Tufts University
School of Engineering
Civil and Environmental Engineering

University of Illinois Chicago
Government Finance Research Center

A Systems Perspective on Contributing Factors to Clean Water Act Noncompliance

Deborah A. Carroll, Ph.D.; Abigail Iuorio; Joseph C. Toland; Christelle Khalaf, Ph.D.; Lauryn A. Spearing, Ph.D.

Project Reporting Period: August 16, 2024 – February 28, 2026
Contract No. 68HERH23P0157

Submitted to:
U.S. Environmental Protection Agency
Georgette A. Fogle, Environmental Protection Specialist
Office of Enforcement and Compliance Assurance
1200 Pennsylvania Ave., NW, Washington, DC 20460
Phone: (202) 564-6746
Email: fogle.georgette@epa.gov

Submitted by:

Civil and Environmental Engineering
Tufts University
200 College Avenue
Medford, MA 02155
Website: https://engineering.tufts.edu/cee/

Government Finance Research Center
University of Illinois Chicago
412 S. Peoria Street (MC 349)
Chicago, IL 60607
Website: https://gfrc.uic.edu/

Principal Investigator: Lauryn Spearing, Ph.D.
Co-Principal Investigators: Deborah A. Carroll, Ph.D. & Christelle Khalaf, Ph.D.

ACKNOWLEDGEMENTS

A Systems Perspective on Contributing Factors to Clean Water Act Noncompliance is a project funded by the U.S. Environmental Protection Agency. This report is based on work completed in the School of Engineering at Tufts University and the Government Finance Research Center at the University of Illinois Chicago. Its contents do not necessarily reflect the views of Tufts University, the Government Finance Research Center, the University of Illinois Chicago, or the U.S. Environmental Protection Agency.

The authors thank the representatives of U.S. Environmental Protection Agency who shared their expertise and guided this project, including: Esha Bhardwaj, Jackie Clark, Leslie Cronkhite, Georgette Fogle, Marissa Halperin, Lauren Jones, Cezanne Lojeski, Aaron Margolis, Michele McKeever, Brandon Mediate, Andrew R Murray, Smiti Nepal, Jan Pickrel, Martin Robinson, Greg Savitske, Elisabeth Schlaudt, Prashant Singh, Allison West, and William Wheeler.

Suggested Citation:

Carroll, Deborah A., Abigail Iuorio, Joseph C. Toland, Christelle Khalaf, and Lauryn A. Spearing. *A Systems Perspective on Contributing Factors to Clean Water Act Noncompliance*. Chicago, IL: Government Finance Research Center, 2026.

TABLE OF CONTENTS

Key Takeaways 6
Executive Summary 7
1. Introduction 10
1.1. Study Objectives and Methodology Overview 12
1.2. Research Design and Report Roadmap 13
2. Clean Water Act Compliance 15
2.1. Data 16
2.2. Methods 31
2.3. Plant-Level Correlates of Significant Noncompliance 33
2.4. Sewershed Correlates of Significant Noncompliance 37
2.5. Government Finance Correlates of Significant Noncompliance 40
2.6. Summary of Quantitative Findings 44
3. Data Collection Tools for Future Noncompliance Assessment 47
3.1. Research Design 47
3.2. Survey Instrument and Interview Guide Development 47
3.3. Implementation Best Practices for Surveys and Interviews 51
4. Recommendations and Conclusions 56
4.1. Evidence-Based Recommendations 56
4.2. Conclusions and Next Steps 58
References 60
Appendix A: Clean Water Act Data and Robustness Checks 65
The Research Team 74

TABLES

Table 2.1. Violations and Resolutions by Noncompliance Category, 2015–2024 16
Table 2.2. Significant Noncompliance Violations, 2023–2024 17
Table 2.3. Summary Statistics: All Publicly Owned Treatment Works 21
Table 2.4. Comparison of Treatment Works Based on Significant Compliance, 2018–2024 26
Table 2.5. Summary Statistics: All Treatment Works Compared to Govt. Owned 28
Table 2.6. Plant-Level Regression Results: All Publicly Owned Treatment Works 34
Table 2.7. System and Sewershed Regression Results: All Publicly Owned Treatment Works 38
Table 2.8. Regression Results: Local Government Owned Treatment Works 41
Table 3.1. Survey Content Overview 48
Table 3.2. Interview Guide Content Overview 49
Table A.1. Dataset Construction: Sewershed Area 65
Table A.2. Dataset Construction: Quarterly Noncompliance Reporting 65
Table A.3. Dataset Construction: Sewershed Characteristics 66
Table A.4. Data Subset: Local Government Characteristics 67
Table A.5. Robustness Check: Functional Form for All Publicly Owned Treatment Works 68
Table A.6. Robustness Check: Excluding Known Data Problems for All Treatment Works 69
Table A.7. Robustness Check: Excluding Known and Potential Data Problems for All Treatment Works 70
Table A.8. Robustness Check: Excluding Known Data Problems for Govt. Owned Treatment Works 71
Table A.9. Robustness Check: Excluding Known and Potential Data Problems for Govt. Owned Treatment Works 72
Table A.10. Robustness Check: Local Government Owned Treatment Works Excluding Govt. Finance 73

FIGURES

Figure 1.1. Research Design Illustration....14
Figure 2.1. Proportion of Significant Noncompliant Treatment Works by State, 2023–2024....18
Figure 2.2. Changes in Publicly Owned Treatment Works Significant Compliance, 2018–2024....20
Figure 2.3. Model-Based Differences in Significant Noncompliance by State....39
Figure 3.1. Common Sampling Strategies for Surveys and Interviews....52
Figure 3.2. Example Systems Map....54

Key Takeaways

- Of the 13,548 publicly owned treatment works with compliance information, 27 percent or 3,660 had a significant noncompliance violation in 2023 or 2024, were reported quarterly as noncompliant a mean of three times, and nearly half had one in the five years prior (2018–2022). These significant noncompliance violations are typically resolved in about nine months with the majority incurred for effluent exceeding monthly average discharge monitoring report limits.

- Significant noncompliance in publicly owned treatment works varies considerably across states. In 2023–2024, Washington, DC was the only jurisdiction with zero significant noncompliance, although it has only one treatment facility. More than 50 percent in West Virginia and Louisiana had a significant noncompliance violation, potentially impacting more than 6.37 million people.

- For oversight, compliance evaluation inspections are most common, as statutorily required, with nearly 35 percent of publicly owned treatment works receiving one in 2022. Yet less than two percent received a follow-up inspection, and about five percent received a formal enforcement action.

- Publicly owned treatment works are more likely to have a significant noncompliance violation and/or expected to spend more time in significant noncompliance if they received a performance audit, follow-up inspection, or formal enforcement action, as these activities reveal problems as intended. Those with a significant noncompliance violation in 2018–2022 are most likely to have one in 2023–2024 and spend the longest expected time in significant noncompliance.

- Publicly owned treatment works operating in more densely populated areas, and those with wealthier residents are less likely to be in significant noncompliance and spend less expected time in it. These are the only sewershed characteristics correlated with significant noncompliance in the model.

- Over 75 percent of publicly owned treatment works are owned by a Municipal Water District, Municipal Government, or County Government. Local government-owned treatment works have similar significant noncompliance rates and time in significant noncompliance compared to all treatment works despite their tendency to serve larger populations, receive industrial user discharges as part of having a pretreatment program, and receive more oversight and formal enforcement actions.

- Local governments that own treatment works spend about 3 percent of total revenue for interest costs on outstanding debt. They would need to levy $3 in property tax revenue to offset a $1 reduction in intergovernmental revenue, dedicate 84 percent of spending to cover operations, and levy exactly the amount needed to fund their water sector utilities. Government finance variables are correlated with significant noncompliance, with debt service burden having the largest impact.

- Publicly available data originating from permit holders and reported by states includes inaccuracies, leading to a 15–39 percent loss of observations to ensure accuracy, potentially diminishing generalizability of research using these data.

- The research team developed two data collection tools: 1) a survey, and 2) a semi-structured interview guide using the outputs from the regression findings, which helped to 1) inform the sampling frames for the survey and interviews, and 2) identify key constructs and hypothesized drivers to be measured in the instruments.

Executive Summary

The United States (U.S.) Environmental Protection Agency commissioned researchers in the School of Engineering at Tufts University and the Government Finance Research Center at the University of Illinois Chicago to conduct a national study on the root causes of significant noncompliance with the Clean Water Act. This work informs recommendations aimed at increasing compliance among publicly owned treatment works. Publicly owned treatment works are treatment works defined by the Clean Water Act as being owned by a state or municipality, including any devices and systems used in storage, treatment, recycling, and reclamation of municipal sewage or industrial wastes of liquid nature (Clean Water Act, 2026). In the U.S., it is estimated that 82 percent of people, about 270 million total, have their wastewater treated by publicly owned treatment works. Yet 21.4 percent of publicly owned treatment works experienced significant noncompliance between 2023 and 2024 (U.S. Environmental Protection Agency, June 25, 2025; U.S. Environmental Protection Agency, 2025). Significant noncompliance refers to serious Clean Water Act violations that increase the risk of contaminant exposure, making monitoring and regulation of these treatment works crucial for public health.

This report is provided as a deliverable of the commissioned study. Throughout the study period, the researchers received guidance from subject matter experts employed by the U.S. Environmental Protection Agency. The researchers compiled a comprehensive dataset for quantitative analysis of all publicly owned treatment works nationwide, as well as developed a survey instrument and semi-structured interview guide to be used for future data collection. The research objectives were to:

1. Identify the plant-level, sewershed, and government finance characteristics correlated with Clean Water Act significant noncompliance by publicly owned treatment works through quantitative regression analysis.
2. Design a research approach, including a survey instrument and semi-structured interview guide, to identify additional contextual factors that influence Clean Water Act significant noncompliance by publicly owned treatment works in preparation for future systems analysis to understand the root causes of noncompliance.

Potential factors correlated with Clean Water Act significant noncompliance were categorized as plant-level, sewershed, and financial to allow for the quantitative research findings to provide preliminary actionable insights that can inform policy direction and operational recommendations. To assess the correlates of significant noncompliance through quantitative analysis, the researchers combined Clean Water Act significant noncompliance violations from the U.S. Environmental Protection Agency's Enforcement and Compliance History Online database with relevant characteristics of each publicly owned treatment works sewershed obtained from the U.S. Census Bureau's American Community Survey and, for treatment works owned by local governments, with the U.S. Census Bureau's Census of Governments Finance Survey data. Findings from the limited prior research and this study are then used to inform the design of a survey instrument and semi-structured interview guide, which are both structured to engage with publicly owned treatment works across the U.S. Once implemented for data collection, the combined findings will allow for a systems analysis to fully understand the root causes of significant

noncompliance and inform the U.S. Environmental Protection Agency on future policy direction to enhance compliance with the Clean Water Act.

Preliminary Conclusions

The number of publicly owned treatment works throughout the U.S. is 17,085; however, only 13,548 (79.3 percent) could be matched to compliance, inspection, enforcement, and data reporting information. The quantitative research findings revealed that among the 13,548 treatment works, 27 percent or 3,660 had at least one significant noncompliance violation in 2023 or 2024, and nearly half had at least one significant noncompliance violation in the five years prior (2018–2022). These violators were reported quarterly as noncompliant a mean of three times, with the majority incurred for effluent exceeding monthly average discharge monitoring report limits.

Publicly owned treatment works are less likely to have a significant noncompliance violation and/or spend less time in significant noncompliance if they have the following plant-level characteristics: a larger population served, serving as an endpoint facility, ownership by state and local governments or municipal water districts, and operating in more densely populated areas with wealthier residents. On the other hand, publicly owned treatment works that received a performance audit, follow-up inspection, or formal enforcement action are more likely to have a significant noncompliance violation and/or to spend more time in significant noncompliance. Publicly owned treatment works with at least one prior significant noncompliance violation in 2018–2022 are more likely to be in significant noncompliance in 2023–2024 and spend the longest time in significant noncompliance.

Over 75 percent of publicly owned treatment works are owned by a Municipal Water District, Municipal Government, or County Government. Examining these separately, local government owned treatment works have similar significant noncompliance rates and time spent in significant noncompliance compared to all publicly owned treatment works. In addition, both groups have similar correlations to significant noncompliance for inspections, formal enforcement, and prior significant noncompliance. However, treatment works owned by municipal governments and municipal water districts are more likely than county government–owned treatment works to have significant noncompliance. Finally, all of the government finance variables correlated with significant noncompliance except for the operating expenditure ratio; however, only debt service burden has a meaningful correlation size compared to other variables analyzed.

Together, the regression results shed light on factors correlated with significant noncompliance. Although these generalizable trends are useful, there is a need to engage directly with publicly owned treatment works to understand contextual details, as well as the operational and managerial challenges, to fully identify the root causes of significant noncompliance. To do so, this study developed data collection tools—a survey instrument and semi-structured interview guide—along with guidance to the U.S. Environmental Protection Agency about how to implement these tools. Pairing the quantitative findings presented here with qualitative research is needed to make causal claims regarding Clean Water Act noncompliance.

Recommendations and Next Steps

Overall, the quantitative research findings lend themselves to the following preliminary recommendations:

- Implement processes to improve data reporting by states of information about publicly owned treatment works, as required by the Clean Water Act.
- Use the survey and interview data collection results to add or redesign the fields used for data collection to produce more varied descriptive information reported on publicly owned treatment works.
- Develop selection criteria to help states focus inspection efforts on those publicly owned treatment works that have had a prior significant noncompliance violation because they are at greatest risk of repeating significant noncompliance.
- Invest in human and financial support for wastewater operations as this might help publicly owned treatment works who are more prone to noncompliance, such as those with fewer full-time staff at the local government and those who serve areas with lower income residents.
- Use fiscal policy tools to enhance access to the municipal debt market for publicly owned treatment works.

The U.S. Environmental Protection Agency may find the recommendations in this report helpful when developing or refining policy or practices. It is important to note that these recommendations would require adequate staffing and training, as well as adequate administrative support, technology, contract support, and access to other resources. Although the above findings provide a basis for understanding correlates of significant noncompliance with the Clean Water Act, qualitative research should be conducted to capture perspectives of utility personnel. The additional data collection tools developed for this study should be deployed to publicly owned treatment works throughout the U.S. to better understand the contextual and managerial factors that serve as root causes of significant noncompliance violations. Once implemented for data collection, the combined findings will allow for a systems analysis to inform the U.S. Environmental Protection Agency on what targeted technical, managerial, or financial assistance could improve Clean Water Act compliance by publicly owned treatment works.

1. Introduction

In the United States (U.S.), it is estimated that 82 percent of people, about 270 million total, have their wastewater treated by publicly owned treatment works, making their monitoring and regulation crucial for public health (U.S. Environmental Protection Agency, April 2024). Wastewater related legislation was first largely enacted in 1948 as the Federal Water Pollution Control Act, which was significantly reorganized and expanded in 1972 to become the Clean Water Act (U.S. Environmental Protection Agency, May 2025). This legislation implemented pollution control programs and national water quality recommendations for pollutants in surface waters. The U.S. Environmental Protection Agency's National Pollutant Discharge Elimination System permitting program controls pollutant discharges into navigable waters of the United States from industrial, municipal, and other facilities.

These regulations are crucial to minimizing water quality issues and protect public health. Surface water pollution can impact human health through consumption of contaminated water and aquatic organisms as well as direct skin exposure (Saha et al., 2026). Microbial pathogens found in water have been found to be correlated with ulcers, fever, and liver failure (Akpor & Munchie, 2011). In fact, waterborne pathogens stemming from both natural and human causes are estimated to cause 7.15 million illnesses, 118,000 hospitalizations, and 6,630 deaths annually in the United States (Centers for Disease Control and Prevention, 2024). Collectively, waterborne pathogen exposure results in $3.33 billion in direct health care costs across the country annually (Centers for Disease Control and Prevention, 2024).

Wastewater utilities throughout the United States are facing operational challenges, such as an aging workforce, inadequate training, lack of funding, divided responsibilities, and high attrition rates, among other concerns (Brown & Baxter, 1993; American Society for Civil Engineers, 2026). Reports estimate there will be more than 9,200 job openings in the water sector annually through 2026 (Government Accountability Office, 2018). Further, it is estimated that more than $300 billion in wastewater infrastructure investments are needed over the next 20 years to maintain the Nation's waters (Environmental Protection Agency, April 2024). Such a funding gap compounds operational issues at wastewater utilities, such as maintaining a capable workforce, adapting to hazards, and managing emerging contaminants such as per- and polyfluoroalkyl substances (PFAS). For example, the Michigan Department of Environment, Great Lakes, and Energy implemented an initiative that requires all municipal wastewater treatment works with required industrial pretreatment programs to identify if PFAS was passing through their system, and if found, to reduce/eliminate the source (Michigan Department of Environment, Great Lakes, and Energy, 2026). Such a requirement increases the managerial, financial, and operational requirements at utilities, which are often already challenged by limited budgets.

