrently, various policy studies and academic reports have documented the high costs of the Clean Water Act (USEPA, 2000). Studies on lakes and estuaries have reported deteriorating trends (Smith and Wolloh, 2012). Until recently, research on ambient water quality has been limited mostly due to concerns about statistical representativeness and comparability across states of long-term water quality measurements (GAO, 2000). Grant and Langpap (2019) consider the measure of Dissolved Oxygen Deficit (DOD) over the period 1996–2008. Keiser and Shapiro's (2019), comprehensive ambient water quality database updated till 2001 finds positive trends in ambient water quality in rivers and streams and unaccounted for benefits components (Keiser, Kling, and Shapiro, 2019). In this paper, we study the impact of upstream pollutant discharges on downstream water quality after controlling for ambient pollution before the points of effluent

outfall and location-specific factors. From our results, we infer that self-reported pollution data does not exhibit underreporting biases, which forms the backbone of all CWA monitoring and enforcement (Shimshack, 2014).[1] This conclusion is contrary to preliminary evidence on under-reporting by sewage treatment plants across the U.S. found in Chakraborti and Shimshack (2012).

We utilize a sample of 87 major polluters in the three neighboring states of Maryland, Pennsylvania, and Virginia, for the period 1990 to 2003. Plants with NPDES permits (National Pollutant Discharge Elimination System) are mandated by law to report monthly average pollutant discharges. We gather a comprehensive water quality database from the EPA's central STORET (Storage and Data Retrieval System) databases and state FOIA (Freedom of Information Act) requests. Our data might be slightly dated. However, both EPA's Permit Compliance System (PCS), the source of self-reported pollution data, and ambient water quality coverages declined during the post-2000 period. Decentralizing EPA's various databases and states transitioning to new reporting protocols and data platforms meant that historical databases failed to remain centralized. As a researcher looking into ambient water quality, long time series is a requirement due to the slow evolution of ambient water quality. Hence, we consider the period with the most coverage of pollutant inputs and ambient water quality. Besides, the implications for self-reporting remain valid to more recent decades, given no significant change in policy since the 2000s.

We estimate panel data models that control for all time-invariant location-specific effects such as biophysical aspects of the stream segment. We consider a more general fixed effects model that controls for time-varying changes at the state level, such as economic or climate

[1] Self-reported pollution forms the basis of monitoring and enforcement for toxic as well as conventional pollutants like biochemical oxygen demand (BOD) and total suspended solids (TSS).

shocks such as drought or flood or extreme weather events, land-use changes, changes in non-point source trends, changes in environmental preferences of government or citizens. We rely on distributional considerations of previous water quality and plant-level pollution studies to estimate linear relationships.

We find that pollutant discharges from major point sources have a significantly negative impact on downstream water quality after controlling for upstream ambient water quality. Our results show that a one percent increase in upstream BOD pollutant inputs leads to a decline in the downstream net of upstream dissolved oxygen levels (DO) by 0.001 mg/L. As expected, the magnitude of the coefficients is small (due to the assimilative capacity of water bodies), but they are consistently negative and statistically significant in our various robustness checks based on distance traveled by pollutants or seasonal considerations.

2. Background and Literature

2.1 The Ambient Water Quality Model

Upstream ambient pollution concentrations, pollution inputs of BOD, flow, temperature, and assimilative capacity of the stream jointly determine ambient dissolved oxygen at downstream locations. In this section, we present the Streeter-Phelps (Dissolved) Oxygen Sag Curve to gain an understanding of the physical relationship between observed ambient dissolved oxygen and the BOD effluent discharges of "major" point source polluters.

Oxygen is essential for the survival and propagation of aquatic organisms. If the amount of oxygen dissolved in water, falls below the minimum requirements for the survival of aquatic life, all organisms, including their eggs and larvae may die. A severe example is a fish kill. Hence, surface waters protected for warm-water fish and aquatic life must meet the minimum dissolved oxygen standard of 5 mg/l. Oxygen enters the water by photosynthesis of aquatic biota

and by the transfer of oxygen across the air-water interface (reaeration). Different forms of pollution cause declines in DO. Matter containing carbon or nitrogen uses dissolved oxygen from the water as it decomposes, which can result in a dissolved oxygen decline. Nitrogenous demand for oxygen (NBOD) arises due to the presence of nitrifying bacteria, which oxidizes ammonia to nitrite first, then to nitrate. Non-point sources of pollution (agriculture primarily) are the predominant factors giving rise to significant NBOD. Carbonaceous organic matter present in the effluent discharges of point sources also creates a demand for oxygen (CBOD), since bacteria oxidize organic carbon into carbon dioxide and water.

Dissolved oxygen (DO) also varies significantly due to natural phenomena resulting in daily and seasonal cycles.[2] Seasonally, DO concentrations are higher in the colder winter months and lower in the warmer summer months. We know that gas solubility increases with decreasing temperature (i.e., colder waters holds more oxygen than warmer waters), decreasing salinity (i.e., freshwater holds more oxygen than saltwater), and decreases with decreasing pressure (i.e., higher altitude waters holds less oxygen because of the decrease in relative pressure). High temperatures encourage the microbial breakdown of organic matter, a process that requires dissolved oxygen. Also, streamflow (in freshwater) that is generally lower during late summer and early fall significantly affects flushing (dilution of pollutant inputs), re-aeration (mixing at the air-water interface), and the extent of saltwater intrusion, all of which affect dissolved oxygen. These low-flow and high-temperature conditions are referred to as the critical condition since it has the potential to produce the worst effect on water quality.

[2] The natural diurnal (daily) cycle of DO concentration is well documented. Dissolved oxygen concentrations are generally lowest in the morning, climbing throughout the day due to photosynthesis and peaking near dusk, then steadily declining during the hours of darkness.

