Does shifting power plants to renewable energy sources cause better water quality? An empirical investigation in the Northeastern United States

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Abstract: The operation of power plants has a substantial impact on water quality. As the United States transitions from fossil fuels to renewable energy sources, it is essential to empirically assess the effects of this shift on local water quality. This study focuses on communities in the Northeastern United States, covering 11 states. Analyzing all power plants in the region from 1980 to 2019, we link water quality data from monitoring stations to each power plant and utilize river flow direction for identification. Our analysis aims to provide a robust foundation for the empirical assessment of the water quality impacts associated with different technologies used in electricity generation.

Keywords: Power Plant, Renewable & Nonrenewable, Water Quality

JEL Codes: Q25, Q53, Q56

1. Introduction

The global surge in environmental pressures, fueled by widespread fossil fuel consumption, compels nations to seek alternatives through the adoption of renewable energy. Recognized for its potential to significantly reduce greenhouse gas emissions, mitigate climate change, and bolster energy security by diminishing reliance on fossil fuels, renewable energy has become a focal point of global efforts. Numerous empirical studies have explored the correlation between renewable energy consumption, gross domestic product (GDP) growth (Aguirre and Ibikunle 2014; Apergis and Payne 2012), and air pollution (Menyah and Wolde-Rufael 2010; Sebri and Ben-Salha 2014). The collective findings of these studies affirm that increased renewable energy consumption contributes positively to GDP growth while concurrently reducing air pollution. In 2020, renewable energy sources, including wind, hydroelectric, solar, biomass, and geothermal energy, generated a record 834 billion kilowatt-hours (kWh) of electricity, constituting approximately 21% of the total electricity generated in the United States. Simultaneously, the Inflation Reduction Act of 2022 provide the most significant climate legislation in U.S. history, offering funding, programs, and incentives to accelerate the transition to a clean energy economy and will likely drive significant deployment of new clean electricity resources.

This transition brings its own set of potential environmental impacts, particularly concerning water quality. After a century of intensive fossil fuel exploration and consumption, water resources are rapidly declining, and water quality is deteriorating, especially in areas with significant water exploitation and energy development (Vengosh and Weinthal 2022). Steam-electric power plants generate electricity by using heat to produce steam that drives a turbine, requiring significant amounts of water. The fuels used to create this heat include coal, natural gas, oil, and nuclear fuel. In 2015, these power plants withdrew 133 billion gallons of water daily, primarily sourced from rivers, lakes, and estuaries. In addition, coal-fired power plants specifically use water for cooling, steam generation, and industrial processes like scrubbing air pollutants and transporting coal ash. The wastewater from these processes, when released back into the environment, can contain toxic metals and other pollutants that contaminate essential water sources(US EPA 2022, 2023). Some power plants utilize a "once-through cooling" method, where water is taken from a lake or river to condense steam and is then released back at a higher temperature. This can raise the temperature of the water near the discharge point, potentially impacting temperature-sensitive plants, fish, microbial activities, and chemical and physical processes in the water. Even with cooling towers instead of once through cooling, discharged process water that is warmer can change the composition of local fisheries, aquatic macroinvertebrate populations, and aquatic plant communities. Moreover, the construction of an electric power plant exposes large areas of bare ground, which can lead to soil, along with attached nutrients and pollutants, being washed into nearby lakes, streams, and wetlands during storms or spring thaws. Pollutants in the surface water can be absorbed by aquatic species, leading to diseases and fish contamination. This contamination also poses serious health risks to humans, including cancer in adults and reduced IQ in children. Furthermore, some of these pollutants can remain in the environment for years after being discharged.