Amid these difficulties, wastewater utilities can struggle to comply with the Clean Water Act, which regulates pollutant discharges and related monitoring and reporting. For example, 21.4 percent of publicly owned treatment works (the focus of this report) experienced significant noncompliance between 2023 and 2024 (U.S. Environmental Protection Agency, June 25, 2025; U.S. Environmental Protection Agency, 2025). Significant noncompliance refers to serious Clean Water Act violations that increase the risk of contaminant exposure. Publicly owned treatment works are treatment works defined by

the Clean Water Act as being owned by a state or municipality, including any devices and systems used in storage, treatment, recycling, and reclamation of municipal sewage or industrial wastes of liquid nature (Clean Water Act, 2026). This includes sewers, pipes, and other conveyances if they convey wastewater to a publicly owned treatment works. Publicly owned treatment works also refers to the municipality, as defined in the Clean Water Act, which has jurisdiction over the indirect discharges to and the discharges from a treatment works. Over 17,000 publicly owned treatment works in the United States discharge more than 34 billion gallons of wastewater per day into water bodies (Center for Sustainable Systems, 2025). As such, it is critical to understand what factors are correlated with significant noncompliance of the Clean Water Act.

To understand the correlates of water utility noncompliance, researchers have explored links between compliance and a variety of factors, both related to the system and characteristics of the region they serve (e.g., sewershed) (e.g., Wang et al, 2024). Much of this research has focused on drinking water, as covered in Khalaf et al., 2026. The work that has explored wastewater systems found that an increase in population served was linked to an increase in probability and number of wastewater violations (Elbakidze & Beeson, 2021), departing from work focused on the drinking water sector (Allaire et al., 2018; Scanlon et al., 2022). An increase in per capita income in counties surrounding wastewater plants was also found to be correlated with a decreased probability of violation (Elbakidze & Beeson, 2021). This mirrors findings in drinking water systems, where characteristics of the area served by systems has been correlated with compliance outcomes (Earnhart, 2004b), and utilities serving lower-income communities have been found to have more violations (Fu et al., 2020; Sowby, 2023). This is likely due to less financial capacity to leverage necessary resources from their tax bases, illustrated by the fact that funding challenges have been found to be a key factor limiting sanitation access in the United States (Maxcy-Brown et al., 2023).

In terms of ownership, government owned treatment works were found to have the highest number of both effluent and reporting violations compared to privately owned wastewater facilities and other government owned systems that are not publicly owned treatment works (Earnhart & Jacobson, 2025). This aligns with a few studies focused on drinking water systems (Wallsten & Kosec, 2008; Konisky & Teodoro, 2016). Violation risk may also be higher for smaller treatment works, as the probability of certain violations has been linked to an increase in influent flow (Suchetana et al., 2019). External factors may also play a role in compliance, illustrated by the fact that as water-focused environmental nonprofits in a watershed increases, Clean Water Act compliance increases (Grant & Grooms, 2017).

Operational and governance factors influence noncompliance, as higher levels of inspections are correlated with higher levels of wastewater system noncompliance, likely due to inspections happening at already struggling facilities (Grant & Grooms, 2017; Wang et al. 2024). Nationally, there is some evidence that cumulative violations increased when additional state water quality standards were introduced (Earnhart, 2007; Elbakidze & Beeson, 2021). However, these effects were transitory; they not only dissipated within a year of implementing the new standards, but cumulative violations also appeared to decline relative to pre-regulation levels. Similarly, evidence on the effectiveness of compliance

assistance programs is mixed (Ferraro & Shimshack, 2025). As expected, the probability of noncompliance at wastewater treatment works may also be driven by the failure of key operational components associated with an increased probability of systemic failure (e.g., Choudhury et al. 1992) and aging infrastructure (American Society for Civil Engineers, 2026).

Although previous research has explored noncompliance with the Safe Drinking Water Act, there is limited work focused on compliance with the Clean Water Act. Literature has only focused on a subset of factors, often overlooking local government fiscal capacity and failing to link together multiple types of factors (e.g., characteristics of the sewershed with attributes of the treatment work). This work aims to fill these literature gaps by exploring the root causes of significant noncompliance with the Clean Water Act. Recommendations stemming from this work can facilitate targeted compliance efforts to protect the waters of the United States and public health. Notably, such environmental monitoring and enforcement activities have been found to reduce both violations and emissions (Gray & Shimshack, 2011).

1.1. Study Objectives and Methodology Overview

This study includes multiple sets of variables including oversight information (i.e., on-site visits and inspections), local government financial data, and contextual factors to identify the correlates of publicly owned treatment work significant noncompliance with the Clean Water Act. Departing from previous literature that uses county-level data (Elbakidze & Beeson, 2021), this study uses sewershed boundaries to understand characteristics of the population served. Ultimately aiming for a mixed-methods approach, this study pursues the following research objectives:

1. Identify the plant-level, sewershed, and government finance characteristics correlated with Clean Water Act significant noncompliance by publicly owned treatment works through quantitative regression analysis.
2. Design a research approach, including a survey instrument and semi-structured interview guide, to identify additional contextual factors that influence Clean Water Act significant noncompliance in preparation for future systems analysis to understand the root causes of noncompliance.

Potential factors correlated with Clean Water Act significant noncompliance were categorized as system-level, service area, and government finance to allow for the quantitative research findings to provide preliminary actionable insights that can inform policy direction and operational recommendations. To assess the correlates of significant noncompliance through quantitative analysis, the researchers combined Clean Water Act significant noncompliance violations from the U.S. Environmental Protection Agency's Enforcement and Compliance History Online database with relevant characteristics of each publicly owned treatment works sewershed obtained from the U.S. Census Bureau's American Community Survey and, for treatment works owned by local governments, with the U.S. Census Bureau's Census of Governments Finance Survey data.

Wastewater significant noncompliance is divided into three categories: (1) effluent, (2) discharge monitoring reporting, and (3) compliance/permit schedule. Permit schedule violations occur when date-based requirements are not met as part of a permit or

enforcement. Effluent violations pertain to discharged water quality in violation of discharge monitoring reporting limits. Discharge monitoring reporting violations occur when discharge monitoring reports have not been reported within 30 days of the due date (U.S. Environmental Protection Agency, March 2023). Schedule violations and discharge monitoring reporting violations have the potential to shield larger issues with effluent discharge through a lack of timely reporting. In turn, this research considers all three types of violations, focusing on significant noncompliance violations, when exploring noncompliance with the Clean Water Act.

Findings from the limited prior research and this study are then used to inform the design of the survey instrument and semi-structured interview guide, which are both structured to engage with publicly owned treatment works across the U.S. Once implemented for data collection, the combined findings will allow for a systems analysis to fully understand the root causes of noncompliance and inform the U.S. Environmental Protection Agency on future policy direction to enhance compliance with the Clean Water Act.

1.2. Research Design and Report Roadmap

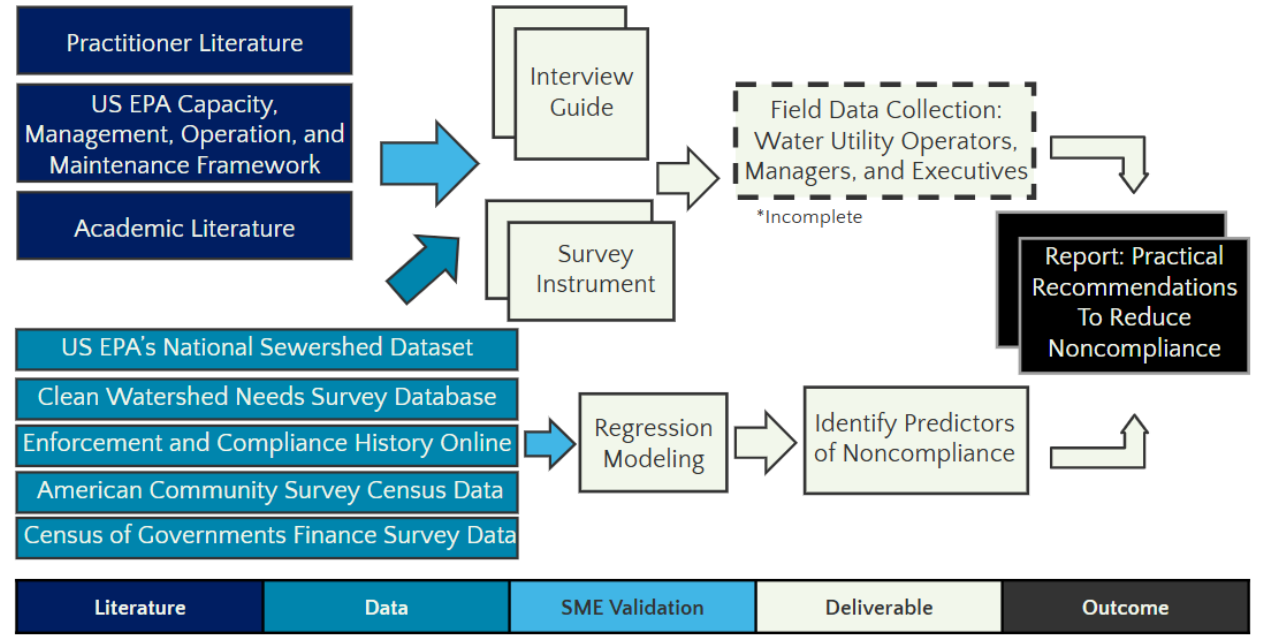
The limited prior research is used to inform the research design for the quantitative analysis in this study, as illustrated in Figure 1.1. The findings from both prior research and this study are then used to inform the design of the survey instrument and semi-structured interview guide, which are both structured to engage with publicly owned treatment works across the U.S. Although statistical models can provide insight into large-scale trends, there is a need to understand nuanced operational and managerial challenges that influence significant noncompliance. Such information can be captured through surveys and interviews (e.g., Spearing et al., 2020). These data collection tools focus on potential internal factors leading to significant noncompliance. Once implemented for data collection, the combined findings will allow for a systems analysis to fully understand the root causes of significant noncompliance and inform the U.S. Environmental Protection Agency on future policy direction to improve the capacity, management, operations, and maintenance (known as CMOM) of publicly owned treatment works and ultimately enhance Clean Water Act compliance.

Section two of this report provides an overview of the Clean Water Act and how the U.S. Environmental Protection Agency defines compliance with the Act. The section proceeds with a description of the data collection and dataset compilation process, methods used for quantitative analysis, and regression results of the plant-level and sewershed correlates of significant noncompliance from analysis of all publicly owned treatment works throughout the country. Section 2 concludes by providing the regression results of fiscal indicators correlated with significant noncompliance from analysis of a subset of local government-owned publicly owned treatment works.

Section three describes the research design used for development of a survey instrument and semi-structured interview guide to be implemented for future primary data collection. Along with descriptions of these primary data collection tools, this section also provides a discussion of best practices for implementing surveys and conducting semi-structured interviews for qualitative and quantitative data collection. Section three concludes with a

description of how data collected with these tools might be analyzed. Doing so will help to inform the U.S. Environmental Protection Agency and policymakers on the root causes of noncompliance and the most effective approaches for increasing Clean Water Act compliance by publicly owned treatment works.

Figure 1.1. Research Design Illustration



Note: This figure illustrates the research design developed by the authors and used to guide this study.

Section four offers a discussion of overall conclusions and next steps to advance this analysis intended to help reduce Clean Water Act significant noncompliance. Additional information pertaining to data collection, dataset compilation, and robustness checks for the quantitative analyses are provided in Appendix A. The primary data collection tools themselves are provided in Appendices B and C.

2. Clean Water Act Compliance

In 1972, the Federal Water Pollution Control Act was significantly revised, becoming known as the Clean Water Act. Over time, the Act has been amended, such as in 1977, when amendments introduced technology-based standards to reduce toxic pollutants (U.S. Environmental Protection Agency, 2022). Under the Clean Water Act, the U.S. Environmental Protection Agency regulates pollutant discharge into the waters of the United States, making it unlawful to discharge pollutants into navigable waters without a permit (U.S. Environmental Protection Agency, 2022). Direct oversight of wastewater discharge occurs through the National Pollutant Discharge Elimination System, which issues permits establishing discharge limits and reporting requirements for wastewater treatment works (U.S. Environmental Protection Agency, June 5, 2025). Almost all states and one territory are granted "primacy," meaning they can implement the Clean Water Act and issue permits to discharging facilities (U.S. Environmental Protection Agency, December 2025).

Implementing the Clean Water Act entails routine monitoring of wastewater discharges through discharge monitoring reports, review of permit applications and modifications, on-site inspections and compliance evaluations, training and certification of wastewater treatment works operators, and enforcement actions against facilities that fail to meet established standards (Pennsylvania Department of Environmental Protection, 2021). Specifically, primacy agencies collect detailed operational and monitoring data from the National Pollutant Discharge Elimination System permitted facilities under their jurisdiction and submit a subset of this information to the U.S. Environmental Protection Agency. The data reported to the U.S. Environmental Protection Agency include system-specific details, such as system name, permitting information, flow rates, and facility details, along with information about noncompliance (U.S. Environmental Protection Agency, December 2025).

The range of acceptable enforcement for noncompliance involves informal and formal actions aimed at restoring compliance as quickly as possible. These can begin with informal actions, including reminder letters, warning letters, notices of violation, field visits, and telephone communications. If a violation persists or recurs, the primacy agency escalates enforcement to formal actions that obligate treatment works to achieve compliance on a specified schedule. Formal actions may include citations, administrative orders with or without penalties, civil referrals to state attorneys general or the U.S. Department of Justice, criminal prosecutions, and other sanctions. In cases where public health is at immediate risk, the U.S. Environmental Protection Agency and the primacy agency may issue emergency orders requiring treatment works to take immediate corrective action to protect public health and restore compliance (U.S. Environmental Protection Agency, December 2025). Despite this regulatory framework, compliance challenges remain. Between 2007 and 2017, counties in the United States were found to experience an average of 14.58 wastewater violations annually, with some counties experiencing over 1,000 wastewater violations (Elbakidze & Beason, 2021).

Table 2.1 presents data by historic noncompliance category from 2015 to 2024. Violations are separated by those pertaining to significant noncompliance (the focus of this analysis) and other noncompliance, as well as compliance resolution status. These data are

aggregated from quarterly estimates, so the mean number of quarters that treatment works are observed within each category are provided along with the number of publicly owned treatment works and the corresponding percentage of total. Among the 58,589 publicly owned treatment works violations reflected in Table 2.1, the greatest proportion of significant noncompliance results from effluent violations (a combined 10.53 percent) and failure to report discharge monitoring reports (7.86 percent). Treatment works spend a mean of 4.63 quarters (nearly 14 months) in significant noncompliance for failure to report discharge monitoring reports and three to nearly six quarters (nine to 18 months) in noncompliance for effluent violations, depending on whether the violation involved the monthly average limit or not.

Table 2.1. Violations and Resolutions by Noncompliance Category, 2015–2024

Noncompliance Category	Number in Category	Percent of Total	Mean Quarters in Category	Std. Dev. Quarters in Category
Significant Noncompliance				
Compliance/Permit Schedule – Violations	1,402	2.39%	5.88	6.05
Compliance/Permit Schedule – Reporting	271	0.46%	4.58	4.65
Effluent – Monthly Average Limit	4,454	7.60%	5.75	6.66
Effluent – Non-monthly Average Limit	1,716	2.93%	3.06	3.62
Failure to Report Discharge and Monitoring Report – Not Received	4,607	7.86%	4.63	4.73
Other Noncompliance				
Failure to Report Discharge Monitoring Report – Not Received	2,380	4.06%	3.96	2.88
Reportable Noncompliance	9,378	16.01%	10.93	9.79
Non-Reportable Noncompliance Violations	10,692	18.25%	6.69	5.54
Compliance Resolutions				
Resolved Pending	2,048	3.50%	10.30	9.77
Resolved Pending – Manual	30	0.05%	2.90	3.16
Resolved	10,227	17.46%	3.39	2.64
Undetermined or Not Coded	11,384	19.43%	5.62	4.81

Note: This table presents the number and percentage of Clean Water Act violations and resolutions by historic noncompliance category for all publicly owned treatment works in the US. The data are aggregated from quarterly estimates between 2015 and 2024, so the last two columns present the mean and standard deviation for the number of quarters that publicly owned treatment works are in each category. There are a total of 58,589 treatment plant violations and resolutions during this time. Data source: US Environmental Protection Agency's Integrated Compliance Information System National Pollutant Discharge Elimination System (ICIS-NPDES), obtained from: https://echo.epa.gov/tools/data-downloads#NPDES.

2.1. Data

2.1.1. Clean Water Act Significant Noncompliance

A binary variable (i.e., coded 1 or 0) was created to indicate whether a publicly owned treatment works was in significant noncompliance (i.e., had any of the five types of violations reported in Table 2.2) in 2023 or 2024 (e.g., *Any Significant Noncompliance*). In addition, a variable was created measuring the total number of quarters that each treatment

works was in significant noncompliance in 2023–2024. This information is available for 13,548 publicly owned treatment works (Tables A.1 and A.2). These quarterly noncompliance designations were calculated in aggregate, as well as by violation category (Table 2.2).[1]

Table 2.2. Significant Noncompliance Violations, 2023–2024

	All Treatment Works		All Treatment Works		Noncompliant Treatment Works	
Violation Categories	Number Noncompliant	Percent Noncompliant	Mean Quarters Noncompliant	Std. Dev. Quarters Noncompliant	Mean Quarters Noncompliant	Std. Dev. Quarters Noncompliant
Any Significant Noncompliance	3,660	27.02%	0.7877	1.6937	2.9158	2.1009
Compliance/Permit Schedule - Violations	447	3.30%	0.0977	0.6608	0.3617	1.2333
Compliance/Permit Schedule - Reporting	133	0.98%	0.0310	0.3934	0.1148	0.7507
Effluent - Monthly Average Limit	1,992	14.70%	0.3851	1.1838	1.4254	1.9248
Effluent - Non-monthly Average Limit	511	3.77%	0.0672	0.4242	0.2489	0.7880
Failure to Report DMR - Not Received	1,172	8.65%	0.2067	0.8581	0.7650	1.5162

Note: Total number of observations is 13,548 publicly owned treatment works, which represents all publicly owned treatment works in the U.S. for which compliance data are available. The table presents numbers and percentages of treatment works in significant noncompliance, defined as having at least one violation in any of the five listed categories in 2023–2024. Of the 3,660 treatment works in significant noncompliance, 3,102 (84.75 percent) had one violation type, 521 (14.23 percent) had two violation types, and 37 (1.01 percent had three violation types. The means and standard deviations are calculated from the numbers of quarters a treatment works is in significant noncompliance from the eight possible quarters for each violation type. Data source: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets, obtained from https://echo.epa.gov/tools/data-downloads#downloads.