The differential equation that outlines the process of evolution of deficit (D) in ambient dissolved oxygen is:

$$\frac{dD}{dt} = k_D L_0 e^{-k_D t} - k_R D \quad \text{.....(1)}$$

Where $D = DO$ deficit $= DO_S - DO$, i.e., the difference between the equilibrium concentration$DO_S$and the actual concentration$DO$is the oxygen deficit, and DO_S is the maximum amount of dissolved oxygen in the water. It depends on water temperature, salinity, and pressure. Equation (1) is essentially a balance between DO consumption due to BOD inputs and stream reaeration. The first term captures the rate of deoxygenation, i.e., consumption of DO, while the second term captures the reaeration process. $k_R$and $k_D$are the reaeration time constant (depends on stream velocity and depth) and the de-oxygenation constant, respectively. $t$is time, and$L_0$is the initial DO deficit in the stream, at the point of discharge of effluents from a point source. The oxidation of carbonaceous (and nitrogenous) substances present in the wastewater of the municipal and industrial plants creates an initial oxygen deficit at the point of the outfall of the effluents. BOD of the river/wastewater mixture (L_0), also known as the ultimate BOD is given by:

$$L_0 = \frac{Q_r L_r + Q_w L_w}{Q_r + Q_w} \quad \text{.....(2)}$$

Where:

$L_0 =$ BOD concentration (mg/L) at the point of wastewater discharge

$Q_r =$ Flow of the river, upstream of the wastewater discharge

$L_r =$ BOD concentration (mg/L) measured in the river, upstream of the wastewater discharge

$Q_w =$ Flow of the wastewater discharge

$L_w =$ BOD concentration (mg/L) measured in the wastewater discharge

Ceteris paribus, a plant with a higher load, i.e., a higher effluent flow, has a bigger weight on the effluent concentration and a smaller weight on the ambient upstream concentration. Since the concentration of BOD measured in the wastewater is greater than the ambient BOD concentration before the point of wastewater discharge, on account of natural attenuation, the ultimate BOD is higher.[3] In the limit (i.e., as design effluent flow approaches an infinitesimally large number, ultimate BOD is determined only by the effluent concentration L_w (in equation (2)).[4] Consequently, regulators (federal and state EPAs) focus their permitting, monitoring, and compliance activities towards "major" polluters where one of the criteria used is design flow greater than 1 million gallons per day.

The solution to the differential equation (1) gives the ambient water quality at distance$d$ (downstream to wastewater discharges) where u is average water velocity:

$$D = \frac{k_D L_0}{k_R - k_D}(e^{-k_D d/u} - e^{-k_R d/u}) + D_0 e^{-k_R d/u} \qquad \ldots\ldots\ldots(3)$$

The above equation is the well-known Streeter-Phelps oxygen-sag curve formula (Streeter and Phelps, 1925), which was originally developed for use on the Ohio River, back in 1914. Expressing the relationship in equation (3) in terms of ambient dissolved oxygen levels instead of DO deficits by substituting for initial dissolved oxygen deficit $D_0 = DO_S - DO_0$, and dissolved oxygen deficit $D = DO_S - DO$:

[3] For example, Summers, Kazyak, and Weisberg (1991) utilize the QUAL2E-UNCAS water quality model to simulate the impact of a reduction in the effluent discharge rate (flow) by 55 percent of a large paper mill discharging its effluents to the Pigeon River in NC. The authors find that simulated BOD in the river is reduced by 20 ppm in the vicinity of the discharge.

[4] On the other hand, as stream flow approaches an infinitesimally big number ultimate BOD is determined solely by the upstream concentration of BOD,Lr (in equation (2)). Hence, it is suspected that non-point sources of pollution are contributing the most to ambient pollution during high stream flow seasons.

$$DO = DO_S(1 - e^{-k_R t}) - \frac{k_D L_0}{k_R - k_D}(e^{-k_D t} - e^{-k_R t}) + DO_0 e^{-k_R t} \quad \text{.....(4)}$$

The initial dissolved oxygen (DO_0) has the same formula as the one for calculating BOD of the river/wastewater mixture at the point of the outfall, L_0(equation (2)). Thus, ambient water qualityDOat a certain distance downstream (given stream velocity) depends on initial dissolved oxygen DO_0, the concentration of BOD of the river/wastewater mixture at the outfall L_0, reaeration (k_R) and deoxygenation (k_D) coefficients, and the saturation level of DO in the river waterDO_S. The equation (4) above is a steady-state model relating dissolved oxygen concentration in a free-flowing stream to BOD. It predicts a negative relation between BOD at the point of effluent outfall $L_0$and downstream ambient water quality measured by the concentration of dissolved oxygen,DO.

2.2 Streeter-Phelps and the CWA

The Streeter-Phelps model of a free-flowing stream is used by regulators undertaking water quality evaluations to determine whether water quality-based effluent limits for BOD are needed. The Streeter-Phelps model uses background and point source loadings of BOD and simulates oxygen addition through atmospheric re-aeration and photosynthesis. For example, in Maryland and Virginia, water quality-based limits for BOD were derived from non-TMDL (Total Maximum Daily Load) waste load allocations in the 1990s. Given the effluent limits of a plant determined by technology-based standards, dissolved oxygen sag analysis simulates the lowest concentration of ambient DO under critical low flow conditions.[5] If the predicted DO level does not meet the ambient standard required to meet the designated use of the stream,

[5] For Maryland, critical low flow condition is representative of a drought condition and is defined as the minimum 7 consecutive day average stream discharge having a recurrence interval of 10 years (7Q10). It is so called because the ability of a water body to assimilate pollutants without exhibiting adverse impacts is at a minimum.

permit writers can choose more stringent water quality-based limits compared to the technology-based levels.

The Streeter-Phelps equation is now extensively used as an evaluation tool for the implementation and adoption of TMDLs for stream segments with low dissolved oxygen problems.[6] Low dissolved oxygen can arise either on account of increases in point sources pollution or excessive algal growth due to high dissolved nitrogen levels. Excessive inputs of nutrients (nitrogen and phosphorus) can lead to excessive growth of aquatic plants, which eventually die and decompose, leading to bacterial consumption of dissolved oxygen. As a result, ambient concentrations might fall below what is necessary to support the designated use of the stream segment. The DO sag analysis determines how much more load allocations from all non-point sources and waste-load allocations from all point sources could be permitted so that actual water quality does not fall below its minimum standard.[7] Alternatively, it determines how much pollutant inputs from all relevant sources need to fall in order to maintain the water quality standard for a stream segment.[8]

Our empirical strategy relies on studies such as El-Shaarawi, Esterby, and Kuntz (1983), Bodo (1992), and Esterby (1996) that discuss the standard practice of using robust and multivariate regression analysis for determining water quality trends. Other empirical papers

---

[6] TMDLs utilize a steady-state model that is a modified Streeter-Phelps DO sag equation. The in-stream DO target for a TMDL is a daily average of not less than 5.0 mg/l for surface water.

[7] Load Capacity is calculated using the formula:
Permit limit average daily load = (Design flow of facility in cubic feet per second) X (effluent pollutant concentration in mg/L) X (the constant 5.395 to convert to pounds/day.)