However, there is a significant gap in empirical research on the impact of power plants functionality with different technologies on local water quality. As we adopt renewable energy technologies, it is increasingly important to understand and address the potential effects on water quality. When a country chooses to replace fossil fuel energy with renewables, it becomes imperative to consider the consequences on water, encompassing both quantity and quality aspects, given the global scarcity of water availability. This study aims to investigate the impact of transitioning power plants to renewable energy sources on water quality, shedding light on the implications associated with this critical aspect of our clean energy future. The primary objectives of our research are: 1) to analyze the dynamic transition pattern of power plants in the research region; 2) to identify the local economic and environmental factors influencing the shift of power plants to renewable energy sources; and 3) to quantify the causal effect of transitioning power plants to renewable energy sources on water quality.

2. Data

We constructed a regional wide, comprehensive data to estimate the impacts of the power plant functionality on local water quality. The study focuses on communities in the Northeastern United States, encompassing 11 states (MD, NJ, DE, PA, NY, CT, RI, MA, VT, NH, and ME. Our research draws from various data sources, with the primary database comprising information on all power plants obtained from the monthly survey Form EIA-860M. This regularly updated database effectively covers nearly all power plants in the U.S. The inclusion of location data enables us to map the positions of all plants within the Northeastern states. Additionally, the database provides details on plant status (operating, retired, etc.), technology employed (gas, oil, solar, wind, etc.). To supplement this information with surrounding demographic and sociographic data for all power plants, we incorporate the EPA's eGRID historical data into our analysis. We obtained water quality data from monitoring stations via the Water Quality Portal. Additionally, we constructed a national river and stream topology network using the U.S. Geological Survey's (USGS) National Hydrography Dataset. This spatial network connects water quality monitoring stations to power plants at the watershed level. The following sections provide a detailed description of the data preparation process.

2.1 Power Plants Data

Our dataset includes all power plants in the study region from 1980 to 2019, with monthly data tracking the current status of existing generating units at electric power plants with a combined nameplate capacity of 1 megawatt or greater (EIA, 2024). The dataset includes unique generator identifiers, operating times, retirement times, energy sources and technologies, as well as latitude and longitude. The analysis was conducted at the power plant level. Figure 1 illustrates the number of new and retired power plants between 1980 and 2019. A quick glance at Figure 1 reveals a clear trend over time: the number of new renewable power plants has steadily increased. Concurrently, although new fossil fuel power plants continue to be commissioned, their numbers are significantly lower compared to those from renewable sources. In contrast, the number of retired fossil fuel power plants is higher than that of retired renewable power plants. Consequently, by the end of 2019, the study region had a total of 2,667 power plants, with 1,992 utilizing renewable fuels such as solar, wind, water, biomass and others, and 712 still relying on fossil fuels like coal, natural gas, and petroleum products. Additionally, 33 power plants were using other types of fuels.

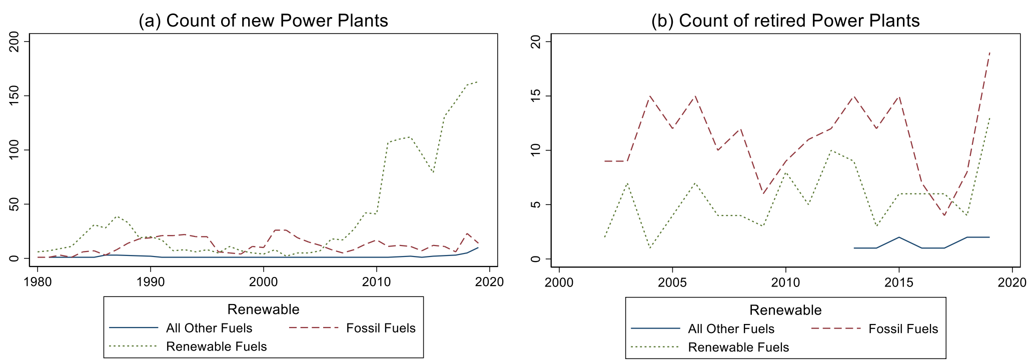

Figure 1. Number of new and retired power plants from 1980 to 2019.