The main takeaway from Table 2.2 is that 27 percent of the 13,548 publicly owned treatment works in the U.S. had at least one significant noncompliance violation in 2023 or 2024, amounting to 3,660 publicly owned treatment works in noncompliance with the Clean Water Act. Treatment works with a significant noncompliance violation in 2023–2024 were reported quarterly as noncompliant a mean of three times. The majority of significant noncompliance violations were for effluent exceeding monthly average discharge monitoring report limits.

Table 2.2 shows that 27.02 percent of the 13,548 publicly owned treatment works in the U.S. had at least one violation in 2023 or 2024, amounting to 3,660 publicly owned treatment works in significant noncompliance with the Clean Water Act. Treatment works with a significant noncompliance violation in 2023–2024 were reported quarterly as noncompliant a mean of nearly three times (2.9158).

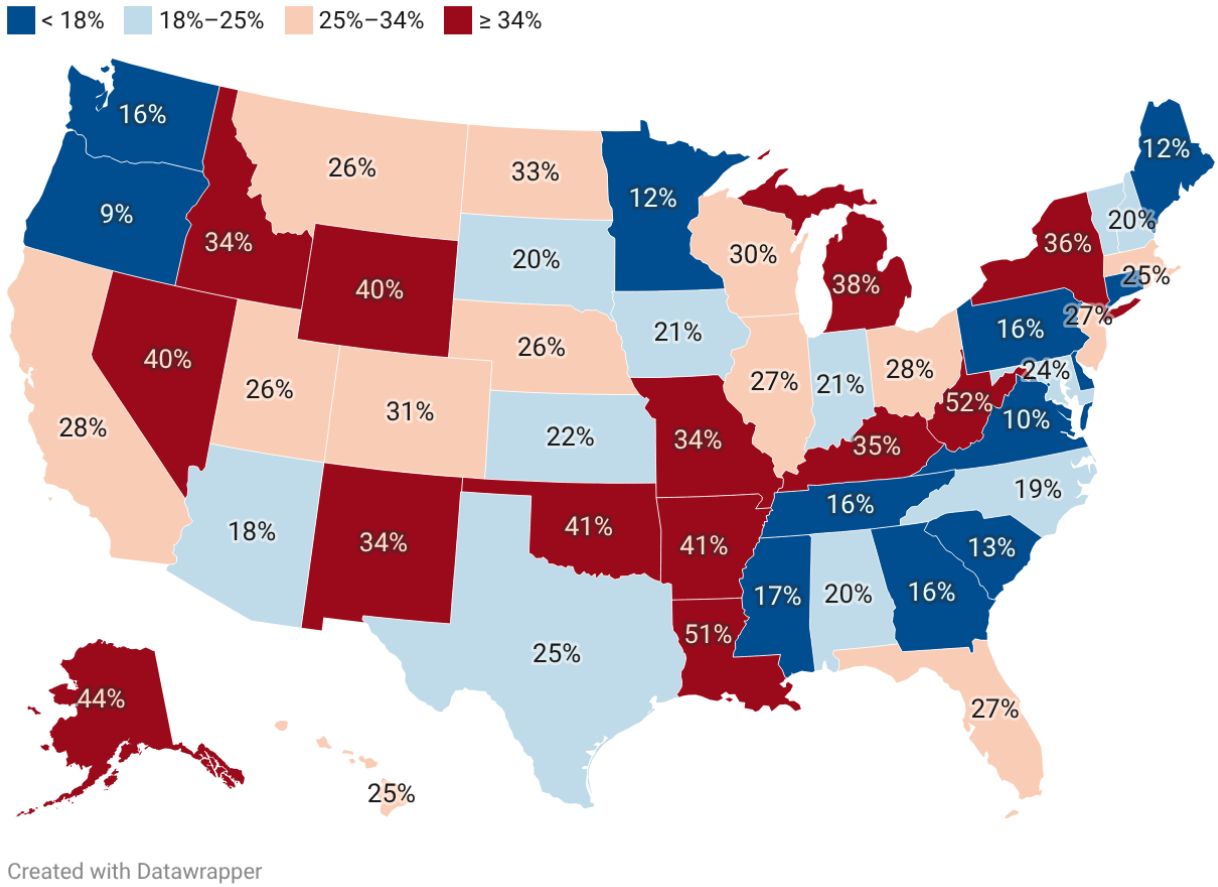
The majority of significant noncompliance violations are effluent violations exceeding average discharge monitoring report limits, with 14.70 percent of publicly owned treatment

[1] The dataset for quantitative analysis was constructed by combining the US Environmental Protection Agency's 2025 Sewershed Boundaries Map containing information for 17,272 unique publicly owned treatment works with permit information and treatment works characteristics from the US Environmental Protection Agency's Clean Watershed Needs Survey (Table A.1) and the US Environmental Protection Agency's Enforcement and Compliance History Online Integrated Compliance Information System for the National Pollutant Discharge Elimination System dataset for 2025 Q2 (Table A.2).

works in significant noncompliance due to effluent violations. The second most common significant noncompliance reason is reporting violations from non-receipt of discharge monitoring reports, with 8.65 percent of treatment works having at least one of these violations. These two violations also take the longest to resolve with a mean number of quarters in significant noncompliance of 0.3851 (roughly 1 month) for effluent violations and 0.2067 (a little more than one month) for failing to report discharge monitoring reports.

Figure 2.1 illustrates the geographical variation in Clean Water Act significant noncompliance by mapping the proportions of publicly owned treatment works that had at least one significant noncompliance violation in 2023 or 2024 within each state. The map is color coded to reflect four quantiles of equal counts (i.e., the same number of states in each quantile), where the darkest blue color indicates less than 18 percent of treatment works within a state are significantly noncompliant.

Figure 2.1. Proportion of Significant Noncompliant Treatment Works by State, 2023-2024



Note: This figure illustrates the proportions of publicly owned treatment works that had at least one significant noncompliance violation in 2023 or 2024 within each state. The map is color coded to reflect four quantiles of equal state counts. Data source: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets, from https://echo.epa.gov/tools/data-downloads#downloads.

The main takeaway from Figure 2.1 is there is considerable variation in publicly owned treatment works' significant noncompliance across states. The treatment works facility in Washington DC was compliant with the Clean Water Act in 2023 and 2024, while more than 50 percent of treatment works in West Virginia and Louisiana had at least one significant noncompliance violation during these two years, potentially impacting more than 6.37 million people. West Virginia also had the highest proportions of its community water systems (71 percent) in violation of the Safe Drinking Water Act in 2023 and 2024 (Khalaf et al., 2026).

As shown in Figure 2.1, Oregon (9 percent), Delaware (9 percent), Virginia (10 percent), Maine (12 percent), Minnesota (12 percent), and South Carolina (13 percent) have the lowest proportions of publicly owned treatment works in significant noncompliance with less than 15 percent in each state having a violation in 2023 or 2024. Notably, Minnesota, Delaware, and South Carolina are also among the states with the lowest proportions of community water systems in noncompliance with the Safe Drinking Water Act during this same time (Khalaf et al., 2026). In addition, DC's one treatment works facility is in significant compliance both years.[2]

In contrast, Figure 2.1 shows Louisiana (51 percent) and West Virginia (52 percent) have the highest proportions of treatment works in significant noncompliance, with more than 50 percent in each state having such violations in 2023 or 2024. West Virginia also had the highest proportion of noncompliance with the Safe Drinking Water Act with 71 percent of its community water systems having one or more violations in 2023 or 2024 (Khalaf et al., 2026).

Figure 2.2 illustrates changes in all publicly owned treatment works nationwide between significant compliance and significant noncompliance with the Clean Water Act year-over-year from 2018-2024. Although not shown, 6,065 (44.77 percent) treatment works were in significant compliance with the Clean Water Act each year 2018-2024, 338 (2.49 percent) had at least one significant noncompliance violation each year during this time, and the remaining 7,145 (52.74 percent) moved between significant compliance and significant noncompliance.

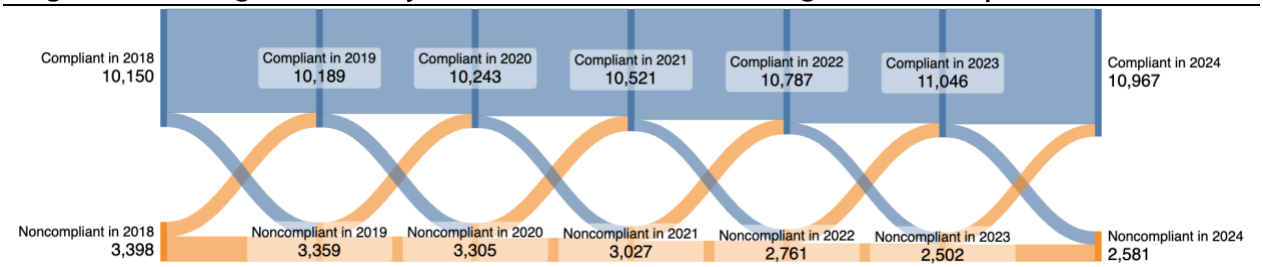
The main takeaway from Figure 2.2 is that the number of publicly owned treatment works in significant compliance with the Clean Water Act increased eight percent during 2018-2024, from 10,150 to 10,967, while those in significant noncompliance decreased 24 percent, from 3,398 to 2,581.

As shown in Figure 2.2, the number of publicly owned treatment works in significant compliance with the Clean Water Act increased eight percent during 2018-2024, from 10,150 to 10,967. Those in significant noncompliance decreased 24 percent, from 3,398 to 2,581. Generally, the number of publicly owned treatment works in significant

[2] This study uses the term 'significant compliance' to describe publicly owned treatment works that are not in significant noncompliance but may unknowingly (because it is outside the scope of this study) be in noncompliance with the Clean Water Act for violations that are not categorized as significant noncompliance.

noncompliance decreased year-over-year, with declines of 39 (1.15 percent) 2018-2019, 54 (1.61 percent) 2019-2020, 278 (8.41 percent) 2020-2021, 266 (8.79 percent) 2021-2022, and 259 (9.38 percent) 2022-2023. However, the change in significant noncompliant treatment works increased 2023-2024 by 79 or 3.16 percent.

Figure 2.2. Changes in Publicly Owned Treatment Works Significant Compliance, 2018-2024



Note: This figure illustrates changes in all publicly owned treatment works nationwide between significant compliance and significant noncompliance with the Clean Water Act year-over-year from 2018-2024. Data source: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets, obtained from https://echo.epa.gov/tools/data-downloads#downloads.

2.1.2. Treatment Works and Sewershed Characteristics

Table 2.3 lists summary statistics for all publicly owned treatment works of all variables used for analysis. As described above, *Significant Noncompliance* is a binary variable equal to one if a publicly owned treatment works is in significant noncompliance, i.e., had any significant noncompliance violation in 2023 or 2024, and zero otherwise. The *Quarters Significant Noncompliance* is a count of the total number of quarters of each significant noncompliance violation that each publicly owned treatment works had in 2023 and 2024. If a treatment works had no violations in either year, the *Quarters Significant Noncompliance* equals zero. *Significant Noncompliance 2018-2022* is also a binary variable equal to one if a publicly owned treatment works had at least one significant noncompliance violation at any point from 2018 to 2022, and zero otherwise.

The main takeaway for these significant noncompliance variables in Table 2.3 is that 27 percent of publicly owned treatment works were in significant noncompliance in 2023 or 2024, and nearly half had a history of significant noncompliance with at least one significant noncompliance violation in the five years prior. The mean quarters in significant noncompliance in 2023 and 2024 is 0.7877, indicating that treatment works can resolve their significant noncompliance violations in a little over two months.

The mean for *Significant Noncompliance* is 0.2702, indicating that 27.02 percent of treatment works were in significant noncompliance in 2023 or 2024. The mean *Quarters Significant Noncompliance* in 2023 and 2024 is 0.7877, indicating that treatment works are able to resolve their significant noncompliance violations in a little over two months. However, among those treatment works with a significant noncompliance violation in 2023-2024, the mean time in significant noncompliance is nearly three quarters (Table 2.6), reflecting that the violations for this group typically take nearly nine months to resolve. Finally, nearly half (49.09 percent) of publicly owned treatment works had at least one significant noncompliance violation in the years 2018-2022.

Table 2.3. Summary Statistics: All Publicly Owned Treatment Works

Variables	Mean	Standard Deviation	Minimum	Maximum
Dependent Variables				
Significant Noncompliance	0.2702	0.4441	0	1
Quarters Significant Noncompliance	0.7877	1.6937	0	13
Plant-Level Characteristics				
Ownership				
Federal Facility	0.0006	0.0242	0	1
County Govt.	0.0131	0.1135	0	1
Municipal Govt.	0.1734	0.3786	0	1
Municipal Water District	0.5726	0.4947	0	1
Mixed Ownership	0.0051	0.0712	0	1
Tribal Govt.	0.0010	0.0315	0	1
State Govt.	0.0043	0.0652	0	1
Privately Owned	0.0084	0.0911	0	1
Population Served	15,632.91	86,574.21	1	3,353,576
Part of Sewershed Network	0.1797	0.3839	0	1
Endpoint Facility	0.9796	0.1413	0	1
Pretreatment Program	0.1909	0.3930	0	1
Compliance Evaluation Inspection	0.3479	0.4763	0	1
Reconnaissance Inspection	0.0472	0.2120	0	1
Performance Audit Inspection	0.0266	0.1608	0	1
Follow-Up Inspection	0.0158	0.1247	0	1
Formal Enforcement Action	0.0654	0.3308	0	9
Sig. Noncompliance 2018-2022	0.4909	0.4999	0	1
Proportion Unreported Data	27.84%	5.30%	10.71%	71.43%
Known Data Problems	0.1515	0.3585	0	1
Potential Data Problems	0.3859	0.4868	0	1
Sewershed Characteristics				
Population Density (per sq km)	2,234.11	28,963.31	0.78	2,695,594.00
Median Household Income	$71,396.19	$25,040.15	$17,900.00	$250,000.70
Median Age	42.52	6.27	20.85	73.80
Proportion of Housing Stock				
Built Before 1960	29.12%	17.00%	0.00%	90.70%
Built 1960-1969	9.08%	4.79%	0.00%	57.05%
Built 1970-1979	15.52%	6.14%	0.00%	68.37%
Built 1980-1989	12.19%	6.30%	0.00%	73.44%

Note: The number of publicly owned treatment works is 17,085; however, only 13,548 (79.30 percent) treatment works could be matched to compliance, inspection, enforcement, and data reporting information. Due to highly skewed distributions, natural log values are used to normalize the distributions for analysis for Population Served, Population Density, and Median Household Income. Missing data for sewershed variables (Median Household Income, Median Age, and Proportion of Housing Stock) were imputed using the median of the observed values. The imputation impacts 3.89% of observations for income, 1.74% for age, and 2.36% for the housing stock proportions. Robustness checks were conducted to assess the sensitivity of the regression results to the imputations by (i) excluding imputed observations and (ii) including indicator variables for imputed values, and the results were substantively unchanged. Data sources: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets obtained from https://echo.epa.gov/tools/data-downloads#downloads, and U.S. Census Bureau's American Community Survey 2018-2022 5-year estimates obtained from https://www.census.gov/programs-surveys/acs.html.

In the U.S. Environmental Protection Agency's Integrated Compliance Information System for the National Pollutant Discharge Elimination System dataset, publicly owned treatment works are coded to indicate the ownership categories included in this analysis: federal facility, county government, municipal government, municipal water district, mixed

ownership, tribal government, state government, or privately owned.[3] In this analysis, each ownership category is a binary variable coded one to reflect each ownership type and zero otherwise. The means of these variables in Table 2.3 indicate that the majority (57.26 percent) of publicly owned treatment works are owned by a *Municipal Water District*, 17.34 percent by a *Municipal Government*, and 1.31 percent by a *County Government*. The remaining ownership categories (*Federal Facility*, *Mixed Ownership*, *Tribal Government*, *State Government*, and *Privately Owned*) each comprise less than one percent of publicly owned treatment works. Treatment works' ownership parallels that of community water systems in which nearly 50 percent of the 44,481 active systems during this same time period were owned by local governments (Khalaf et al., 2026).

Population Served is a measure of publicly owned treatment works' size, which varies significantly from one to 3.35 million, but with treatment works serving a mean population of 15,633.[4] *Part of a Sewershed* (referred to here as *Part of a Sewershed Network*) and *Endpoint Facility* are binary variables from the U.S. Environmental Protection Agency National Sewershed Dataset. These variables result from modeling sewershed hexagons, based on the probability that a hexagon is part of the sewershed network for a given endpoint location associated with a publicly owned treatment works (U.S. Environmental Protection Agency, 2025). The U.S. Environmental Protection Agency defines a sewershed as the geographic area from which all sewers flow to a single endpoint wastewater treatment facility, which is where wastewater is treated to meet environmental standards before it is discharged as clean effluent into the environment.[5] Nearly 18 percent (mean value 0.1797) of publicly owned treatment works may be *Part of a Sewershed Network*, while almost all of them (97.96 percent) include an *Endpoint Facility*.