[8] Using the basic concept of Streeter-Phelps many increasingly complex mathematical models have cropped up to accurately simulate DO dynamics in streams. "Most were developed to simulate parameters associated with [the NPDES] permits" (Vellidis et al. 2006, 1007), while some specifically simulated DO, others were broader in-stream water quality models, and yet others were watershed-scale transport models incorporating the contribution of non-point sources to water quality degradation. QUAL2E (Enhanced Stream Water Quality Model) is one of the two most popular (one-dimensional, steady-state) models for developing DO TMDLs (USGS, 2005), while HSPF (Hydrological Simulation Program- Fortran) is a dynamic model. Soil and Water Assessment Tool (SWAT) is another example of a river basin model that quantifies the impact of land management practices in large watersheds, at the same time as simulating in-stream processes such as DO.

such as Hirsch and Slack (1984) have noted that among the conventional water quality variables, only temperature, pH, and DO can be considered close to normal.[9] Therefore, we estimate a non-linear relationship using the least-squares method, after controlling for the constants of the Streeter-Phelps equation that are specific to each station.

Drawing from the above discussion, we estimate a linear relationship between ambient DO at a certain distance downstream, and the log of aggregate BOD pollution from all the relevant point sources (across distinct monitoring locations). Water quality data immediately upstream or downstream to the point of discharge of a plant is not available. Instead, DO data is available at monitoring stations located at a certain distance upstream or downstream to the point of the outfall. Hence, we could not identify a unique pair of upstream and downstream stations for each plant in the sample. We present the empirical water quality model in section 4.

3. Data

3.1 *Matching Water Quality and Pollution Inputs*

EPA's STORET databases (Legacy and Warehouse), Chesapeake Bay Program (CBP), and Virginia Department for Environmental Quality (VADEQ) are the primary sources for ambient water quality data. We consider the period from 1990 to 2003. Water Quality coverage and data varied a lot by state. More recent data beyond 2000 is scarcer for Pennsylvania and Virginia. At least one of the three states considered were among the most monitored for water quality based on its importance relative to the Chesapeake Bay (Maryland). Dissolved oxygen (DO) is the measure of water quality data that was collected. It is also the most monitored measure of water quality across the U.S. (Keiser and Shapiro, 2019). Higher DO levels in mg/L

[9] Most other water quality parameters such as nutrients, BOD, and biological indicators such as biomass and bacterial counts have been found to be non-normally (in particular, log normally) distributed (USEPA, 1991; Gilliom and Helsel, 1986).

means better water quality as it reflects the oxygen that is available for fish and aquatic life to survive.

We consider the nearest downstream and upstream monitoring stations that had water quality data. We mapped the NPDES majors reporting monthly BOD5 from 1990 to 2003 to identify the relevant upstream and downstream monitoring stations for each polluter.[10] In total, 97 major industrial and municipal plants reported monthly BOD5 (either concentration or quantity loads). Monitors are assigned based on water quality data from the most appropriate pair of monitoring stations for purposes of assessing the impact of pollutant inputs on downstream water quality. For example, there are three pairs of upstream and downstream monitoring locations with one plant on a tributary, whereas the others are on the main river. For these plants, we assign water quality data from the upstream and downstream monitoring stations on the main river, i.e., before and after the tributary joins it. There is no monitoring data available from the tributaries.[11]

There are 76 water quality monitoring locations with its corresponding upstream water quality data. These monitoring stations were downstream to at least one major point source (either industrial or municipal plant). They also have good coverage of dissolved oxygen data from 1990 to 2003. For each station, we consider monthly average water quality if there are multiple records. Of the 97 major manufacturing and sewage treatment facilities sampled, we could assign a unique pair of upstream and downstream stations for 59 plants. For the remaining 38, 26 of them have one other major facility discharging into the same stream segment, and

[10] The BOD 5-day test measures the amount of DO consumed by the decomposition of carbonaceous and nitrogenous matter in a sample of the wastewater (under laboratory conditions e.g. 20 degree centigrade) over a five-day period. It has a detection limit of 1 mg/L.

[11] Another plant could not be included since we could not identify its relevant upstream station. The plant discharged its effluents near the point of confluence of two tributaries.

hence they have the same pair of upstream and downstream stations. The other 12 plants have two other plants polluting into the same stream segment, i.e., four locations with three plants that have the same pair of upstream and downstream monitoring stations.

3.2 ***Summary Statistics***

For the regression sample, we focus on plants reporting monthly BOD concentration with limits. In the section on empirical strategy, we explain that the concentration measure of BOD has an unambiguously negative impact on dissolved oxygen that, in turn, is determined by the ultimate BOD in the river/wastewater mixture, i.e., at the point of effluent outfall (equation (2)). Our final sample of NPDES majors drops to 87 plants reporting the concentration of BOD in the EPA's Permit Compliance System (PCS) database. We could match these 87 plants to 67 distinct downstream (and upstream) monitoring locations. By states, the distribution of stations is 37 for Virginia, 18 for Maryland, and 12 for Pennsylvania. The distribution of the 87 major facilities is 47 plants in VA, 24 plants in Maryland, and 16 plants in Pennsylvania. More than 62% of the 87 plants are municipal plants (54), and the remaining 33 plants are industrial facilities.

[Insert Table 1]

Table 1 first presents summary statistics on fixed factors such as the average downstream, upstream distance of each plant to water quality monitoring stations for the 87 plants, and the total distance between upstream and downstream monitoring stations. All distance is in miles. Following previous practices, e.g., Sigman (2005), we use 50 miles upstream/downstream criterion based on the physical rates of attenuation for oxygen depletion. In robustness checks, we apply more stringent criteria of the total distance between upstream and downstream monitoring stations less than 40 miles, distance to downstream/upstream monitor less than 25 miles (Keiser and Shapiro 2019). Table 1 also presents summary statistics on the monthly

average downstream and upstream dissolved oxygen, measured in concentration units of mg/L, for the regression sample. It also presents the monthly average aggregate BOD concentration in mg/L and the dependent variable and the primary regressor for the empirical models.