2.2 Water Quality Data

We accessed water quality readings from monitoring stations through the Water Quality Portal, the most complete water pollution repository in the U.S. For each station within the study region, we obtained its HUC10 geocode, latitude and longitude, as well as state and county identifiers. The Water Quality Portal is a collaborative service sponsored by the USGS, USEPA, and the National Water Quality Monitoring Council (NWQMC). Given that the water quality data were collected by various agencies, we took great care to ensure consistent measures of water quality, particularly when units varied across agencies. Additionally, since nitrogen and phosphorus can exist in multiple forms in water, our standardized nitrogen measure includes ammonia-nitrogen, inorganic nitrogen, nitrogen in mixed forms (e.g., nitrate-nitrogen and nitrite-nitrogen), and organic nitrogen. For phosphorus, we included inorganic phosphorus and phosphate-phosphorus concentrations. The other four water quality measures were more straightforward to standardize.

Table 1. Descriptive statistics for water quality measures.

Variables	N	Mean	10th.Pct.	90th Pct.	Min	Max	S.D.
Biochemical oxygen demand (mg/L)	77,153	2.04	0.8	3.7	0.5	6.28	1.17
Total suspended solids (mg/L)	456,262	15.65	3.3	36	2.0	80	14.71
Fecal coliform (CFU/100 ml)	66,917	542.82	20	1500	6.0	6,100	992.62
Dissolved oxygen deficit (mg/L)	156,786	10.01	7.3	13	5.6	14.20	2.10
Phosphorus (mg/L)	434,053	0.038	0.01	0.09	0.01	0.17	0.03
Nitrogen (mg/L)	324,899	1.15	0.27	2.62	0.07	4.60	0.98

For each water quality measure, we collected readings from all monitoring stations between January 1, 1980, and December 31, 2019. To mitigate the impact of extreme readings (i.e., outliers), we excluded values above the 99.5th percentile and below the 0.5th percentile of the distribution within a watershed. Table 1 presents the descriptive statistics for these water quality measures, including the number of observations, mean, 10th and 90th percentiles, minimum, maximum, and standard deviation. Figure 2 illustrates the kernel density distribution for each water quality measure, including standard biochemical oxygen demand (BOD), total suspended solids (TSS), fecal coliform (FC), dissolved oxygen deficit (O), Nitrogen (N), and Phosphorus (P). The distributions of BOD and DOD approximate a normal distribution, while the distributions of TSS, FC, nitrogen, and phosphorus exhibit right skewness.