Also measured as a binary variable, a smaller portion (19.09 percent) of publicly owned treatment works implement a *Pretreatment Program*, which is a component of the National Pollutant Discharge Elimination System program designed to protect publicly owned treatment works' infrastructure by reducing conventional and toxic pollutant levels discharged by industries and other nondomestic wastewater sources into municipal sewer systems and into the environment. Specifically, the National Pretreatment Program is a federally mandated, local regulatory framework that requires some industrial and commercial dischargers to treat wastewater to remove harmful pollutants before sending it to a municipal sewage system. This program helps to prevent interference with treatment processes, protects sewer infrastructure, ensures safety for workers, and prevents toxins from entering into the environment.[6] It is important to note that many variables related to the plant-level characteristics, such as Total Design Flow (MGD) or Average Actual Flow (MGD), contained large amounts of missing data and were not included in the report.

[3] Despite the name, Publicly Owned Treatment Works can be privately owned, operated, or managed through various privatization methods, such as sales, long-term leases, or contract operations.
[4] Due to its highly skewed distribution, natural log values are used to normalize the distribution for analysis for Population Served.
[5] For additional information, see: https://www.epa.gov/cwns/sewersheds.
[6] For additional information, see: https://www.epa.gov/npdes/national-pretreatment-program.

The main takeaway from these treatment works-level variables in Table 2.3 is that over 75 percent of publicly owned treatment works are owned by a Municipal Water District, Municipal Government, or County Government. Over 19 percent of publicly owned treatment works implement a pretreatment program.

Ensuring compliance with the Clean Water Act requires state site visits that are conducted for different purposes, which may be accomplished simultaneously or through multiple visits. In this analysis, each of these site visit reasons are coded as mutually exclusive binary variables to indicate whether a publicly owned treatment works received such a visit in 2022. While it is entirely possible that one site visit could fulfill more than one of these needs, these variables provide insight into the extent to which oversight was provided during this time. As Table 2.3 shows, the largest proportion of inspections are for evaluation purposes, as 34.79 percent of publicly owned treatment works had a *Compliance Evaluation Inspection* in 2022. A compliance evaluation inspection is a non-sampling inspection designed to verify a publicly owned treatment work's compliance with applicable chemical and biological self-monitoring requirements, effluent limits, effluent toxicity, and compliance schedules (U.S. Environmental Protection Agency, 2017b).

Showing less frequency, 4.72 percent of publicly owned treatment works had a *Reconnaissance Inspection*, 2.66 percent had a *Performance Audit Inspection*, and 1.58 percent required a *Follow-Up Inspection* in 2022. A reconnaissance inspection is an on-site inspection (conducted with or without sampling) used to obtain a preliminary overview of a publicly owned treatment works' compliance program, including a visual inspection of the treatment facility, effluents, and receiving waters (U.S. Environmental Protection Agency, 2017b). A performance audit inspection is used to evaluate a publicly owned treatment works' self-monitoring program by evaluating procedures for sample collection, flow measurement, chain-of-custody, laboratory analyses, data compilation, and reporting, among other areas (U.S. Environmental Protection Agency, 2017b). Finally, a follow-up inspection is conducted when a routine inspection or complaint identifies a compliance problem to determine the appropriate enforcement action (U.S. Environmental Protection Agency, 2017b).

Perhaps due to problems revealed by inspections, publicly owned treatment works received between zero and nine *Formal Enforcement Actions* in 2023 and 2024. Although not shown in Table 2.3, 12,815 of the 13,548 publicly owned treatment works (94.59 percent) required no formal enforcement action either year. Of the 733 plants (5.41 percent) receiving a formal enforcement action, the majority (649 or 88.54 percent) required only one. Of the remaining 84 publicly owned treatment works, 56 received two formal enforcement actions, 14 received three, and the remaining 14 received four or more. These trends are noteworthy since 49.09 percent of publicly owned treatment works had at least one significant noncompliance violation in the years (2018-2022) leading up to the inspections conducted in 2022 and enforcement actions undertaken in 2023 and 2024.

The U.S. Environmental Protection Agency's Integrated Compliance Information System database presents data reported to the U.S. Environmental Protection Agency by states

from National Pollutant Discharge Elimination System permit holders, as mandated by the Clean Water Act. However, there is considerable variation in how much information is reported, which could occur for a number of unknown reasons, including the extent of work conducted by each state. Similarly, the U.S. Environmental Protection Agency National Sewershed Dataset is subject to limitations, including data and positional inaccuracies, reporting inconsistencies, and modeling artifacts, which may affect boundary delineation and endpoint location (U.S. Environmental Protection Agency, 2025). In addition, there are publicly owned treatment works with either known or suspected problems with their reported data. Thus, a measure of information completeness capturing the proportion of missing information in the self-reported data, as well as two measures of data problems, are included in the quantitative analysis.

The *Proportion Unreported Data* has a mean of 27.84 percent, indicating more than one-quarter of self-reported characteristic fields in the U.S. Environmental Protection Agency's Integrated Compliance Information System database contain missing values. In addition, 15.15 percent of publicly owned treatment works have *Known Data Problems*, and 38.59 percent have *Potential Data Problems* with their self-reported information provided to the U.S. Environmental Protection Agency. This means that the U.S. Environmental Protection Agency has flagged the data from these treatment works as having some issues when the data were migrated from the states to the national database (U.S. Environmental Protection Agency, January 2026). Treatment works with *Known Data Problems* have specific documented data issues that might impact the results of analysis that include them, whereas systems with *Potential Data Problems* have general documented data issues that may or may not impact results of analysis that include them. Robustness checks presented in Appendix A provide regression results by excluding treatment works with known and potential data problems.

The main takeaway from these treatment works-level oversight and enforcement variables in Table 2.3 is that compliance evaluation inspections are most common, as they are statutorily required, with nearly 35 percent of publicly owned treatment works receiving one in 2022. Yet less than two percent required a follow-up inspection, and about five percent of treatment works required a formal enforcement action for observed noncompliance.

Population Density reflects how concentrated the population is in a given publicly owned treatment works' sewershed. This was calculated based on the total residential population served by each publicly owned treatment work in 2022 divided by the area of the sewershed, in square kilometers. A treatment works' sewershed has a mean of 2,234 individuals per km^2, a *Median Household Income* equal to $71,396, and a *Median Age* of 43.[7] The final set of variables in the *Proportion of Housing Stock* category focuses on the age of housing stock in a publicly owned treatment works' sewershed. A treatment works'

[7] Publicly owned treatment work's sewershed variables are spatially weighted averages of information available at the Census tract level. Due to highly skewed distributions, natural log values are used to normalize the distributions for analysis for Population Density, and Median Household Income.

sewershed has a mean of 29.12 percent of houses *Built Before 1960*, 9.08 percent *Built 1960–1969*, 15.52 percent *Built 1970–1979*, and 12.19 percent *Built 1980–1989*.

2.1.3. Historical Noncompliance

Table 2.4 groups publicly owned treatment works into those that were *Consistently Significantly Compliant* (i.e., never had any significant noncompliance violation), *In/Out of Significant Compliance* (i.e., had a significant noncompliance violation at least once), and in *Persistent Significant Noncompliance* (i.e., had a significant noncompliance violation every year) between 2018 and 2022 to provide comparisons among these three groups with all variables of interest. Column (4) in Table 2.4 reports the p-values from one-way Analysis of Variance (ANOVA) tests.[8] Each p-value reflects the result of testing for statistically significant differences in the means of each variable among the three groups. So, the numbers listed in columns (1)-(3) are the means for publicly owned treatment works within each group.

Since the first p-value listed in Table 2.4 is statistically significant (i.e., $p<0.01$), the test result indicates there are differences among the three groups in terms of significant noncompliance violations in 2023-2024. As shown, all publicly owned treatment works in persistent significant noncompliance 2018-2022 also had a significant noncompliance violation in 2023-2024 (mean=1.0; $p<0.01$). These persistent violators were also in significant noncompliance for a greater number of quarters ($p<0.01$), at 5.6953 (roughly 17 months) compared to 1.2242 (approximately three and a half months) for those in and out of significant compliance.

The main takeaway from Table 2.4 is that all persistently noncompliant publicly owned treatment works with at least one significant noncompliance violation each year 2018-2022 were also in significant noncompliance in 2023-2024 and were in significant noncompliance for about 17 months longer than treatment works in and out of compliance. Persistently noncompliant treatment works are associated with a higher proportion of County Government ownership, smaller total populations served, fewer pretreatment programs, lower membership in sewershed network, and lower rates of compliance evaluation inspections, while at the same time having the highest proportions of reconnaissance inspections, follow-up inspections, formal enforcement actions, unreported data, and known data problems.

In terms of ownership, county governments, municipal governments, and municipal water districts own most of the publicly owned treatment works. Among those owned by county governments ($p<0.01$), the greatest proportion (4.73 percent) are persistently in significant

[8] One-way Analysis of Variance is a statistical method used to determine if there are statistically significant differences in the means of three or more groups by comparing the variance between groups to the variance within groups using an F-statistic. Specifically, ANOVA tests the null hypothesis that all group means are equal against the alternative hypothesis that at least one group mean differs from the others. Reported p-values below conventional statistical thresholds ($p<0.05$ or $p<0.01$) allow for the null hypothesis to be rejected, thereby leading to the conclusion that there are observed differences among group means that are unlikely to be due to random sampling variation alone.

Table 2.4. Comparison of Treatment Works Based on Significant Compliance, 2018–2024

Variables	Consistent Significant Compliance (1)	In/Out of Significant Compliance (2)	Persistent Significant Noncompliance (3)	P-value (ANOVA) (4)
Dependent Variables				
Significant Noncompliance	0	0.4649	1	<0.001
Quarters Significant Noncompliance	0	1.2242	5.6953	<0.001
Plant-Level Characteristics				
Ownership				
Federal Facility	0.0010	0.0006	0.0000	0.5839
County Govt.	0.0206	0.0115	0.0473	<0.001
Municipal Govt.	0.2483	0.1978	0.1302	<0.001
Municipal Water District	0.6852	0.7523	0.7456	<0.001
Mixed Ownership	0.0043	0.0078	0.0148	0.0058
Tribal Govt.	0.0008	0.0010	0.0148	<0.001
State Govt.	0.0043	0.0064	0.0030	0.2005
Privately Owned	0.0106	0.0105	0.0118	0.9727
Population Served	19,970.44	16,681.41	7,212.72	0.0153
Part of Sewershed Network	0.2147	0.1740	0.1479	<0.001
Endpoint Facility	0.9784	0.9818	0.9645	0.0482
Pretreatment Program	0.2852	0.2109	0.0710	<0.001
Compliance Evaluation Inspection	0.3425	0.3551	0.2929	0.0314
Reconnaissance Inspection	0.0392	0.0516	0.0947	<0.001
Performance Audit Inspection	0.0280	0.0259	0.0148	0.2954
Follow-Up Inspection	0.0087	0.0213	0.0266	<0.001
Formal Enforcement Action	0.0284	0.0925	0.1568	<0.001
Sig. Noncompliance 2018–2022	0	0.8836	1	<0.001
Proportion Unreported Data	0.2764	0.2795	0.2915	<0.001
Known Data Problems	0.1322	0.1638	0.2367	<0.001
Potential Data Problems	0.3977	0.3790	0.3195	0.0036
Sewershed Characteristics				
Population Density (per sq km)	2,392.42	1,948.77	1,254.74	0.5638
Median Household Income	$74,530.65	$70,564.81	$64,003.27	<0.001
Median Age	42.44	42.42	41.95	0.3332
Proportion of Housing Stock				
Built Before 1960	0.2849	0.2996	0.2789	<0.001
Built 1960–1969	0.0894	0.0931	0.0926	<0.001
Built 1970–1979	0.1528	0.1556	0.1633	<0.001
Built 1980–1989	0.1204	0.1178	0.1297	<0.001
Number of Observations	6,065	7,145	338	

Note: The *Consistent Significant Compliance* category includes all publicly owned treatment works that never had any significant noncompliance violation 2018–2022. *In/Out of Significant Compliance* includes all treatment works with at least one significant noncompliance violation 2018–2022. *Persistent Significant Noncompliance* includes treatment works with a significant noncompliance violation each year 2018–2022. The values in columns (1)–(3) reflect the means of each variable for publicly owned treatment works within each group. The p-values in column (4) are from one-way Analysis of Variance (ANOVA) tests comparing the means of each variable across the three compliance groups. Data sources: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets obtained from https://echo.epa.gov/tools/data-downloads#downloads, and U.S. Census Bureau's American Community Survey 2018–2022 5-year estimates obtained from https://www.census.gov/programs-surveys/acs.html.

noncompliance, compared to 2.06 percent in consistent significant compliance, and 1.15 percent in/out of significant compliance. Municipal government owned treatment works are most likely to consistently remain in significant compliance ($p<0.01$) with 24.83 percent in this category, compared to 19.78 percent in/out of significant compliance, and 13.02 percent

persistently in significant noncompliance. Municipal water district owned treatment works fall in between ($p<0.01$), as 75.23 percent are in/out of significant compliance compared to 74.56 percent in persistent significant noncompliance and 68.52 percent consistently in significant compliance.

Publicly owned treatment works in consistent significant compliance are also larger, with a mean of 19,970.44 population served, while those in persistent significant noncompliance are smallest with a mean of 7,212.72 population served ($p=0.153$). Treatment works in consistent significant compliance are more likely to be part of a sewershed network ($p<0.01$) and implement a pretreatment program ($p<0.01$). Consistently significantly compliant treatment works have a lower proportion of unreported data ($p<0.01$) and known data problems ($p<0.01$) but have the highest proportion of potential data problems ($p=0.0036$). Unsurprisingly, publicly owned treatment works in consistent significant compliance had the lowest rates of reconnaissance inspections ($p<0.01$), follow-up inspections ($p<0.01$), and formal enforcement actions ($p<0.01$).

Publicly owned treatment works in persistent significant noncompliance are least likely to be part of a sewershed network ($p<0.01$) or implement a pretreatment program ($p<0.01$). Interestingly, this group of treatment works receives the least amount of evaluation inspections (0.0134). However, treatment works in persistent significant noncompliance receive the highest proportions of reconnaissance inspections ($p<0.01$), follow-up inspections ($p<0.01$), and formal enforcement actions ($p<0.01$). These publicly owned treatment works also have the highest rates of unreported data ($p<0.01$) and known data problems ($p<0.01$), suggesting persistent significant noncompliance with the Clean Water Act may be tied to oversight and enforcement as intended.

In terms of sewershed characteristics, publicly owned treatment works consistently in significant compliance have the highest median household income, while those persistently in significant noncompliance have the lowest median household income ($p<0.01$). Although the p-values for each of the housing stock variables is statistically significant ($p<0.01$), the mean differences among the three groups do not display a consistent pattern.

Notably, there are no statistically significant differences in mean values among the groups in terms of publicly owned treatment works owned by the federal or state governments and private entities, those receiving performance audit inspections, or treatment works operating in communities with varied population densities or median ages.

2.1.4. Government Finance Characteristics

Table 2.5 provides comparisons of all variables for analysis between all publicly owned treatment works (N=17,085) to a subset of only those owned by local governments (N=12,969), which comprise 75.91 percent. Notably, local government ownership of publicly owned treatment works exceeds that of community water systems in which 52.11 percent are owned by municipal, county, or township governments (Khalaf et al., 2026). Due to the higher ownership rate by local governments of publicly owned treatment works, the summary statistics for this group are relatively comparable to all treatment works.