Table 1 shows that average upstream and downstream distance for the current sample of plants are 10 and 11 miles, respectively, with 75% of the observations less than 14.0 and 16.5 miles. The total distance between upstream and downstream monitoring stations is 19.3 miles, with 75% of the observations less than 28 miles. On average, both downstream and upstream dissolved oxygen levels at 9.5 mg/L are significantly higher than the ambient standards of 4-5 mg/L required to maintain aquatic life. In the current sample, the correlation between contemporaneous upstream and downstream water quality is about 75%. The monthly average BOD concentration for 87 plants is 8.6 mg/L. Compared to the average concentration limits of 30 mg/L, these plants were significantly overcomplying with their permits (Bandyopadhyay and Horowitz, 2006). On average, the monthly aggregate BOD concentration of 10.5 mg/L means that the significant overcompliance pattern is maintained even across multiple polluters. Last, we present the dependent variable, downstream net of upstream dissolved oxygen levels. On average, the mean difference in water quality is close to zero with a standard deviation close to 1.5, meaning that like previous studies, the measure of the downstream, net of upstream, dissolved oxygen roughly follows the normal distribution. On the other hand, studies have cited BOD following a log-normal distribution, which can be seen upon log transforming the aggregate BOD measure with mean 1.95 and standard deviation close to 1.

4. Empirical Strategy

The objective of this paper is to show that pollution discharges from major point sources have a significant impact on downstream water quality. Any finding on self-reported pollution

data exerting a negative impact on ambient water quality can allay concerns of underreporting biases (found in Latin American countries, e.g., Caffera and Lagomarsino 2014). On the other hand, if self-reported data is not accurate, then upstream pollution from major polluters might not have any impact on downstream water quality net of ambient pollution levels as captured by water quality upstream to these polluters, and controlling for other location or stream specific factors.

4.1 *Model*

Our model draws on the theoretical foundations of the Streeter-Phelps dissolved oxygen sag curve with downstream water quality determined by upstream water quality, pollution inputs, and temperature and streamflow conditions. The dependent variable is the downstream net of upstream dissolved oxygen in month t. For each stream segment, we identify the relevant upstream and downstream monitoring locations with dissolved oxygen data. Upstream water quality in the same month is endogenous as weather, and biophysical conditions of the stream are similar if the monitoring station is on the same stream segment as the station downstream to the point source's point of the outfall of effluents. This strategy also controls for unobserved or hard to measure ambient conditions such as terrain, land use, and elevation, that jointly determine water quality at nearby locations. [12]

Our primary regressor is pollution inputs from major point sources. The pollutant input that is relevant for dissolved oxygen is biochemical oxygen demand (BOD). Given that we could not match each point source to a distinct pair of downstream-upstream monitoring stations, our measure of pollution inputs is aggregate BOD discharged by one or more major point sources in

[12] Location specific "physical" effects such as velocity and depth (determining natural attenuation rates), pressure (and topography) and salinity (determining saturated oxygen levels) might be captured reasonably well by upstream water quality if the two monitors are close to each other.

each stream segment. We check for sensitivity by considering only single polluter stream segments in our estimations.

Equation (5) below, presents the empirical model to estimate the impact of pollutant inputs from point source dischargers on ambient water quality. Dissolved oxygen measured at location $j$downstream to the point of the outfall of plant$i$in month$t$ (DO_{jt}) net of dissolved oxygen measured at an upstream location$u$ in month$t$ (DO_{ut}) is the dependent variable. This measure allows us to isolate the effect of BOD discharges from point sources on ambient water quality. Upstream water quality also serves as a control for all other time-varying, location-specific factors that determine ambient water quality in that particular stream segment. Notably, in the absence of data on non-point source pollution, while conducting TMDL analysis, regulators extensively use field data on water quality in order to approximate the impact of pollution from non-point sources.

$$DO_{jt} - DO_{ut} = \alpha + \beta log\left(\sum_{i=1}^{3} BOD_{ijt}\right) + \delta_j + \gamma_T + \theta_s + \varepsilon_{jt} \quad \ldots\ldots\ldots(5)$$

Where:

$DO_{jt} =$ concentration of DO in the river at monitoring location j and month t, downstream to the point source polluters

$DO_{ut} =$ concentration of DO in the river at location u and month t, upstream to the plant location i

$BOD_{ijt} =$ concentration of BOD5 reported in plant i's wastewater in month t, d_{ij}miles upstream to monitoring location $j, i = 1,2,3$

δ_j = dummy variable for monitoring location j

γ_T = dummy variable for year T,with$T = 1,2.\ldots13$

θ_s = quarterly seasonal indicator for each month with s = 1,2,3,4

ε_{jt} = error term for monitor j in month t

The primary explanatory variable of interest is the logarithm of the sum of the concentration of BOD5 measured in each plant i's wastewater in month t (BOD_{ijt}) with its point of outfall between locations j and u. In the current sample, there are at most three plants in between monitoring locations j and u (i ={1,2,3}). We record the linear distance based on the streamflow for the distance of each plant i to its downstream monitoring location j (d_{ij}). We expect pollutants from plants that are further upstream from station j has traveled longer, and hence are likely to have undergone more attenuation. In later robustness, we focus on plants within 25 miles downstream to verify if the estimated coefficients are larger in magnitude than the entire sample of 87 plants.

Among the controls, station level dummy variables capture all other time-invariant location-specific effects not captured by upstream water quality (primarily because we could not match each plant to the nearest upstream and downstream stations). [13] For example, it controls for long-term variations in non-point source pollution for the segment of the stream in between the upstream and downstream stations. Yearly dummy variables capture annual changes in the downstream net of upstream water quality conditions across the three states from 1990 to 2003. Seasonal variations in temperature and rainfall affects ambient water quality at downstream and upstream locations. However, monthly BOD discharged by the plants also exhibits seasonal variability. Hence, we include seasonal indicators in order to capture the effect of BOD inputs

[13] For example, differences in land use across downstream locations since this is unlikely to change rapidly in a short period of time.

net of seasonal effects.[14] Lastly, annual dummy variables control for annual trends over the 14 years of data.

For our empirical model, we consider the concentration measure of BOD5 in order to capture the impact of pollutant discharges on downstream water quality net of upstream ambient pollution, i.e., before point sources' effluent outfalls. For this discussion, we go back to equation (2), which calculates the ultimate BOD in the wastewater- river mixture at a point source's effluent outfall. Consider a plant, which faces only concentration limits, and hence discharges high loads into the river during high flow seasons. Equation (2) tells us that the impact of high loads on ultimate BOD is not clear, i.e., it might not lead to higher pollution in the river/wastewater-mixing zone. In general, we expect the effluent flow of a plant to be less than streamflow, especially during high flow conditions.[15] Consequently, high waste loads imply that Q_w in equation (2) increases but Q_r rises more during high flow seasons, meaning that the weight assigned to the effluent concentration (L_w) actually goes down. On the other hand, the weight assigned to upstream concentration (L_r in equation (2)) is higher, since Q_w/Q_r falls. Therefore, ceteris paribus, ultimate BOD, falls under the condition that effluent concentration exceeds upstream concentration.