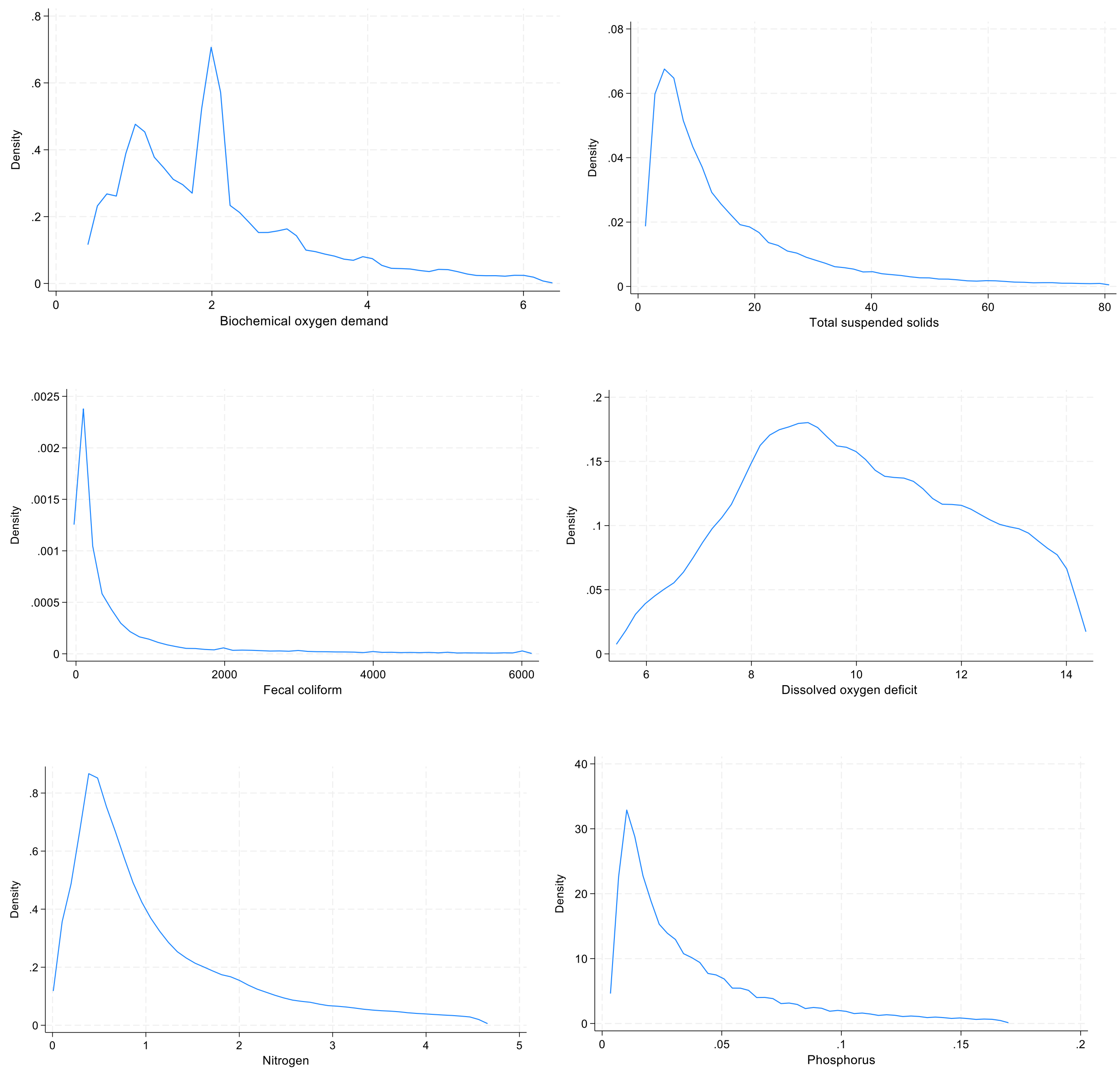

Figure 2. Kernel density distributions of water quality measures.

2.3 Socioeconomic and weather data

We developed agricultural production control variables using data from the Census of Agriculture. The influence of agricultural production on water quality is represented by the amount of agricultural land, the number of cropland operations, total animal sales, and farm-related income. Additionally, we used population and personal income data from the Census Bureau to control general economic factors that might impact water quality. Since socioeconomic data at the watershed level is unavailable, we matched each watershed to the corresponding county's socioeconomic data. About a third of the watersheds lie entirely within a single county. For watersheds spanning multiple counties, we used the socioeconomic data from the county containing the largest share of the watershed area. We also calculated the annual mean temperature and precipitation for each watershed using data from PRISM (Parameter-elevation Regressions on Independent Slopes Model).

2.4 Geospatial analysis of water and stream network

To connect water quality readings with power plant locations, we mapped the geographic locations of watersheds and water quality monitoring stations using geospatial information from the USGS Watershed Boundary Dataset (WBD) and the National Hydrologic Dataset (NHD). We constructed panel data at the year-quarter and power plant level, incorporating power plants and water quality measures. Monitoring station readings for each water quality measure were averaged to create year-quarter level water quality metrics. Our panel is unbalanced because some water quality monitoring stations do not record data every year.

The NHD data includes information on points along rivers, allowing us to determine if a water quality monitoring station is located upstream or downstream of specific power plants. First, we use the "fid-point" variable in the NHD (points along the "comid" or river segment) to establish the flow direction of a river or stream. We also identify the nearest "fid-point" to each power plant to locate the power plants along a river or stream. Next, we determine the nearest upstream and downstream monitoring points with long-term water quality data for each power plant within a specified distance. Finally, we obtain the readings from these upstream and downstream monitoring stations within the defined distance.