Table 2.5. Summary Statistics: All Treatment Works Compared to Govt. Owned

	All Treatment Works		Local Govt. Owned Works	
Variables	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**
Dependent Variables				
Significant Noncompliance	0.2702	0.4441	0.2703	0.4441
Quarters Significant Noncompliance	0.7877	1.6937	0.7779	1.6701
Plant-Level Characteristics				
Ownership				
Federal Facility	0.0006	0.0242		
County Govt.	0.0131	0.1135	0.0172	0.1300
Municipal Govt.	0.1734	0.3786	0.2285	0.4199
Municipal Water District	0.5726	0.4947	0.7543	0.4305
Mixed Ownership	0.0051	0.0712		
Tribal Govt.	0.0010	0.0315		
State Govt.	0.0043	0.0652		
Privately Owned	0.0084	0.0911		
Population Served	15,632.91	86,574.21	18,330.58	96,655.04
Part of Sewershed Network	0.1797	0.3839	0.1939	0.3954
Endpoint Facility	0.9796	0.1413	0.9803	0.1391
Pretreatment Program	0.1909	0.3930	0.2485	0.4322
Compliance Evaluation Inspection	0.3479	0.4763	0.3532	0.4780
Reconnaissance Inspection	0.0472	0.2120	0.0476	0.2129
Performance Audit Inspection	0.0266	0.1608	0.0256	0.1579
Follow-Up Inspection	0.0158	0.1247	0.0161	0.1259
Formal Enforcement Action	0.0654	0.3308	0.0669	0.3350
Sig. Noncompliance 2018-2022	0.4909	0.4999	0.4914	0.4999
Proportion Unreported Data	27.84%	5.30%	0.2766	0.0518
Known Data Problems	0.1515	0.3585	0.1508	0.3579
Potential Data Problems	0.3859	0.4868	0.3874	0.4872
Sewershed Characteristics				
Population Density (per sq km)	2,234.11	28,963.31	2,124.63	28,513.15
Median Household Income	$71,396.19	$25,040.15	$72,120.79	$25,123.34
Median Age	42.52	6.27	42.41	5.86
Proportion of Housing Stock				
Built Before 1960	29.12%	17.00%	29.60%	16.77%
Built 1960-1969	9.08%	4.79%	9.19%	4.77%
Built 1970-1979	15.52%	6.14%	15.42%	5.94%
Built 1980-1989	12.19%	6.30%	11.84%	6.03%
Government Finance				
Debt Service Burden			0.0342	0.7169
Risk Exposure Factor			3	128
Operating Expenditure Ratio			0.8450	0.2190
Water Revenue Expenditure Ratio			1	13
Full Time Employees			1,240.653	4,971.614

Note: The number of observations is 17,085 (or 13,548 for compliance-related variables) for all publicly owned treatment works and 12,969 for local government owned treatment works. Missing data for Full Time Employees (0.59 percent of observations) as well as for those publicly owned treatment works that could not be matched to census of governments finance data (0.65 percent of observations) were recoded as zeros. Robustness checks were conducted to assess the sensitivity of the regression results to the recoding by excluding recoded observations, and the results were substantively unchanged. Data sources: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets obtained from https://echo.epa.gov/tools/data-downloads#downloads, U.S. Census Bureau's American Community Survey 2018-2022 5-year estimates obtained from https://www.census.gov/programs-surveys/acs.html, and U.S. Census Bureau's Census of Governments Finance Survey data for 2022 obtained from: https://www.census.gov/programs-surveys/cog.html.

The main takeaway from Table 2.5 is that local governments own 75 percent of all publicly owned treatment works, so these treatment works have very similar significant noncompliance rates and quarters in significant noncompliance compared to all. However, local government owned treatment works tend to serve larger populations, are more likely to implement a pretreatment program, and receive more oversight and formal enforcement actions.

The mean for *Significant Noncompliance*, the dependent binary variable in this analysis, is 0.2702, indicating that 27.02 percent of publicly owned treatment works had a significant noncompliance violation in 2023 or 2024 for the full sample compared to 27.03 percent for local government owned treatment works. The standard deviations are the same between the two groups. *Quarters Significant Noncompliance* shows a little more variation, with all publicly owned treatment works having a mean of 0.7877 quarters in significant noncompliance compared to 0.7779 for local government owned treatment works.

Finally, in terms of data problems that may reflect oversight intensity, the *Proportion Unreported Data* among all publicly owned treatment works has a mean of 27.84 percent compared to 27.66 percent of local government owned treatment works. *Known Data Problems* are present for 15.15 percent of all publicly owned treatment works and 15.08 percent of those owned by local governments. *Potential Data Problems* have been identified for 38.59 percent of all publicly owned treatment works versus 38.74 percent of local government owned treatment works.

Population Density has a mean of 2,234.11 and 2,124.63 individuals per km^2 for all publicly owned treatment works and those owned by local governments, respectively. *Median Household Income* is equal to $71,396.19 for all publicly owned treatment works compared to $72,120.79 for local government owned treatment works, while the *Median Age* is roughly 42 for both groups.[9] In addition, local government owned treatment works have sewersheds with a mean of 29.60 percent (compared to 29.12 percent for all publicly owned treatment works) *Proportion of Housing Stock Built Before 1960*, 9.19 percent (compared to 9.08 percent) *Built 1960–1969*, 15.42 percent (compared to 15.52 percent) *Built 1970–1979*, and 11.84 percent (compared to 12.19 percent) *Built 1980–1989*.

The final group of variables included in Table 2.5 focus on local government financial conditions. In the Census of Governments Finance survey data, total revenues and total expenditures reflect all four sectors of government activity: general government, utilities, liquor stores, and social insurance trust. General revenue reflects revenue earned by the general government sector only (excluding utility, liquor store, and insurance trust sectors) from external sources and consists of: 1) taxes, 2) intergovernmental revenue, 3) current charges, and 4) miscellaneous general revenue, net of internal or interfund transfers.[10] This

[9] Due to highly skewed distributions, natural log values are used to normalize the distributions for analysis for Population Density, and Median Household Income.

[10] See U.S. Bureau of the Census, Government Finance and Employment Classification Manual, available at: https://www2.census.gov/govs/pubs/classification/2006_classification_manual.pdf.

classification is based on the nature of the revenue source and not the fund or administrative unit that accounts for or controls a particular activity.

Among the four categories of general revenue, intergovernmental revenue comprises monies from other governments and is therefore the only category outside of a government's own controllable sources. Further, all intergovernmental revenue is reported by the Census of Governments in the general government sector, even if it is used to support activities in other sectors, like publicly owned treatment works. The remaining portion of general revenue (i.e., taxes, current charges, and miscellaneous revenue, net of internal or interfund transfers) is considered own-source revenue. In addition, the Census of Governments Finance survey data include information on indebtedness, which is also only reported in the general government sector, regardless of its use. Debt information includes total debt outstanding and interest expenditures paid on outstanding debt, among other variables.

The main takeaway for the government finance variables in Table 2.5 is that local governments that own treatment works spend about 3 percent of their total revenue to cover interest costs on outstanding debt, would need to levy an additional $3 in property tax revenue to offset a $1 reduction in intergovernmental revenue, and dedicate 84 percent of total spending to cover operations. In addition, these local governments levy exactly the amount needed to fund their water utilities.

In this analysis, *Debt Service Burden*, calculated as interest expenditures on debt (from all sectors) divided by total revenue (from all sectors), has a mean value of 0.0342, suggesting that local governments are required to expend a mean of 3.42 percent of total revenue to cover interest costs on outstanding debt. The *Risk Exposure Factor* is defined as intergovernmental revenue (reflecting the amount of revenue that might decline due to factors totally outside of the local government's control) divided by property tax revenue (reflecting the largest source of controllable revenue for most local governments). The mean value of 3 indicates that a $1 decline in uncontrollable revenue would require an additional $3 levied in property tax revenue to make up the difference.

The *Operating Expenditure Ratio*, measured as total current operating expenditure (for all sectors) divided by total expenditure (for all sectors), has a mean of 0.8450, indicating that most spending (84.50 percent) is devoted to ongoing operations and must therefore be funded by revenue collected in the same fiscal year. However, the *Water Revenue Expenditure Ratio*, defined as water utility sector revenue divided by water utility sector expenditure has a mean of one, indicating local governments that own treatment works levy exactly the amount needed for expenditures. Finally, local governments with treatment works employ a mean of nearly 1,240 full time employees; however, the number of full-time local government employees varies considerably depending on the size of the population served with a standard deviation of nearly 4,972.

2.2. Methods

2.2.1. Binary Dependent Variable

As previously mentioned, one of the dependent variables used for analysis is binary and equal to one if a publicly owned treatment works had any Clean Water Act significant noncompliance violations in 2023 or 2024. As such, this model is estimated using Probit, with Logit and Linear Probability estimation results reported for robustness in Table A.5. It is important to note that the estimated coefficients from the Probit model do not directly reflect changes in outcome probabilities. Thus, marginal effects are calculated and also reported to translate the coefficients into meaningful changes in the probability of a publicly owned treatment works being in significant noncompliance. All estimations also include state fixed effects to account for unobserved, time-invariant state-level factors that may also correlate with significant noncompliance.

Supplemental Technical Documentation

For binary dependent variables, commonly used estimation methods include the Linear Probability Model (LPM) (Lee et al., 2025), Logit (Demaris, 1992), and Probit (Allaire et al., 2018). The LPM estimates the probability of compliance using ordinary least squares, which allows for a straightforward interpretation of the coefficients as percentage-point changes in the likelihood of compliance. However, because the LPM assumes a linear relationship and can yield predicted probabilities outside the 0–1 range, the use of nonlinear models, e.g. Logit and Probit, that constrain predicted probabilities between 0 and 1, is preferred.

The Logit model uses a logistic cumulative distribution function, while the Probit model uses the standard normal distribution to estimate the probability of noncompliance. Both Logit and Probit provide nearly identical substantive results, though the Probit estimation assumes normally distributed errors and typically produces smoother probability transitions. The Probit model is estimated using the following functional form:

$$Pr\ (Y_i = 1|X) = \Phi\ (B_0 + B_1 P_i + B_2 A_i + \phi_s)$$

where Y_i is a binary indicator of whether publicly owned treatment works i had a significant noncompliance violation in 2023 or 2024, and $\Phi\ (\cdot)$ denotes the cumulative distribution function (CDF) of the standard normal distribution. The probability of a publicly owned treatment works having a significant noncompliance violation is modeled as a function of time-invariant plant-level characteristics (P_i) and sewershed characteristics (A_i).

Each publicly owned treatment works i is correlated with a state s, and the model includes state fixed effects (ϕ_s), which are binary indicator variables for each state to account for unobserved, time-invariant state-level factors. Accounting for unobserved, time-invariant factors is important because the Clean Water Act is primarily enforced at the state level, and enforcement may vary due to differences in sampling protocols, technical capacity, and financial resources (Allaire et al., 2018).

2.2.2. Count Dependent Variable

The other dependent variable is the count of quarters in 2023 and 2024 for which a publicly owned treatment works was in significant noncompliance. Since the number of quarters is measured with whole, non-negative integers representing discrete outcomes, and the

variance in the data exceeds the mean indicating overdispersion, this model is estimated using a Negative Binomial model. Here again, the estimated coefficients from the Negative Binomial model do not directly represent changes in the number of significant noncompliance quarters. Instead, coefficients describe changes in the log of the expected count. Marginal effects are therefore calculated and reported to translate these estimates into meaningful changes in the expected number of quarters for which publicly owned treatment works are in significant noncompliance. All estimations also include state fixed effects to account for unobserved, time-invariant state-level factors.

Supplemental Technical Documentation
For count data as dependent variables, Poisson or Negative Binomial regression is typically used to estimate the correlations of independent variables on the mean count, using maximum likelihood. These models are needed to accurately model the probability distribution because count variables violate the normality and homoskedasticity assumptions of the Linear Probability Model, likely leading to predictions of negative values, which are impossible for count data. Negative Binomial regression is used in this analysis because the variance in the data exceeds the mean, indicating overdispersion (Cameron & Trivedi, 2013).

The Negative Binomial model estimates the expected number of significant noncompliance quarters conditional on a set of covariates and assumes a log link function between the conditional mean and the linear correlates. The model is estimated using the following functional form:

$$E\ (Y_i|X_i) = exp\ (B_0 + B_1 P_i + B_2 A_i + \phi_s)$$

where Y_i denotes the number of quarters in significant noncompliance for publicly owned treatment works i in 2023 and 2024. The expected count of significant noncompliance quarters is modeled as a function of time-invariant plant-level characteristics (P_i) and sewershed characteristics (A_i). The exponential link function ensures that predicted values are strictly non-negative. Each publicly owned treatment works i is correlated with a state s, and the model includes state fixed effects (ϕ_s).

2.2.3. Model Estimations

Covariates included in the Probit and Negative Binomial models were selected based on a review of the extant literature, multicollinearity diagnostics, and expert feedback. These variables are all observed in 2022 and categorized as 1) *Plant-Level*, capturing ownership, service capacity, treatment works attributes, oversight, enforcement, prior significant noncompliance, and reporting, 2) *Sewershed*, capturing population density, median household income, median age, and the age of the housing stock, and for those treatment works owned by local governments, 3) *Government Finance*, capturing local government fiscal capacity.

Since residual errors are likely correlated within states as they share the same regulatory structure and regional water quality, standard errors are clustered at the state level. Failing to account for this within-state correlation could lead to underestimated standard errors and overstated statistical significance.

Supplemental Technical Documentation
Covariates included in the Probit and Negative Binomial models were selected based on a review of the extant literature, multicollinearity diagnostics, and expert feedback. Plant-Level Characteristics (X_i) include variables capturing ownership, service capacity, treatment works attributes, oversight, enforcement, prior significant noncompliance, and reporting. Sewershed Characteristics (C_i) include variables capturing population density, median household income, median age, and the age of the housing stock. The covariates are observed in 2022. Thus, significant noncompliance in 2023-2024 is explained by characteristics determined before the behavior is observed, helping to reduce concerns about potential endogeneity in the model specification (Heberling et al., 2022).

In addition, for a subset of the data, specifically local government owned treatment works, the models are expanded as follows:

$$Pr\ (Y_i = 1|X) = \Phi\ (B_0 + B_1 P_i + B_2 A_i + B_3 G_i + \phi_s)$$
$$E\ (Y_i|X_i) = exp\ (B_0 + B_1 P_i + B_2 A_i + B_3 G_i + \phi_s)$$

where Government Finance Characteristics (G_i) include variables capturing aspects of local government fiscal capacity using commonly used measures obtained from review of extant research.

2.3. Plant-Level Correlates of Significant Noncompliance

Table 2.6 presents regression estimates of plant-level correlates of Clean Water Act significant noncompliance during 2023–2024 across three models. Columns (1)–(2) estimate the likelihood of any significant noncompliance violation for all publicly owned treatment works using Probit. Columns (3)–(4) estimate the number of quarters in significant noncompliance among all publicly owned treatment works using a Negative Binomial regression. Columns (5)-(6) estimate the number of quarters in significant noncompliance for only those publicly owned treatment works with at least one significant noncompliance violation using a Negative Binomial regression.[11]

The main takeaway from Table 2.6 is that publicly owned treatment works are less likely to have a significant noncompliance violation and/or spend less time in significant noncompliance if they have the following plant-level characteristics: a larger population served, serving as an endpoint facility, and ownership by state and local governments or municipal water districts. On the other hand, publicly owned treatment works that received a performance audit or follow-up inspection, or if they received a formal enforcement action, are more likely to have a significant noncompliance violation and/or spend more time in significant noncompliance. Further, publicly owned treatment works with at least one prior significant noncompliance violation in 2018-2022 are most likely to be in significant noncompliance in 2023-2024 and spend the longest amount of time in significant noncompliance.

[11] All models include state fixed effects and cluster standard errors at the state level. Robustness checks are reported in Appendix A. Table A.6 assesses the sensitivity of the results to the functional form. Tables A.7 and A.8 assess the sensitivity of the regression results to missing data imputations by (i) excluding imputed observations and (ii) including indicator variables for imputed values. Table A.9 examines the sensitivity of the results to a shorter timeframe (only 2024) when defining noncompliance.

Table 2.6. Plant-Level Regression Results: All Publicly Owned Treatment Works

	Any Sig. Noncompliance 2023-2024 All Treatment Works		Quarters in Sig. Noncompliance 2023-2024 All Treatment Works		Quarters in Sig. Noncompliance 2023-2024 Noncompliant Works	
Variables	Coefficient (Std. Error) (1)	Marginal Effect (2)	Coefficient (Std. Error) (3)	Marginal Effect (4)	Coefficient (Std. Error) (5)	Marginal Effect (6)
Plant-Level Characteristics						
Ownership						
Federal Facility	0.0298	0.0086	-0.0674	-0.0528	-0.1591	-0.4642
	(0.4801)		(0.7375)		(0.5733)	
County Govt.	**-0.2719***	-0.0780	-0.3542	-0.2778	-0.0804	-0.2346
	(0.1534)		(0.2322)		(0.1088)	
Municipal Govt.	0.1002	0.0288	-0.0692	-0.0543	**-0.2985*****	-0.8706
	(0.1183)		(0.1821)		(0.0838)	
Municipal Water District	0.0110	0.0032	-0.1351	-0.1059	**-0.2539*****	-0.7406
	(0.0917)		(0.1334)		(0.0623)	
Mixed Ownership	**-0.4937*****	-0.1417	**-1.0783****	-0.8456	**-0.4272****	-1.2462
	(0.1619)		(0.4427)		(0.2025)	
Tribal Govt.	0.1315	0.0377	0.1046	0.0820	0.1014	0.2957
	(0.4079)		(0.3824)		(0.1506)	
State Govt.	-0.2711	-0.0778	**-0.8808****	-0.6908	**-0.6986*****	-2.0379
	(0.2088)		(0.3658)		(0.2030)	
Privately Owned	-0.1757	-0.0504	-0.1315	-0.1031	-0.0184	-0.0538
	(0.1628)		(0.2145)		(0.1260)	
Population Served (Ln)	**-0.0241***	-0.0069	**-0.0403****	-0.0316	**-0.0254****	-0.0740
	(0.0125)		(0.0183)		(0.0104)	
Part of Sewershed Network	-0.0396	-0.0114	-0.0668	-0.0524	0.0114	0.0334
	(0.0359)		(0.0519)		(0.0318)	
Endpoint Facility	**-0.2358*****	-0.0677	**-0.2471****	-0.1938	-0.0473	-0.1381
	(0.0776)		(0.1210)		(0.0723)	
Pretreatment Program	-0.0803	-0.0230	-0.1055	-0.0827	-0.0063	-0.0185
	(0.0535)		(0.0786)		(0.0475)	
Compliance Evaluation Inspection	0.0212	0.0061	0.0281	0.0220	-0.0073	-0.0212
	(0.0363)		(0.0559)		(0.0281)	
Reconnaissance Inspection	0.0804	0.0231	0.1345	0.1055	0.0061	0.0177
	(0.0638)		(0.0859)		(0.0713)	
Performance Audit Inspection	**0.1575****	0.0452	0.1499	0.1176	-0.1126	-0.3286
	(0.0745)		(0.1321)		(0.1045)	
Follow-Up Inspection	**0.1202*****	0.0345	**0.3033*****	0.2378	**0.1044*****	0.3045
	(0.0334)		(0.0507)		(0.0346)	
Formal Enforcement Action	**0.3060*****	0.0878	**0.3197*****	0.2507	**0.0895*****	0.2610
	(0.0486)		(0.0537)		(0.0207)	
Sig. Noncompliance 2018-2022	**0.8889*****	0.2551	**1.5803*****	1.2393	**0.4358*****	1.2714
	(0.0409)		(0.0678)		(0.0402)	
Proportion Unreported Data	0.3606	0.1035	0.5761	0.4518	0.0736	0.2148
	(0.4961)		(0.7012)		(0.5169)	
Known Data Problems	0.0802	0.0230	-0.1247	-0.0978	-0.0051	-0.0149
	(0.1107)		(0.3365)		(0.1796)	
Potential Data Problems	**0.4569*****	0.1311	**0.9243*****	0.7249	0.2779	0.8105
	(0.1062)		(0.3347)		(0.1813)	
Mean	0.2702		0.7877		2.9174	
Pseudo R2	0.1287		0.0668		0.0378	
Number of Observations	13,547		13,548		3,658	

Note: Columns (1)-(2) present results from a probit model while Columns (3)-(6) present results from a negative binomial model. Coefficients are presented in Column (1), (3), and (5), while mean marginal effects are presented in Columns (2), (4), and (6). Ln indicates natural log values are used for analysis to reduce skewness in the data distribution and improve model fit. In the probit model, one observation from DC is excluded as the DC treatment works had no significant noncompliance violations. In all columns, state fixed effects are included. Clustered standard errors are in parentheses. Statistical significance of each variable is determined by the relevant test statistic and corresponding p-value (not shown), and denoted as: * p < 0.1, ** p < 0.05, *** p < 0.01. Data source: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets obtained from https://echo.epa.gov/tools/data-downloads#downloads.