On the contrary, consider a plant that faces only quantity limits and hence can discharge a high concentration of BOD during low flow seasons. In terms of ultimate BOD, low flow conditions imply that both Q_w and Q_r are lower. However, the decline in the effluent flow rate

[14] Seasonal average sum of BOD5 concentration was 12 mg/L during winter, 10.2 in spring, 8.5 in summer, and 10.1 in fall. Plants can reduce discharges during higher temperatures that support better efficiency in the biological processes involving wastewater treatment technology.

[15] We illustrate using a simple numerical example: receiving stream 7Q10 is 30 cubic feet per second (cfs), while the design flow of the POTW in concern has a design flow of 5 mgd or 7.7 cfs. Actual stream flow during low flow conditions are higher than the 7Q10, while the actual recorded flows of wastewater will never exceed the volume that a plant is designed to accommodate.

$Q_w$is expected to be less than the reduction in the streamflowQ_r. In equation (2), the weight assigned to the effluent concentrationL_w is higher, while the weight assigned to upstream concentrationL_r is lower. Therefore, the impact of higher effluent concentration (under low flow conditions) results in unambiguously higher ultimate BOD. Hence, we choose the measure of BOD5 concentration rather than quantity loads as we have clear expectations on the sign of the estimated coefficient on the log of aggregate BOD5 concentration.

Policies are also implemented based on BOD concentration. For instance, regulators assign TMDLs for stream segments that are "impaired" (i.e., not meeting minimum ambient standards for designated uses) in terms of limits on the concentration of BOD5 under critical 7Q10 drought-like streamflow conditions. Since background pollution (L_r) is zero under 7Q10 conditions, BOD in the river/wastewater mixture depends on the effluent concentration only. The corresponding maximum allowable load is the product of the effluent limit of BOD5 and the design effluent flow of a plant. See, for example, numerous TMDLs implemented by various states and the EPA across the US: MODNR (1999), MODNR (2005), MDE (1999), MDE (2000), MDE (2002) and SCDHEC (1998).

4.2 Results

From the discussion in the previous section, we expect the impact of BOD concentration on ambient dissolved oxygen to have a negative sign. BOD is from organic pollutants discharged by plants that are significant sources of oxygen demand, and hence their impact on ambient dissolved oxygen levels is expected to be negative. Empirical evidence of this negative impact of higher BOD concentration on water quality, i.e. lower dissolved oxygen at downstream locations is absent in the literature, controlling for other location-specific factors and upstream ambient pollution.

[Insert Table 2]

Overall, we find that BOD concentration discharges from major polluters exert a negative impact on the downstream net of upstream ambient DO levels. Table 2 presents the fixed effects estimation results for the regression sample of 87 plants (Panel A) and sample of 51 single polluters' stream segments (Panel B). The balanced criterion applied in the second and fourth columns of both panels is for ambient water quality measurements with at least 50% coverage, i.e., the 84 months out of the total possible 168 months. As seen in the number of stations reported, the water quality coverage is good in general as the sample size falls from 67 to 53. The coefficients show that a one percent increase in aggregate BOD concentration discharged by polluters results in 0.0010 mg/L decline in net downstream DO (second column in Panel A of Table 2). As expected, the estimated impact is small but statistically significant and negative in sign. In Panel B, for the single polluter stream segments, the estimated coefficients are similar in magnitude (0.0012 mg/L in the second column). We find no evidence on free-riding as the coefficients for the 87 plants (including multiple polluter stream segments) are not much different from the single polluter stream segments. The coefficients in Model 2 that control for time-varying state-level changes show that a one percent increase in aggregate BOD concentration discharged by polluters results in 0.0009 mg/L decline in net downstream DO (fourth column in Panel A of Table 2).

4.3 ***Robustness***

Our first set of robustness tests is for alternative distance criterion. We expect that since ambient water quality dilutes pollutant concentrations, the further downstream it travels, the coefficients will be larger in magnitude upon applying stricter distance criteria, i.e., smaller stream segments with upstream and downstream monitoring stations. Table 3 presents three

panels of estimations: Panel A applies total stream segments, i.e., distance between upstream and downstream monitoring locations, less than 40 miles, Panel B applies distance to downstream monitor for each plant less than 25 miles, and Panel C applies distance to upstream monitor for each plant less than 25 miles.

Overall, results are robust to all three distance criteria with larger magnitudes for downstream monitoring stations less than 25 miles. As expected, distance traveled downstream by pollutant inputs from major polluters is more significant in determining its impact on ambient water quality (net of ambient concentrations) than either total distance or distance from the upstream monitoring location. The number of stations in Panel A shows that most of our stream segments are less than 40 miles (less than 39 miles in the data). The sample size drops slightly from 67 to 62. The magnitudes are somewhat smaller compared to Table 2 results. For the balanced sample criterion of 50% coverage of ambient water quality, the coefficient shows that a one percent increase in aggregate BOD concentration discharged by polluters results in a 0.0008 mg/L decline in net downstream DO (second column of Table 3). In Panel B, the estimated coefficients are larger than those in Panel A, with sample size dropping from 67 to 56. For the balanced sample, the coefficient shows that a one percent increase in aggregate BOD concentration discharged by polluters results in 0.0011 mg/L decline in net downstream DO (second column in Panel B). Panel C applies the criterion of distance from the upstream monitoring station less than 25 miles for each plant (mostly for consistency checks). The sample size falls from 67 to 60 for the "full" sample and from 53 to 47 for the "balanced" sample. Results are somewhat smaller in magnitude than the coefficients in Panel B of Table 3 (downstream distance less than 25 miles) and Panel A of Table 2 (entire sample of 87 plants); however, similar in magnitude to the coefficients in Panel A of Table 3(total distance less than

40 miles). The coefficient in the second column in Panel C (of Table 3) shows that a one percent increase in aggregate BOD concentration discharged by polluters results in a 0.0008 mg/L decline in net downstream DO (rounding up to four decimal places).