3. Identification and Economic Models

This section outlines the empirical strategies employed to identify the influence of different types of power plants functionality and retirement on local water quality. The first strategy involves estimating a watershed-fixed effects model, leveraging variations in power plants over time and across watersheds to assess their impact on water quality. The second strategy utilizes the flow direction of rivers as an exogenous variation to estimate the effect power plants on downstream water quality (Keiser and Shapiro 2019; Liu, Wang, and Zhang 2023). We compare water quality over time between downstream and upstream areas for each power plant with different technologies.

3.1 Fixed effects model

Initially, we employ the following fixed effects model to estimate the impact of various energy sources used by power plants on local water quality.

$$Q_{pt} = \gamma R_p O_{pt} + X'_{pt}\beta + \eta_p + \eta_{pt} + \eta_{wy} + \epsilon_{pt} \quad (1)$$

Here, Q_{pt} represents the water quality at the nearest monitoring sites to a power plant p in year-quarter t. We utilize both the mean and median of readings from monitoring stations to assess water quality. The variable O_{pt} denotes the operational status (O = 1 if in operation) of the power plant p in year-quarter t, while the variable R_p indicates the technology (R = 1 if renewable) utilized by plant p. The primary coefficient of interest, γ, signifies the mean effect of renewable energy production on water quality. The matrix X'_{pt} incorporates economic and environmental controls. The plant fixed effects η_p permit different mean levels of water pollution associated with each power plant. These fixed effects account for time-invariant sources of pollution such as agricultural farms. The plant × year-quarter fixed effects η_{pt} allow for variations in water pollution near each power plant in each quarter, controlling for factors like local industry growth, other environmental regulations, and changes in population density affecting each power plant. The watershed × year fixed effects η_{wy} enable variations in water quality by year, shared across all plants in a river watershed.

The fixed effects model assesses the impact of various energy sources utilized by power plants on local water quality by leveraging the variation in energy technologies and water quality across time and different watersheds. However, the validity of this approach may be violated if power plant siting decisions are influenced by time-varying unobservable factors that are correlated with water quality measures. For instance, if a fossil fuel power plant selects locations with better water quality to minimize its waste management costs and protect its facilities from erosion, our estimation of γ could be biased. Additionally, strategic water-quality monitoring practices could introduce bias into our estimates, as not all monitoring stations adhere to regular schedules. In an extreme scenario, if only monitoring stations upstream of rivers were operational after power plants were established, our estimates would be biased. To address these concerns, we adopt an alternative empirical strategy that utilizes the upstream of a watershed as a counterfactual for the downstream, enabling us to identify the impact of power plant operations on downstream water quality.

3.2 Flow direction model

Following Keiser and Shapiro (2019), and Liu et al. (2023), we use the following flow-direction model to estimate the impact of various energy sources used by power plants on local water quality:

$$Q_{pdt} = \gamma R_p O_{pt} d_d + X'_{pdt}\beta + \eta_{pd} + \eta_{pt} + \eta_{dwy} + \epsilon_{pdt} \qquad (2)$$

This regression involves two observations for each power plant (p) and quarter (t): one observation describing the mean water quality upstream (d = 0) and another describing the mean water quality downstream (d = 1). The plant × downstream fixed effects η_{pd} permit different mean levels of water pollution for both upstream and downstream waters associated with each power plant. These fixed effects account for time-invariant sources of pollution such as factories and farms, which may be located exclusively upstream or downstream of a plant. The plant × quarter fixed effects η_{py} allow for variations in water pollution near each power plant in each quarter affecting both upstream and downstream pollution. The downstream × watersed × year fixed effects η_{dwy} enable separate variations in upstream and downstream water quality by year, shared across all plants in a river watershed.

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