In terms of ownership, Table 2.6 results indicate that publicly owned treatment works with mixed ownership are 14.17 percentage points (see Marginal Effect (2) in Table 2.6) less likely to have a significant noncompliance violation relative to corporation owned treatment

works (i.e., the omitted category). Mixed ownership treatment works are also correlated with a little less than one quarter (0.8456) or 2.5 months shorter expected time in significant noncompliance among all publicly owned treatment works and a little more than one quarter (1.2462) or 3.75 months shorter expected time in significant noncompliance among those publicly owned treatment works with at least one significant noncompliance violation in 2023 or 2024. However, when excluding publicly owned treatment works with both known and potential data problems in migrating from states to the national database (Table A.7 in Appendix A), the coefficients in both the probit and negative binomial models analyzing all treatment works become statistically insignificant, while the correlation when analyzing only significantly noncompliant treatment works remains.[12]

Treatment works owned by municipal governments and municipal water districts are correlated with 0.8706 quarters and 0.7406 quarters, respectively, or roughly 2.5 months shorter time expected in significant noncompliance but only among publicly owned treatment works with at least one significant noncompliance violation in 2023 or 2024. State owned treatment works are correlated with 0.6908 (about two months) and 2.0379 (about six months) fewer quarters expected in significant noncompliance among all treatment works and noncompliant treatment works, respectively.

The results indicate that system size is also inversely correlated with significant noncompliance. An increase of 1,000 in the population served (natural log increase of 6.9078) is correlated with a 4.78 percentage point reduction in the likelihood of a significant noncompliance violation and 0.2182 quarters or about 2.5 weeks less time expected in significant noncompliance among all publicly owned treatment works. However, this latter correlation becomes statistically insignificant when sewershed characteristics are introduced into the model (Table 2.7), and both correlations become statistically insignificant when excluding treatment works with known data problems (Table A.6). At the same time, each of these correlations become statistically significant at the 95 percent and 90 percent, respectively, confidence levels when excluding treatment works with both known and potential data problems (Table A.7). Among only those treatment works with a significant noncompliance violation, Table 2.6 shows that a 1,000-increase in the population served is correlated with 0.5111 quarters or 1.5 months less time expected in significant noncompliance. This finding remains robust to the exclusion of treatment works with known and/or potential data problems (Table A.6 and Table A.7), likely capturing economies of scale. Larger systems often have additional fiscal and human resources to operate compared to smaller systems. These trends have been reflected in previous literature in the water sector (Allaire et al., 2018; Konisky & Teodoro, 2016; Scanlon et al., 2022).This finding differs from findings in one paper focused on the wastewater sector that found an increase in population served is linked to an increase in probability and number of wastewater violations (Elbakidze & Beeson, 2021).

[12] The binary variable for Tribal government ownership becomes statistically significant when excluding known data problems (Table A.6) and excluding both known and potential data problems (Table A.7) when analyzing only significantly noncompliant publicly owned treatment works but only at the 90 percent confidence level.

Publicly owned treatment works that serve as an endpoint facility are correlated with a 6.77 percentage point lower likelihood of a significant noncompliance violation among all publicly owned treatment works. In addition, endpoint facility treatment works are correlated with 0.1938 fewer quarters or a little over ½ month in significant noncompliance among all publicly owned treatment works (except when excluding those with known data problems in Table A.6) but not among only those treatment works with at least one significant noncompliance violation in 2023–2024. Although implementing a pretreatment program fails to achieve statistical significance in Table 2.6 and in Table A.6, the variable becomes statistically significant at the 95 percent confidence level among all publicly owned treatment works when analyzed without those having known and potential data problems (Table A.7). Among these treatment works with greater data reliability, implementing a pretreatment program is correlated with a 3.5 percent lower likelihood of having a significant noncompliance violation and with 0.1265 quarters or about 1.5 weeks less expected time in significant noncompliance. Being part of a sewershed network bears no association with significant noncompliance for publicly owned treatment works.

In terms of regulatory oversight, publicly owned treatment works receiving a compliance evaluation inspection or reconnaissance inspection in 2022 are no more or less likely to be in significant noncompliance in 2023–2024. However, having a performance audit inspection in 2022 is correlated with a 4.52 percentage point higher likelihood of a significant noncompliance violation in 2023 or 2024 (Table 2.6) and with 0.2150 quarters or about 2.5 weeks less expected time in significant noncompliance among compliant and significantly noncompliant treatment works without known data problems are analyzed separately (Table A.6). Further, follow-up inspections are correlated with both the likelihood of noncompliance and the amount of expected time in noncompliance, suggesting that on-site visits occurring after a complaint is received or noncompliance is discovered through routine inspections is more effective at assessing significant noncompliance, as intended. Publicly owned treatment works that received a follow-up inspection in 2022 are 3.45 percentage points more likely to have a significant noncompliance violation in 2023–2024 and are expected to remain in significant noncompliance for 0.2378 (for all treatment works) to 0.3045 (for noncompliant treatment works) quarters or nearly one month longer. These findings related to follow-up inspections remain robust even when excluding from analysis treatment works with known and/or potential data problems (Table A.6 and Table A.7).

The regulatory oversight results are unsurprising considering the even more pronounced results pertaining to formal enforcement and prior significant noncompliance. Publicly owned treatment works that received a formal enforcement action in 2022 are correlated with an 8.78 percentage points greater likelihood of having a significant noncompliance violation in 2023–2024 and are expected to remain in significant noncompliance for 0.2507 (for all treatment works) to 0.2610 (for noncompliant treatment works) quarters or about three weeks longer. However, the formal enforcement variable becomes statistically insignificant when analyzing treatment works with at least one significant noncompliance violation in 2023–2024 but excluding those with known and/or potential data problems (Table A.6 and Table A.7). Treatment works with at least one significant noncompliance violation during 2018–2022 are correlated with a 25.51 percent greater likelihood of having a significant noncompliance violation in 2023–2024 and are expected to remain in

significant noncompliance 1.2393 to 1.2714 quarters or about 3.75 months longer. These results for prior significant noncompliance are the strongest among all results presented in Table 2.6.

2.4. Sewershed Correlates of Significant Noncompliance

Table 2.7 presents the results from regressions that add sewershed characteristics as additional control variables to the models. The coefficients on plant-level characteristics are robust to the inclusion of these sewershed control variables and are consistent with the results presented in Table 2.6 and the robustness checks reported in Tables A.6 and A.7.

The main takeaway from Table 2.7 is that the addition of sewershed characteristics into the model does not change the results of plant-level correlates of significant noncompliance. In addition, publicly owned treatment works operating in more densely populated areas and those with wealthier residents are correlated with a lower likelihood of significant noncompliance as well as less time expected in significant noncompliance. These are the only sewershed characteristics correlated with significant noncompliance.

Among the sewershed characteristics, population density and median household income are the only variables correlated with significant noncompliance. Population density is measured as the number of persons per km^2. So, a 100-person increase per km^2 (natural log increase of 4.6052) is correlated with a 4.33 percentage point decrease in the likelihood of a significant noncompliance violation and 0.1960 quarters or about ½ month less time expected in significant noncompliance among all publicly owned treatment works. However, these population density correlations become statistically insignificant when excluding known and potential data problems from analysis (Table A.7), while median age becomes statistically significant at the 95 percent confidence level and is associated with a very small (about one day) reduction of time in significant noncompliance among those treatment works that had at least one such violation in 2023-2024.

A $1,000 increase in median household income (natural log increase of 6.9078) is correlated with 1.0144 quarters or about three months less time expected in significant noncompliance for all publicly owned treatment works. Further, for those treatment works with at least one significant noncompliance violation, a $1,000 increase in median household income is correlated with 1.5612 fewer quarters or more than four months less time expected in significant noncompliance. This aligns with prior literature that found an increase in income per capita to be associated with a decrease in effluent contamination (Earnhart, 2004a).

Highlighting the role that state characteristics play in ensuring compliance, Figure 2.3 maps the state fixed effect coefficients,[13] representing differences in the likelihood of Clean Water

[13] The illustrated coefficients are derived from the probit model (Table 2.7), so one observation from DC is excluded as the DC system had zero significant noncompliance violations. Texas serves as the omitted or reference category because it has the highest number of publicly owned treatment works. It is important to note that it is not possible to directly compare two non-reference state coefficients to each other without conducting a formal statistical test. To do so, a Wald test is typically used to assess whether the difference between two coefficients is statistically significant.

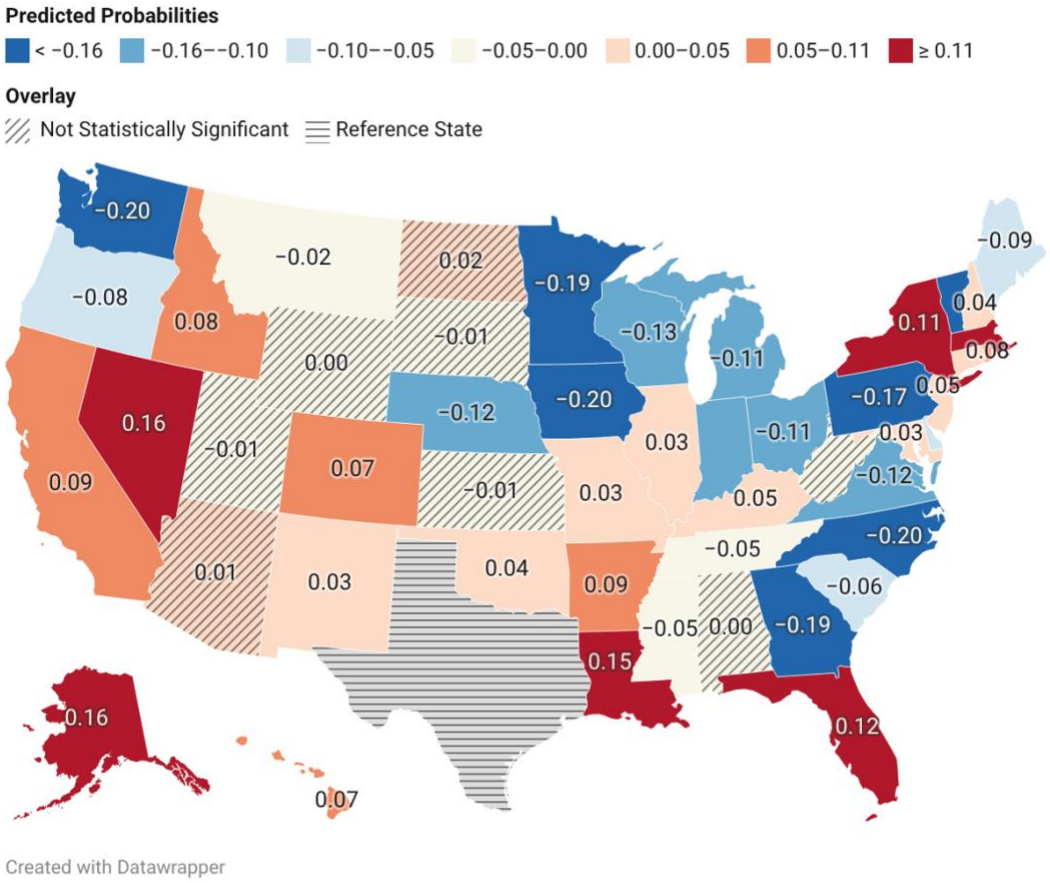
Table 2.7. System and Sewershed Regression Results: All Publicly Owned Treatment Works

	Any Sig. Noncompliance 2023-2024 All Treatment Works		Quarters in Sig. Noncompliance 2023-2024 All Treatment Works		Quarters in Sig. Noncompliance 2023-2024 Noncompliant Works	
Variables	Coefficient (Std. Error) (1)	Marginal Effect (2)	Coefficient (Std. Error) (3)	Marginal Effect (4)	Coefficient (Std. Error) (5)	Marginal Effect (6)
Plant-Level Characteristics						
Ownership						
Federal Facility	0.0243	0.0070	-0.0614	-0.0481	-0.1642	-0.4789
	(0.4710)		(0.7474)		(0.5780)	
County Govt.	-0.2399	-0.0687	-0.2816	-0.2209	-0.0530	-0.1547
	(0.1572)		(0.2376)		(0.1109)	
Municipal Govt.	0.0963	0.0276	-0.0847	-0.0664	**-0.3055*** **	-0.8910
	(0.1209)		(0.1842)		(0.0835)	
Municipal Water District	0.0105	0.0030	-0.1409	-0.1106	**-0.2574*** **	-0.7508
	(0.0918)		(0.1310)		(0.0596)	
Mixed Ownership	**-0.4916*** **	-0.1409	**-1.0796** **	-0.8471	**-0.4288** **	-1.2508
	(0.1606)		(0.4302)		(0.1966)	
Tribal Govt.	0.0637	0.0183	0.0029	0.0023	0.0629	0.1835
	(0.4040)		(0.3917)		(0.1423)	
State Govt.	-0.2484	-0.0712	**-0.8463** **	-0.6640	**-0.7001*** **	-2.0421
	(0.2116)		(0.3638)		(0.1998)	
Privately Owned	-0.1518	-0.0435	-0.0983	-0.0772	0.0007	0.0021
	(0.1702)		(0.2138)		(0.1189)	
Population Served (Ln)	**-0.0214** *	-0.0061	-0.0331	-0.0260	**-0.0248** **	-0.0723
	(0.0129)		(0.0204)		(0.0116)	
Part of Sewershed Network	-0.0343	-0.0098	-0.0618	-0.0485	0.0142	0.0413
	(0.0352)		(0.0510)		(0.0316)	
Endpoint Facility	**-0.2487*** **	-0.0713	**-0.2913** **	-0.2286	-0.0587	-0.1711
	(0.0776)		(0.1249)		(0.0715)	
Pretreatment Program	-0.0726	-0.0208	-0.0957	-0.0751	-0.0040	-0.0116
	(0.0534)		(0.0799)		(0.0496)	
Compliance Evaluation Inspection	0.0208	0.0060	0.0243	0.0190	-0.0081	-0.0237
	(0.0364)		(0.0556)		(0.0285)	
Reconnaissance Inspection	0.0863	0.0247	0.1323	0.1038	0.0074	0.0215
	(0.0640)		(0.0810)		(0.0684)	
Performance Audit Inspection	**0.1528** **	0.0438	0.1456	0.1142	-0.1129	-0.3293
	(0.0748)		(0.1312)		(0.1036)	
Follow-Up Inspection	**0.1072*** **	0.0307	**0.2957*** **	0.2320	**0.0960*** **	0.2800
	(0.0350)		(0.0500)		(0.0361)	
Formal Enforcement Action	**0.3053*** **	0.0875	**0.3205*** **	0.2515	**0.0898*** **	0.2619
	(0.0481)		(0.0542)		(0.0210)	
Sig. Noncompliance 2018-2022	**0.8837*** **	0.2533	**1.5690*** **	1.2310	**0.4314*** **	1.2584
	(0.0414)		(0.0660)		(0.0383)	
Proportion Unreported Data	0.3955	0.1133	0.6506	0.5105	0.1410	0.4113
	(0.4944)		(0.7347)		(0.5198)	
Known Data Problems	0.0676	0.0194	-0.1505	-0.1181	-0.0262	-0.0765
	(0.1126)		(0.3424)		(0.1805)	
Potential Data Problems	**0.4440*** **	-0.0326	**0.8982*** **	0.7047	0.2874	0.8384
	(0.1048)		(0.3400)		(0.1775)	
Sewershed Characteristics						
Population Density (per sq km) (Ln)	**-0.0328*** **	-0.0094	**-0.0542*** **	-0.0426	**-0.0176** *	-0.0513
	(0.0110)		(0.0204)		(0.0103)	
Median Household Income (Ln)	**-0.0905** *	-0.0259	**-0.1872** **	-0.1468	**-0.0775** **	-0.2260
	(0.0539)		(0.0771)		(0.0377)	
Median Age	-0.0039	-0.0011	-0.0041	-0.0032	-0.0025	-0.0073
	(0.0026)		(0.0038)		(0.0024)	
Proportion of Housing Stock						
Built Before 1960	0.0832	0.0238	0.1225	0.0961	0.0334	0.0973
	(0.1590)		(0.2378)		(0.1112)	
Built 1960-1969	-0.4029	-0.1155	-0.2752	-0.2159	0.2998	0.8745
	(0.2831)		(0.4158)		(0.2310)	
Built 1970-1979	0.1113	0.0319	0.3431	0.2692	0.0166	0.0484
	(0.2365)		(0.3288)		(0.2174)	
Built 1980-1989	0.0614	0.0176	0.2296	0.1802	0.3658	1.0671
	(0.2959)		(0.5223)		(0.2839)	
Mean	0.2702		0.7877		2.9174	
Pseudo R2	0.1298		0.0675		0.0386	
Number of Observations	13,547		13,548		3,658	

Note: Columns (1)-(2) present results from a probit model while Columns (3)-(6) present results from a negative binomial model. Coefficients are presented in Column (1), (3), and (5), while mean marginal effects are presented in Columns (2), (4), and (6). Ln indicates natural log values are used for analysis to reduce skewness in the data distribution and improve model fit. In the probit model, one observation from DC is excluded as the DC treatment works had no significant noncompliance violations. In all columns, state fixed effects are included. Clustered standard errors are in parentheses. Statistical significance of each variable is determined by the relevant test statistic and corresponding p-value (not shown), and denoted as: * p < 0.1, ** p < 0.05, *** p < 0.01. Data sources: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets obtained from https://echo.epa.gov/tools/data-downloads#downloads and U.S. Census Bureau's American Community Survey 2018-2022 5-year estimates obtained from https://www.census.gov/programs-surveys/acs.html.