[Insert Table 3]

Our second set of robustness tests explores heterogeneous impacts based on seasons. As discussed earlier, high temperatures and low stream flows are critical conditions due to the minimal assimilative capacity of water bodies. Some of the plants in our sample, face seasonal limits during a year with higher permitted levels during low-temperature high streamflow seasons and lower permitted levels during high temperature and low stream flow seasons. We expect a larger negative impact of pollutant inputs during high temperatures and low stream flow seasons in contrast to low temperature and high streamflow seasons.

Table 4 presents results by quarter. The coefficients in Table 4 for summer months are larger in magnitude than in winter months. The first column in Panel C (for summer months) shows that a one percent increase in aggregate BOD concentration discharged by polluters results in a 0.0014 mg/L decline in net downstream DO (rounding up to four decimal places). By contrast, the coefficient in the first column in Panel A (for winter months) shows that a one percent increase in aggregate BOD concentration discharged by polluters results in a 0.0008 mg/L decline in net downstream DO (rounding up to four decimal places). The difference in the magnitude of coefficients in spring (Panel B) versus fall (Panel D) is due to streamflow conditions. For Maryland, Pennsylvania, and Virginia, streamflow is higher during fall than spring (other than snowmelt in higher altitudes), so coefficients for spring months exert a statistically significant negative impact on net downstream DO (Panel B) as opposed to coefficients for fall months that are not of the expected sign (neither statistically significant).

[Insert Table 4]

Our last robustness test consists of exploring heterogeneity based on different seasonal classification. We divide each year into two 6-month periods: November to April as low temperature and high streamflow conditions and May to October as the high temperature and low streamflow conditions. Table 5 presents the results for every six months of each year covered. Coefficients in Panel A are for low temperatures and high streamflow conditions, and those in Panel B are for high temperatures and low streamflow conditions. We expect higher temperatures to have a larger negative impact on ambient water quality in contrast to lower temperature conditions. The coefficient in the fourth column for Model 2 in Panel B (for higher temperature conditions) shows that a one percent increase in aggregate BOD concentration discharged by polluters results in a 0.0013 mg/L decline in net downstream DO. The coefficient in the fourth column for Model 2 in Panel A (for lower temperature conditions) shows that a one percent increase in aggregate BOD concentration discharged by polluters results in a 0.0005 mg/L decline in net downstream DO (rounding up to four decimal places). The magnitude falls by more than half for lower temperature months.

[Insert Table 5]

5. Conclusions

In this study, we find empirical evidence that pollutant inputs from major point sources worsens downstream water quality, net of upstream pollution levels, and controlling for location-specific factors. To our knowledge, this is the first attempt to estimate an empirical water quality model using plant-level pollution data from the Clean Water Act. We rely on the Streeter-Phelps equation to link upstream pollution with downstream ambient water quality. From our results, we infer that self-reported pollution does not exhibit underreporting biases. Besides, the implications

for lack of evidence on underreporting remain valid to more recent decades; self-reported pollution data is the primary instrument for most monitoring and enforcement (Shimshack, 2014). This conclusion is contrary to preliminary evidence on under-reporting by sewage treatment plants across the U.S. found in Chakraborti and Shimshack (2012).

We consider the period with the most coverage of pollutant inputs and ambient water quality. We estimate station-level fixed effect models that control for all time-invariant location-specific factors. Also, the inclusion of upstream water quality controls for all time-varying factors that affect water quality at nearby monitoring locations, e.g., changes in non-point source pollution. We estimate a more general model that allows for time-varying changes at the state level by including state interacted with year fixed effects.

We find that indeed, upstream pollutant inputs of BOD lead to a decline in the downstream net of upstream ambient DO levels. The magnitude of the estimated coefficients is small as expected from the natural attenuation of water bodies but negative and statistically significant in our main results as well as various robustness checks. We find that a one percent increase in upstream BOD leads to a decline in the downstream DO net of upstream DO (before pollutant discharges) by 0.0010 mg/L. We find no evidence on free-riding as the coefficients for the 87 plants (including multiple polluter stream segments) are not much different from the single polluter stream segments (sample of 51 plants). We find larger coefficients upon restricting distance to downstream monitoring stations to less than 25 miles (-0.0011 mg/L) compared to the criteria of total distance less than 40 miles and distance from upstream monitor less than 25 miles (-0.0008 mg/L). Also, we find more significant impacts during high temperatures and low stream flow seasons (-0.0013 mg/L) in contrast to low temperature and high streamflow seasons (-0.0005 mg/L).

Overall, our results are consistent with the physical impact of pollution inputs on ambient water quality. We infer that BOD concentration reported by major polluters might not suffer from any reporting biases.

References

Bandyopadhyay, S. & Horowitz, J. K. (2006). Do Plants Overcomply with Water Pollution Regulations? The Role of Discharge Variability. *Topics in Economic Analysis & Policy*, 6(1) Article 4, Available at: http://www.bepress.com/bejeap/topics/vol6/iss1/art4.

Bodo, B. A. (1992). Statistical Analyses of Regional Surface Water Quality in Southeastern Ontario. *Environmental Monitoring and Assessment*, 23(1-3): 165-187.

Caffera, M. & Lagomarsino, A. (2014). Under reporting of water pollution by industrial plants: empirical evidence. Latin American and Caribbean Environmental Economics Program *LACEEP Working Paper Series*, #WP66.

Chakraborti, L. & Shimshack, J.P. (2012). Assessing the accuracy of self-reported pollution Data. *Tulane University Working Paper*.

El-Shaarawi, A. H., Esterby, S. R. & Kuntz, K. W. (1983). A Statistical Evaluation of Trends on the Water Quality of the Niagara River. *Journal of Great Lakes Research,* 9(2): 234-240.

Esterby, S. R. (1996). Review of Methods for the Detection and Estimation of Trends with Emphasis on Water Quality Applications. *Hydrological Processes*, 10(2): 127-149.

GAO (General Accounting Office). (2000). Water quality: key EPA and state decisions limited by inconsistent and incomplete data. Washington, DC: United States General Accounting Office. GAO/RCED-00-54.

Gilliom, R.J. & Helsel, D. R. (1986). Estimation of Distributional Parameters for Censored Trace Level Water Quality Data: 1. Estimation Techniques. *Water Resources Research*, 22(2): 135-146.

Grant, L. E. & Langpap, C. (2019). Private provision of public goods by environmental groups. *PNAS*, 116 (12) 5334-5340.

Hirsch, R. M. & Slack, J. R. (1984). A Nonparametric Trend Test for Seasonal Data With Serial Dependence. *Water Resources Research*, 20(6): 727-732.