Act significant noncompliance across states that are not explained by the variables in the model. The color-coded coefficients represent how each state's mean probability of noncompliance differs from that of Texas (the excluded state), holding all other variables constant.

Figure 2.3. Model-Based Differences in Significant Noncompliance by State



Note: This Figure maps the state fixed effect coefficients derived from probit estimation results reported in Table 2.7 to illustrate geographical differences in the likelihood of publicly owned treatment works' significant noncompliance that is not explained by the variables in the model. The color-coded coefficients represent how each state's mean probability of significant noncompliance differs from that of Texas (the reference category because it has the highest number of publicly owned treatment works), holding all other variables constant. One observation from DC is excluded as the DC system had zero significant noncompliance violations.

Figure 2.3 indicates that publicly owned treatment works in Vermont are 21 percentage points less likely to be in significant noncompliance than those in Texas, followed by Washington, North Carolina, and Iowa at 20 percentage points, and Georgia and Minnesota at 19 percentage points. Conversely, publicly owned treatment works in Nevada and Alaska are 16 percentage points more likely to be in significant noncompliance than plants in Texas, followed by Louisiana at 15 percentage points, and Massachusetts and Florida at 12 percentage points. Notably, the state fixed effects coefficients for Kansas, Utah, South Dakota, West Virginia, Wyoming, Alabama, Arizona, and North Dakota all fail to reach

statistical significance, indicating publicly owned treatment works in those states are no more or less likely to be in significant noncompliance than the plants in Texas.

2.5. Government Finance Correlates of Significant Noncompliance

The association between fiscal capacity and Clean Water Act significant noncompliance is assessed through analysis of the subset of local government owned treatment works, because this group is the only one for which financial data are publicly available and can be matched to treatment works' sewersheds. Table 2.8 presents regression estimates of all correlates of Clean Water Act significant noncompliance across three models. Columns (1)–(2) estimate the likelihood of any significant noncompliance violation in 2023-2024 for all publicly owned treatment works using Probit. Columns (3)–(4) estimate the number of quarters in significant noncompliance among all publicly owned treatment works using a Negative Binomial regression. Columns (5)-(6) estimate the number of quarters in significant noncompliance for only those publicly owned treatment works with at least one significant noncompliance violation using a Negative Binomial regression. Table 2.8 uses the same model specification as that used for analysis of all publicly owned treatment works, except the number of system ownership type variables are reduced, since the subset analysis only includes local government owned treatment works. In addition, this analysis adds local government fiscal capacity variables.[14]

The statistically significant results in Table 2.8 for the plant-level characteristics are consistent with the results from the full analysis (Table 2.7) and robustness checks for data accuracy (Table A.6 and Table A.7) for the variables pertaining to serving as an endpoint facility as well as for all the inspection, formal enforcement, and prior significant noncompliance. Yet the results in Table 2.8 differ from those presented in Table 2.7 with respect to the ownership variables and some of the sewershed characteristics.

The main takeaway from Table 2.8 is that the plant-level correlates of local government owned treatment works are largely consistent with those for all publicly owned treatment works for the variables measuring endpoint facility, inspections, formal enforcement, and prior significant noncompliance. However, treatment works owned by municipal governments and municipal water districts are more likely to have a significant noncompliance violation in addition to remaining in significant noncompliance for an expected longer amount of time. Among local government owned treatment works, system size is still correlated with less expected time in significant noncompliance for those with at least one of these violations, but the population served is no longer correlated with the likelihood of having a significant noncompliance violation. All of the government finance variables are statistically significant in at least one model estimation except for the operating expenditure ratio; however, only debt service burden has a meaningful correlation size compared to other variables analyzed.

[14] All models include state fixed effects and cluster standard errors at the state level. Robustness checks are reported in Appendix A. Table A.10 can be used to better understand how the results from Table 2.7 compare to those in Table 2.8, as Table A.10 presents results for local government owned systems prior to the inclusion of local government fiscal capacity variables.

Table 2.8. Regression Results: Local Government Owned Treatment Works

	Any Sig. Noncompliance 2023-2024 All Treatment Works		Quarters in Sig. Noncompliance 2023-2024 All Treatment Works		Quarters in Sig. Noncompliance 2023-2024 Noncompliant Works	
Variables	Coefficient (Std. Error) (1)	Marginal Effect (2)	Coefficient (Std. Error) (3)	Marginal Effect (4)	Coefficient (Std. Error) (5)	Marginal Effect (6)
Plant-Level Characteristics						
Ownership						
Municipal Govt.	**0.3147****	0.0903	0.1921	0.1495	**-0.2227****	-0.6408
	(0.1354)		(0.1975)		(0.0990)	
Municipal Water District	**0.2132***	0.0612	0.0775	0.0603	**-0.2132****	-0.6134
	(0.1220)		(0.1981)		(0.0912)	
Population Served (Ln)	-0.0186	-0.0053	-0.0260	-0.0202	**-0.0229****	-0.0658
	(0.0138)		(0.0226)		(0.0111)	
Part of Sewershed Network	-0.0138	-0.0040	-0.0285	-0.0222	0.0220	0.0633
	(0.0340)		(0.0504)		(0.0309)	
Endpoint Facility	**-0.2509*****	-0.0720	**-0.2948****	-0.2296	-0.0596	-0.1716
	(0.0848)		(0.1288)		(0.0725)	
Pretreatment Program	-0.0458	-0.0131	-0.0739	-0.0575	-0.0199	-0.0572
	(0.0569)		(0.0829)		(0.0507)	
Compliance Evaluation Inspection	0.0244	0.0070	0.0258	0.0201	-0.0066	-0.0189
	(0.0365)		(0.0539)		(0.0283)	
Reconnaissance Inspection	0.0633	0.0181	0.1022	0.0796	0.0019	0.0056
	(0.0619)		(0.0801)		(0.0659)	
Performance Audit Inspection	**0.1690****	0.0485	0.2057	0.1601	-0.0761	-0.2189
	(0.0740)		(0.1342)		(0.1113)	
Follow-Up Inspection	**0.1052*****	0.0302	**0.2905*****	0.2262	**0.0925*****	0.2663
	(0.0362)		(0.0470)		(0.0354)	
Formal Enforcement Action	**0.3112*****	0.0893	**0.3345*****	0.2605	**0.0918*****	0.2641
	(0.0491)		(0.0569)		(0.0205)	
Sig. Noncompliance 2018-2022	**0.8582*****	0.2462	**1.5249*****	1.1873	**0.4265*****	1.2275
	(0.0402)		(0.0647)		(0.0370)	
Proportion Unreported Data	0.5794	0.1663	0.8235	0.6412	-0.1259	-0.3623
	(0.5802)		(0.8322)		(0.5389)	
Known Data Problems	**0.3090****	0.0887	**0.5814*****	0.4527	0.2485	0.7152
	(0.1281)		(0.2136)		(0.1521)	
Potential Data Problems	0.1835	0.0527	0.1525	0.1188	0.0269	0.0774
	(0.1139)		(0.2005)		(0.1464)	
Sewershed Characteristics						
Population Density (per sq km) (Ln)	**-0.0268****	-0.0077	**-0.0434****	-0.0338	-0.0151	-0.0436
	(0.0111)		(0.0192)		(0.0104)	
Median Household Income (Ln)	-0.0730	-0.0209	**-0.1279***	-0.0996	-0.0438	-0.1261
	(0.0473)		(0.0781)		(0.0382)	
Median Age	-0.0037	-0.0011	-0.0039	-0.0030	-0.0024	-0.0069
	(0.0026)		(0.0041)		(0.0025)	
Proportion of Housing Stock						
Built Before 1960	0.0705	0.0202	0.1234	0.0961	0.0397	0.1141
	(0.1594)		(0.2513)		(0.1118)	
Built 1960-1969	-0.3618	-0.1038	-0.2202	-0.1715	0.2722	0.7833
	(0.2750)		(0.4150)		(0.2488)	
Built 1970-1979	0.1125	0.0323	0.2907	0.2263	-0.0618	-0.1778
	(0.2438)		(0.3415)		(0.2064)	
Built 1980-1989	0.0854	0.0245	0.3061	0.2384	0.4172	1.2006
	(0.2737)		(0.5144)		(0.2976)	
Government Finance						
Debt Service Burden	-0.0882	-0.0253	**-0.1827****	-0.1422	**-0.0670****	-0.1929
	(0.0755)		(0.0923)		(0.0274)	
Risk Exposure Factor	**-0.0215*****	-0.0062	-0.0741	-0.0577	-0.0571	-0.1644
	(0.0052)		(0.1231)		(0.1734)	
Operating Expenditure Ratio	0.0113	0.0032	0.0151	0.0118	-0.0003	-0.0007
	(0.0145)		(0.0230)		(0.0127)	
Water Revenue Expenditure Ratio	0.0190	0.0055	**0.0130*****	0.0101	**0.0071*****	0.0204
	(0.0126)		(0.0047)		(0.0012)	
Full Time Employees (Ln)	**-0.0246*****	-0.0071	**-0.0413*****	-0.0322	-0.0075	-0.0216
	(0.0061)		(0.0108)		(0.0064)	
Mean	0.2703		0.7779		2.8782	
Pseudo R2	0.1287		0.0669		0.035	
Number of Observations	12,968		12,969		3,505	

Note: Columns (1)-(2) present results from a probit model while Columns (3)-(6) present results from a negative binomial model. Coefficients are presented in Column (1), (3), and (5), while mean marginal effects are presented in Columns (2), (4), and (6). Ln indicates natural log values are used for analysis to reduce skewness in the data distribution and improve model fit. In the probit model, one observation from DC is excluded as the DC treatment works had no significant noncompliance violations. In all columns, state fixed effects are included. Clustered standard errors are in parentheses. Statistical significance of each variable is determined by the relevant test statistic and corresponding p-value (not shown), and denoted as: * p < 0.1, ** p < 0.05, *** p < 0.01. Data sources: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets obtained from https://echo.epa.gov/tools/data-downloads#downloads, U.S. Census Bureau's American Community Survey 2018-2022 5-year estimates obtained from https://www.census.gov/programs-surveys/acs.html, and U.S. Census Bureau's Census of Governments Finance Survey data for 2022 obtained from: https://www.census.gov/programs-surveys/cog.html.

For the ownership variables, Table 2.8 shows that treatment works owned by municipal governments and municipal water districts and with at least one significant noncompliance violation in 2023-2024 remain correlated with less expected time in significant noncompliance compared to those owned by county governments (now the excluded ownership category). In addition, both variables become correlated with greater likelihoods of significant noncompliance in the probit model in Table 2.8. However, most (Table A.8) and all (Table A.9) of these ownership variables become statistically insignificant in all model specifications of local government owned treatment works when those with known and/or potential data problems are excluded from analysis.

The size of treatment works owned by local governments, as measured by the population served, is still correlated with less expected time in significant noncompliance among those treatment works that have at least one of these types of violations. However, this variable is no longer statistically significantly correlated with the likelihood of having a significant noncompliance violation (Table 2.8) except when only those treatment works with reliable data are analyzed separately (Table A.9). Among local government owned treatment works excluding those with known and potential data problems (Table A.9), an increase of 100 in the population served (natural log increase of 4.6052) is correlated with a 2.64 percentage point reduction in the likelihood of a significant noncompliance violation in 2023-2024.

The results in Table 2.8 pertaining to regulatory oversight, federal enforcement, and prior significant noncompliance are rather consistent with the full analysis presented in Table 2.7 as well as all robustness checks for data accuracy (Tables A.6-A.9). In Table 2.8, local government owned treatment works that received a performance audit inspection in 2022 are correlated with a 4.85 percentage point greater likelihood of having a significant noncompliance violation in 2023-2024 compared to 4.38 percentage points for all publicly owned treatment works. Having a follow-up inspection is correlated with a 3.02 percentage point greater likelihood of having a significant noncompliance violation and 0.2262 to 0.2663 quarters or about three weeks more time expected in significant noncompliance for local government owned treatment works compared to 3.07 percentage points and 0.2320 to 0.2800 more quarters (also about three weeks) for all publicly owned treatment works.

Further, local government owned treatment works that received a formal enforcement action in 2022 are correlated with a 8.93 percentage point greater likelihood of having a significant noncompliance violation in 2023-2024 and 0.2605 to 0.2641 quarters or about three weeks more time expected in significant noncompliance compared to a 8.75 percentage points and 0.2515 to 0.2619 more quarters (also about three weeks) for all publicly owned treatment works. At the same time, local government owned treatment works with at least one significant violation in 2018-2022 are correlated with a 24.62 percentage points greater likelihood of having a significant noncompliance violation (compared to 25.33 for all) and 1.1873 to 1.2275 quarters (1.2310 to 1.2584 for all) or about 3.5 months (3.75 months for all) more time expected to remain in significant noncompliance.

Similar to the full analysis (Table 2.7), Table 2.8 shows that population density and median household income are the only sewershed characteristics correlated with significant noncompliance. Also similar, these population density correlations become statistically

insignificant when excluding known and/or potential data problems from analysis (Table A.8 and Table A.9), while median age becomes statistically significant at the 90 percent confidence level and is associated with a very small (about one day) reduction of time in significant noncompliance among treatment works that had at least one such violation in 2023–2024. Further, median household income is only weakly correlated (at the 90 percent confidence level) with significant noncompliance for local government owned treatment works, suggesting sewershed characteristics are not strong indicators of Clean Water Act compliance for this subset of treatment works.

In terms of fiscal capacity, every variable is statistically significant in at least one model estimation except for the operating expenditure ratio.[15] Table 2.8 shows that debt service burden is not correlated with the likelihood of having a significant compliance violation. However, a one standard deviation increase in debt service burden,[16] indicating a greater proportion of revenue being used to cover interest costs on outstanding debt, is correlated with 0.1827 quarters or about a ½ month less time expected in significant noncompliance for all local government owned treatment works and 0.0670 quarters or nearly one week less for those with at least one significant noncompliance violation. Local governments with higher debt service burdens have likely issued long-term debt to meet their capital needs, some of which may be directed toward treatment works to remedy significant noncompliance violations more quickly.

At the same time, one standard deviation increase in the risk exposure factor (calculated as intergovernmental revenue divided by property tax revenue) is correlated with a 0.62 percentage point lower likelihood of a local government owned treatment works having a significant noncompliance violation. In addition, when excluding local government owned treatment works with known and potential data problems from analysis (Table A.9), a one standard deviation increase in the risk exposure factors is correlated with 0.368 quarters or about 3 days less time expected in significant noncompliance. Holding property tax revenue constant, a local government with a higher risk exposure factor is more reliant on state and/or federal intergovernmental revenue. This finding suggests that local governments in significant noncompliance may be using intergovernmental revenue to fund treatment works activities in such ways that help to reduce their Clean Water Act significant noncompliance violations; however, the size of this correlation is rather small compared to other variable correlations in Table 2.8.

The water revenue expenditure ratio is unrelated to the likelihood of a local government owned treatment works having a significant noncompliance violation but is positively correlated with the amount of time in significant noncompliance. A one standard deviation increase in the water revenue expenditure ratio, indicating a greater proportion of water utility revenue is collected to cover needed expenditures, is correlated with more time expected to remain in noncompliance; however, the increase in expected time is very small at 0.0101 to 0.0204 or about ¼ week longer. Although both of these correlations in Table

[15] It should be noted that these specific government finance variables, to the authors' knowledge, have not been tested in prior research.
[16] The financial ratio variables in Table 2.8 were standardized to allow for interpretation as the effect of a one standard deviation increase from the mean.