Keiser D.A., & Shapiro, J. S. (2019). Consequences of the Clean Water Act and the Demand for Water Quality. *The Quarterly Journal of Economics*, 134(1): 349–396, DOI:10.1093/qje/qjy019.

Keiser D.A., Kling, C. L., & Shapiro, J. S. (2019). The low but uncertain measured benefits of US water quality policy. *Proc Natl Acad Sci* USA PNAS October 8, 2018, https://doi.org/10.1073/pnas.1802870115.

McConnell, V. D. & Schwarz, G.E. (1992). The Supply and Demand for Pollution Control: Evidence from Wastewater Treatment. *Journal of Environmental Economics and Management*, 23(1): 54-77.

MDE (Maryland Department of the Environment). (2002). Total Maximum Daily Loads of Biochemical Oxygen Demand (BOD), Nitrogen and Phosphorus for Town Creek into which the Town of Oxford Wastewater Treatment Plant Discharges Talbot County, Maryland. EPA Approval: October 16, 2003 Document version: December 26, 2002: https://mde.state.md.us/programs/Water/TMDL/ApprovedFinalTMDLs/Documents/www.mde.state.md.us/assets/document/Town%20Creek%20Main%20Document_final.pdf.

MDE. (2000). Total Maximum Daily Loads of Biochemical Oxygen Demand (BOD) for

Conococheague Creek", Maryland Department of the Environment, Acceptance Date: February 2, 2001 Completion Date: December 26, 2000: https://mde.state.md.us/programs/Water/TMDL/ApprovedFinalTMDLs/Documents/www.mde.state.md.us/assets/document/conoco_TMDL_ReportFinal(1).pdf.

MDE. (1999). TMDL of Biochemical Oxygen Demand (BOD) for the Western Branch of the Patuxent River, Prince George's County, MD. EPA Submittal: December 3, 1999, EPA Approval: June 6, 2000: https://mde.state.md.us/programs/Water/TMDL/ApprovedFinalTMDLs/Documents/www.mde.state.md.us/assets/document/tmdl/westbranch/wb_tmdl_fin2.PDF.

MODNR (Missouri Department of Natural Resources) (2005). Total Maximum Daily Loads (TMDLs) For West Fork Sni-a-Bar Creek Jackson County, Missouri. Completed: November 21, 2005 Approved: January 6, 2006, https://dnr.mo.gov/env/wpp/tmdl/docs/0400-west-fork-sni-a-bar-tmdl.pdf.

MODNR. (1999). Total Maximum Daily Loads (TMDLs) for Rock Creek, Jefferson County, Missouri. MODNR Water Pollution Control Program Approved by the EPA December 1, 1999, Completed July 21, 1999, https://dnr.mo.gov/env/wpp/tmdl/docs/1714-rock-ck-tmdl.pdf.

SCDHEC (South Carolina Department of Health and Environmental Control). (1998), TMDL Submittal for Sanders Branch/Coosawhatchie River. Bureau of Water Pollution Control, State of South Carolina Administrative Record; EPA Approval: August 17, 1998,

Submittal: January 21, 1998: https://scdhec.gov/sites/default/files/docs/HomeAndEnvironment/Docs/tmdlsand.pdf.

Shimshack, J. P. (2014). The Economics of Environmental Monitoring and Enforcement: A Review. *Annual Review of Resource Economics*, 6: 339–60.

Sigman, H. (2005). Transboundary Spillovers and Decentralization of Environmental Policies. *Journal of Environmental Economics and Management,* 50(1): 82-101.

Sigman, H. (2004). Does Trade Promote Environmental Coordination?: Pollution in International Rivers. *Contributions to Economic Analysis & Policy*, 3(2) Article 2, https://doi.org/10.2202/1538-0645.1251.

Sigman, H. (2002). International Spillovers and Water Quality in Rivers: Do Countries Free Ride? *The American Economic Review*, 92(4): 1152-1159.

Smith, V. K., & Wolloh, C.V. (2012). Has surface water quality improved since the Clean Water Act? *NBER Working Paper* No. 18192, June 2012. Available at www.nber.org/papers/w18192.

Streeter, H.W. & Phelps, E.B. (1925). A Study of the Pollution and Natural Purification of the Ohio River. *Public Health Bulletin* 146, Washington D.C.: U.S. Public Health Service.

Summers, J. K., Kazyak, P. F. & Weisberg, S. B. (1991). A Water Quality Model for a River Receiving Paper Mill Effluents and Conventional Sewage. *Ecological Modelling*, 58: 25-54.

USEPA. (2000). A retrospective assessment of the costs of the Clean Water Act: 1972 to 1997:

Final report. U.S. Environmental Protection Agency, Office of Water; Office of Policy, Economics, and Innovation, October 2000.

USEPA. (1991). Technical Support Document for Water Quality-based Toxics Control. EPA 505-290-001. U.S. Environmental Protection Agency, Office of Water, Washington, DC, March.

USGS. (2005). USGS surface and water quality models information clearinghouse. United States Geological Survey, Washington, DC, available at http://smig.usgs.gov.

Vellidis, G., Barnes, P., Bosch, D.D. & Cathey, A.M. (2006). Mathematical Simulation Tools for Developing Dissolved Oxygen TMDLs. *Transactions of the ASABE*, 49(4): 1003-1022.

Tables

Table 1. Summary Statistics of Water Quality and Pollution Inputs

	Obs.	Mean	Std. Dev.	Max.
FIXED FACTORS				
Distance to downstream station	87	11.11	10.77	48.00
Distance to upstream station	87	9.83	10.02	46.00
Total distance between stations	67	19.31	15.51	64.50
WATER QUALITY				
Downstream, DO	6,514	9.47	2.38	18.40
Upstream, DO	6,514	9.52	2.40	17.50
POLLUTION INPUTS				
Monthly BOD concentration	7,946	8.63	8.98	178.50
Aggregate BOD concentration	6,514	10.53	10.90	199.60
REGRESSION VARS.				
Downstream-Upstream, DO	6,514	-0.05	1.47	8.90
log Aggregate BOD	6,514	1.95	0.91	5.30

NOTES: Distance in miles to downstream/upstream stations are for 87 majors with BOD5 concentration data. The total distance between stations is for 67 upstream-downstream monitoring segments. Water Quality is monthly average Dissolved Oxygen (DO) in mg/L for 67 unique downstream and upstream stations for the period 1990-2003. Pollution Inputs are monthly average concentration of BOD5 in mg/L reported by 87 plants, over 1990-2003. Aggregate BOD is the sum of discharges by plants located in the same upstream-downstream segment. Regression Variables include the dependent variable: downstream net of upstream monthly DO at 67 stream segments, and primary regressor is log aggregate BOD concentration of 87 major polluters.

Table 2. Fixed Effects Estimations, Main Panel Results

Panel A: Monitoring location by month data				
DEP.VAR: Net Downstream DO:	Model 1		Model 2	
Sample:	Full	Balanced	Full	Balanced
log aggregate BOD	-0.078**	-0.100***	-0.071**	-0.091***
	(0.034)	(0.035)	(0.033)	(0.034)
Year FE	X	X		
Year X State FE			X	X
Station FE	X	X	X	X
Season FE	X	X	X	X
# stations	67	53	67	53
# observations	6,514	6,047	6,514	6,047
Panel B: Single polluter monitoring segments				
DEP.VAR: Net Downstream DO:	Model 1		Model 2	
Sample:	Full	Balanced	Full	Balanced
log aggregate BOD	-0.103**	-0.120**	-0.090*	-0.107**
	(0.047)	(0.048)	(0.047)	(0.047)
Year FE	X	X		
Year X State FE			X	X
Station FE	X	X	X	X
Season FE	X	X	X	X
# stations	51	39	51	39
# observations	4,531	4,173	4,531	4,173

NOTES: Model 1 includes year fixed effects and Model 2 includes year interacted with state fixed effects. In Panel A, Full sample refers to monthly downstream net of upstream DO data from 67 stream segments with unique downstream-upstream stations. Balanced sample refers to 53 stream segments with at least 50% coverage i.e. 84 months of the total possible 168 months for each downstream-upstream pair of stations. In Panel B, Full sample refers to downstream net of upstream DO from 51 stream segments with single point source and Balanced sample refers to 39 locations with unique upstream-downstream monitors with single polluter and 50% water quality coverage. Clustered standard errors within stations in parenthesis: * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Table 3. Robustness: Sensitivity to distance

Panel A: Total distance between upstream and downstream stations less than 40 miles				
DEP.VAR: Net Downstream DO:	Model 1		Model 2	
Sample:	Full	Balanced	Full	Balanced
log aggregate BOD	-0.067**	-0.081**	-0.064**	-0.075**
	(0.032)	(0.033)	(0.032)	(0.033)
Year FE	X	X		
Year X State FE			X	X
# stations	62	49	62	49
# observations	6,029	5,616	6,029	5,616
Panel B: Distance to downstream monitors less than 25 miles				
DEP.VAR: Net Downstream DO:	Model 1		Model 2	
Sample:	Full	Balanced	Full	Balanced
log aggregate BOD	-0.106***	-0.112***	-0.107***	-0.110***
	(0.032)	(0.034)	(0.030)	(0.032)
Year FE	X	X		
Year X State FE			X	X
# stations	56	45	56	45
# observations	5,478	5,145	5,478	5,145
Panel C: Distance to upstream monitors less than 25 miles				
DEP. VAR: Net Downstream DO:	Model 1		Model 2	
Sample:	Full	Balanced	Full	Balanced
log aggregate BOD	-0.070**	-0.083**	-0.065*	-0.076**
	(0.034)	(0.034)	(0.033)	(0.033)
Year FE	X	X		
Year X State FE			X	X
# stations	60	47	60	47
# observations	5,857	5,443	5,857	5,443

NOTES: Clustered standard errors within stations in parenthesis: * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Table 4. Robustness: Panel Estimations by Season (Downstream monitors <25 miles)

Panel A: Winter Season (months=1,2,3)				
DEP.VAR: Net Downstream DO:	Model 1		Model 2	
Sample:	Full	Balanced	Full	Balanced
log aggregate BOD	-0.076	-0.100*	-0.068	-0.093*
	(0.051)	(0.050)	(0.048)	(0.049)
# stations	55	44	55	44
# observations	1,262	1,177	1,262	1,177
Panel B: Spring Season (months=4,5,6)				
DEP.VAR: Net Downstream DO:	Model 1		Model 2	
Sample:	Full	Balanced	Full	Balanced
log aggregate BOD	-0.112**	-0.123***	-0.106**	-0.117**
	(0.047)	(0.046)	(0.051)	(0.048)
# stations	55	44	55	44
# observations	1,382	1,308	1,382	1,308
Panel C: Summer Season (months=7,8,9)				
DEP. VAR: Net Downstream DO:	Model 1		Model 2	
Sample:	Full	Balanced	Full	Balanced
log aggregate BOD	-0.144**	-0.136*	-0.174**	-0.162**
	(0.070)	(0.072)	(0.069)	(0.071)
# stations	55	44	55	44
# observations	1,347	1,261	1,347	1,261
Panel D: Fall Season (months=10,11,12)				
DEP. VAR: Net Downstream DO:	Model 1		Model 2	
Sample:	Full	Balanced	Full	Balanced
log aggregate BOD	0.048	0.064	0.036	0.065
	(0.046)	(0.050)	(0.046)	(0.048)
# stations	55	44	55	44
# observations	1,348	1,260	1,348	1,260

NOTES: Model 1 includes year fixed effects and Model 2 includes year interacted with state fixed effects. Clustered standard errors within stations in parenthesis: * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Table 5. Robustness: Panel Estimations by temperature (Downstream monitors <25 miles)

Panel A: Low temperature, high stream flow (November-April)				
DEP.VAR: Net Downstream DO:	Model 1		Model 2	
Sample:	Full	Balanced	Full	Balanced
log aggregate BOD	-0.036	-0.050	-0.035	-0.048
	(0.034)	(0.035)	(0.032)	(0.033)
# stations	55	44	55	44
# observations	2,584	2,415	2,584	2,415
Panel B: High temperature, low stream flow (May-October)				
DEP.VAR: Net Downstream DO:	Model 1		Model 2	
Sample:	Full	Balanced	Full	Balanced
log aggregate BOD	-0.135**	-0.138**	-0.135**	-0.132**
	(0.053)	(0.055)	(0.051)	(0.052)
# stations	55	39	51	39
# observations	2,755	2,591	2,755	2,591

NOTES: Model 1 includes year fixed effects and Model 2 includes year interacted with state fixed effects. Clustered standard errors within stations in parenthesis: * $p<0.1$; ** $p<0.05$; *** $p<0.01$.