2.8 are statistically significant at the 99 percent confidence level, they become statistically insignificant when the analysis of local government owned treatment works excludes those with known (Table A.8) or known and potential (Table A.9) data problems.

Finally, among all local government owned treatment works, an increase of 10 full-time employees (natural log increase of 2.3026) is correlated with a 1.62 lower likelihood of having a significant noncompliance violation and 0.0741 quarters or about one week less time expected to remain in significant noncompliance. This finding likely reflects greater capacity to quickly resolve issues related to Clean Water Act significant noncompliance. These correlations are robust to the exclusion of local government owned treatment works with known and/or potential data problems.

2.6. Summary of Quantitative Findings

The number of publicly owned treatment works throughout the U.S. is 17,085; however, only 13,548 (79.3 percent) could be matched to compliance, inspection, enforcement, and data reporting information. This data loss is indicative of a larger challenge with analyzing publicly owned treatment works data from the U.S. Environmental Protection Agency. As noted earlier, publicly available data provided by the U.S. Environmental Protection Agency originates from permit holders and is then reported by states, as mandated by the Clean Water Act. This information includes data and positional inaccuracies, reporting inconsistencies, and modeling artifacts, which may affect boundary delineation and endpoint location (U.S. Environmental Protection Agency, 2025). As such, the models used for analysis in this study included control variables for publicly owned treatment works with known or potential data problems that were flagged by the U.S. Environmental Protection Agency as having issues when migrated from states to the national database. In addition, models were estimated and reported in Appendix A as robustness checks to ensure validity in the conclusions drawn from this analysis. As shown by the numbers of observations reported in Tables A.6 through A.9, excluding treatment works with these flagged data problems results in a loss of observations (and therefore decrease in sample size analyzed) of 15-39 percent. This amount of data loss to ensure accuracy has the potential to diminish the generalizability of the statistical results, not only for this study, but for all research utilizing these data. In turn, the researchers included these data issues as variables in quantitative models.

Of the 13,548 treatment works that could be analyzed, 27 percent or 3,660 had at least one significant noncompliance violation in 2023 or 2024, and nearly half had a history of Clean Water Act noncompliance with at least one significant noncompliance violation in the five years prior (2018-2022). These publicly owned treatment works with at least one significant noncompliance violation in 2023-2024 had a mean number of quarters in significant noncompliance of nearly three, suggesting these violations are typically resolved in about nine months. The majority of significant noncompliance violations were for effluent exceeding monthly average discharge monitoring report limits.

There is considerable variation in publicly owned treatment works' significant noncompliance across states. The treatment works facility in Washington, DC was compliant with the Clean Water Act in 2023 and 2024, while more than 50 percent of

treatment works in West Virginia and Louisiana had at least one significant noncompliance violation during these two years, potentially impacting more than 6.37 million people. West Virginia also had the highest proportions of its community water systems (71 percent) in violation of the Safe Drinking Water Act in 2023 and 2024 (Khalaf et al., 2026).

Over 75 percent of publicly owned treatment works are owned by a Municipal Water District, Municipal Government, or County Government. Nearly all publicly owned treatment works serve as endpoint facilities, while 18 percent are part of a sewershed network, and 19 percent implement a pretreatment program. In terms of oversight and enforcement, compliance evaluation inspections are most common, as they are statutorily required, with nearly 35 percent of publicly owned treatment works receiving one in 2022. Yet less than two percent required a follow-up inspection and about five percent required a formal enforcement action for observed noncompliance.

Local government owned treatment works have very similar significant noncompliance rates and quarters in significant noncompliance compared to all publicly owned treatment works. However, local government owned treatment works tend to serve larger populations, are more likely to be part of a sewershed network, implement a pretreatment program, and receive more oversight and formal enforcement actions. Further, local governments that own treatment works spend about 3 percent of their total revenue to cover interest costs on outstanding debt, would need to levy an additional $3 in property tax revenue to offset a $1 reduction in intergovernmental revenue, and dedicate 84 percent of total spending to cover operations. In addition, these local governments levy exactly the amount needed to fund their water utilities.

Publicly owned treatment works are less likely to have a significant noncompliance violation and/or spend less expected time in significant noncompliance if they have the following plant-level characteristics: a larger population served, serving as an endpoint facility, and ownership by state and local governments or municipal water districts. On the other hand, publicly owned treatment works that received a performance audit, follow-up inspection, or formal enforcement action are more likely to have a significant noncompliance violation and/or expect to spend more time in significant noncompliance. Publicly owned treatment works with at least one prior significant noncompliance violation in 2018-2022 are most likely to be in significant noncompliance in 2023-2024 and spend the longest amount of time in significant noncompliance.

The addition of sewershed characteristics into the model estimations does not change the results of plant-level correlates of significant noncompliance. In addition, publicly owned treatment works operating in more densely populated areas and those with wealthier residents are correlated with a lower likelihood of significant noncompliance as well as less time expected in significant noncompliance. These are the only sewershed characteristics correlated with significant noncompliance.

When examining the subset of only those treatment works owned by local governments, the plant-level correlates are consistent with those for all publicly owned treatment works for the variables measuring inspections, formal enforcement, and prior significant

noncompliance. However, treatment works owned by municipal governments and municipal water districts are more likely than county government-owned treatment works to have a significant noncompliance violation, as well as to remain in significant noncompliance for an expected longer amount of time. Among local government owned treatment works, system size is still correlated with less expected time in significant noncompliance for those with at least one of these violations, but the population served is no longer correlated with the likelihood of having a significant noncompliance violation.

A novel contribution of this study was the inclusion of fiscal capacity variables to assess significant noncompliance among local government owned treatment works. All the government finance variables are statistically significant in at least one model estimation except for the operating expenditure ratio; however, only debt service burden has a meaningful correlation size compared to other variables analyzed.

3. Data Collection Tools for Future Noncompliance Assessment

While the quantitative regression analysis provides essential insight into the system-level and sewershed area characteristics influencing noncompliance with the Clean Water Act, some factors cannot be captured by publicly available datasets. For example, operator training or managerial challenges might not be accounted for. In turn, there is a need to directly engage with utility staff to understand additional factors that lead to noncompliance and how they might be interrelated. A complementary research approach is needed that can be used to engage with wastewater utilities across the U.S. and collect both qualitative and quantitative data. To do so, the research team developed two data collection tools: 1) a survey, and 2) a semi-structured interview guide. These tools were developed using the outputs from the regression findings, which helped to 1) inform the sampling frames for the survey and interviews, and 2) identify key constructs and hypothesized drivers to be measured in the instruments.

3.1. Research Design

To develop the primary data collection tools, this study employed a mixed-methods research design that combines 1) a survey instrument to capture breadth, through comparable responses across many utilities, and 2) a semi-structured interview guide focused on depth to capture narratives, contextual nuance, and perspectives on interactions between factors. Together, these tools are designed to support a socio-technical systems analysis (Baxter & Sommerville, 2011; Ottens et al., 2006) that identifies the factors driving Clean Water Act noncompliance. Both instruments are organized around Capacity, Management, Operations, and Maintenance (U.S. Environmental Protection Agency, 2005), and include open-ended questions that can capture institutional knowledge on how issues originate within a utility (endogenous factors) and how pressures from outside the utility (exogenous factors—such as regulatory, financial, or environmental conditions) may interact to create barriers to compliance.

Data collected through the survey and interviews can be analyzed to reveal overall trends and relationships between factors. Tools like causal-loop diagramming and cognitive mapping (Gray et al., 2014; Meadows, 2008) can be used to develop systems maps that capture how factors interact and cascade to noncompliance. This approach provides a system-level perspective, offering a deeper understanding of the socio-technical interactions that underpin noncompliance and the connections between utilities and the communities they serve.

3.2. Survey Instrument and Interview Guide Development

An analysis of publicly available data was conducted to identify potential risk factors for noncompliance with the Clean Water Act. Based on this analysis, a survey and interview guide were developed to collect contextual and operational data from wastewater utilities and, in turn, increase understanding of the factors related to noncompliance. While any employee of a U.S. wastewater utility can complete the survey, it is designed for managerial staff, recognizing that not all participants may have expertise on every topic.

These instruments were developed using the Environmental Protection Agency's Capacity, Management, Operation, and Maintenance framework (U.S. Environmental Protection

Agency, 2005). This program considers routine activities taken by wastewater utilities, focusing on how to better manage, operate, and maintain collection systems, and prevent and respond to sanitary sewer overflow events. Within this framework, *capacity* refers to investigating and addressing constrained areas to ensure the utilities can handle current and future flows. *Management* refers to activities that allow for effective operation and maintenance activities, such as training and organizational structure. *Operations* refers to how systems are monitored and controlled, and *maintenance* refers to the processes that maximize service and system reliability while assuring infrastructure sustainability. In the survey and interview guide, the researchers adapted this framework: 1) capacity was combined with general characteristics of the utility, 2) operations and maintenance were combined into one section, and 3) a separate section was created for financial aspects.

Beyond this framework, the survey and interview guide touch on factors that contribute to noncompliance and the success of actions to help remedy violations when they do occur. The survey and interview guide were developed using prior literature to inform the overarching structure, topics addressed, and the way in which questions were asked. Content of the survey is summarized in Table 3.1, and the interview guide is summarized in Table 3.2. Both the survey and interview guide include introductions to provide the participants with information about the study, what to expect, and human-subjects research information. See more details about consent and using these tools in Section 3.3.

Table 3.1. Survey Content Overview

Section	Topics Covered	Survey Questions
Participant Information	Role/activities	2–5
	Experience/certifications	6–7
System Characteristics and Capacity	Utility background	8–12
	Flow/capacity/intake	13–22
	Treatment	23–29
Management	Ownership/governance	30, 48–50
	Workforce management	31–34, 36, 41, 51
	Staff communication/training	35, 37–40, 46
	Customer communication/billing	42–46
	Data	47
Operations and Maintenance	Maintenance and tasks	52–57
	Wastewater quality concerns	58
	Operations and planning documents	59–68
	Challenges	69
Finances	Financial challenges	71–74, 83
	Financial health	70. 75, 82
	Rates	76–79
	Securing funding	80–81
Utility Noncompliance	Experiences with noncompliance	84–93, 100
	Efforts to maintain compliance	94–97
	Desired support	98–99

Table 3.2. Interview Guide Content Overview

Section	Topics Covered
Utility and Participant Background	Utility background Role/activities Experience
System Characteristics and Capacity	Influent Capacity Treatment processes Effluent Technical challenges
Management	Long term planning Workforce management Customer communication Governance Innovation
Operations and Maintenance	Operational challenges Standard operating procedures Emergency planning Asset management planning Infrastructure assets Maintenance
Financial	Financial health Planning and budgeting External financial support Rate structure
Regulatory Noncompliance	Past noncompliance Reasons for maintaining/falling out of compliance Efforts to maintain compliance
Conclusion	Additional thoughts

The semi-structured interview guide and survey were designed to be complementarity to each other, specifically using interviews to deepen insight into high-priority factors identified in survey results (Van Thiel, 2014). Both instruments are structured similarly with sections on 1) utility and participant background, 2) system characteristics and background, 3) management, 4) operations and maintenance, 4) finances, and 5) regulatory compliance. Both the interview guide and survey conclude by asking participants if there is anything else they would like to share.

In each section, beginning with system characteristics and capacity, the questions were informed by prior research. For example, the survey asks about industrial intake because there has been a rise in metal-related Clean Water Act violations since 2014, potentially reflecting intensified industrial activities, mining operations, and urban runoff, pointing to industrial discharge as a key factor in noncompliance (Jaishankar et al., 2014). Questions about flow and how it varies seasonally build on literature showing that an increase in flow capacity at wastewater plants has been associated with an increase in biochemical oxygen

demand of effluent discharged (Earnhart, 2007). This study also shows that seasons play a role in effluent quality, as biochemical oxygen demand of effluent discharged has been shown to be higher in the winter and spring (Earnhart, 2007). Treatment techniques also influence noncompliance, prompting the inclusion of detailed questions on this topic. The ability to adapt varying technology and treatment techniques is also important for compliance. For example, prior research has found that a variety of environmental and economic factors can impact technology use, adoption, and sustainability at water utilities (Wells et al., 2022). These findings motivated the inclusion of questions on system characteristics and capacity.

In the management section, the survey includes questions on community partnership, training for staff, and both ownership and governance, reflecting the socio-technical dimensions of water management. These topics are crucial to understanding wastewater noncompliance, as lack of management attention and resources has been identified as a key cause of notices of violation of the Clean Water Act (Brown & Baxter, 1993). In situations where systems are struggling and there is risk to public health, community-based organizations can play an important role in increasing health outcomes, indicating their importance in water utility operations (Wallerstein et al., 2019). This is also illustrated by findings that as water-focused environmental nonprofits in a watershed increases, Clean Water Act compliance increases, again highlighting the importance of community partnerships (Grant & Grooms, 2017).

Questions on customer communication stem from previous findings that this is important in drinking water utility management. For instance, a study in Saskatoon, Canada investigated successful risk communication from drinking water utilities. The authors found that, in addition to traditional channels, personal networking and social media each played a large role in successful communication, but that official sources were still crucial for alerting customers of disruptions (Bradford et al., 2017). Ownership and governance were each explored in the survey and interview guide as they both likely influence compliance, with government owned treatment works being found to have the highest number of both effluent and reporting violations compared to privately owned wastewater facilities and other government owned systems that are not publicly owned treatment works (Earnhart & Jacobson, 2025).

In the operations and maintenance section, there is a focus on standard operating procedures and asset management planning. Prior research, such as Friedman et al., 2024, has identified these as key components in ensuring drinking water infrastructure resilience, and this survey hopes to uncover if similar links exist in wastewater systems. On the wastewater side, standard operating procedures (Fachhochschule Nordwestschweiz, 2016), asset management planning (Younis & Knight, 2014), and emergency management planning (Choudhury et al., 2025) have all been highlighted as key aspects of successful operations.

The finance sections of the survey and interview guide focus on fiscal operations and financial challenges. On the individual treatment works level, capital costs, cost of operation and maintenance, and user costs have been identified as key indicators of sustainability in

wastewater treatment technologies, prompting the inclusion of questions about capital reserves and rates in this analysis (Muga & Mihelcic, 2008). Going deeper into the user side, the survey asks about customer billing. Cost of service can change substantially based on system size, as research shows that cost of wastewater treatment for a resident of a plant serving a smaller population is much higher than that of a larger plant per capita (Raftelis Financial Consulting, 2004). Both the survey and interview guide ask about securing funding, as this has been shown to be a significant barrier to operations in water utilities overall (Keiser et al., 2023; Marcillo & Krometis, 2019). On the wastewater side specifically, public funding has been identified as a major barrier to safe sanitation (Kryston et al., 2024). Gathering more information on the experiences of individual utilities in securing funding can improve collective understanding of how to remove barriers to increase compliance.

The next section of the survey and interview guide presents questions on regulatory compliance. Questions on enforcement were prompted by findings that enforcement efforts have varied over time, as data shows a dramatic decrease in budgets and staffing levels for monitoring and enforcement at the U.S. Environmental Protection Agency since the 1990s (Gray & Shimshack, 2011). Enforcement has been shown to have an impact on compliance, reducing a firm's violating discharge rate (Lee, 1991), as well as being negatively correlated with biochemical oxygen demand of effluent discharged (Earnhart, 2007). Further, compliance assistance programs have been shown to decrease the number and probability of violations in wastewater treatment facilities (Ferraro and Shimshack, 2025), prompting further questions on what compliance assistance utilities find most helpful.

Both the interview guide and survey conclude by asking participants if there is anything else they would like to share about their experiences with compliance or system performance. It is important to note that the survey instrument includes explicit question skip-logic to facilitate deployment of some or part of the survey through an electronic survey software platform prior to dissemination. The survey was created to cover a broad range of relevant topics, which has led to the inclusion of 100 total questions. The interview guide includes more questions than possible to discuss in 60 minutes. Both instruments are not intended to be deployed at their full length but were kept as expansive resources to give more flexibility in including particular topics that are of interest at the time of deployment.

3.3. Implementation Best Practices for Surveys and Interviews

As part of this project, a survey instrument and interview guide were designed to understand the factors driving Clean Water Act noncompliance at wastewater utilities across the U.S. In this section, best practices for conducting surveys and interviews are outlined, including guidance on how to use the materials shown in Appendices B and C. Both of these instruments are designed to be collected at the utility level. Within this unit of analysis, the target population of respondents and interviewees includes utility managers, supervisors, or personnel with direct knowledge of plant operations and compliance history.

A mixed methods research design, as proposed here, requires consideration of the appropriate sequencing—either parallel or sequential. Parallel design is where quantitative and qualitative research are conducted separately and their findings are later compared.

Sequential design involves two or more consecutive phases. Sequential designs are commonly classified as explanatory, when the quantitative phase precedes and informs the qualitative phase, or exploratory, where the qualitative phase comes first (Hendren et al., 2023; Mele & Belardinelli, 2019). For this project, the survey will most likely be administered first, using the results to recruit a broad sample for interviews (see Section 3.2.2 for more details).

3.2.1. Survey

It is important to note that the survey questions are intended to provide the U.S. Environmental Protection Agency with options for questions to ask, but this list of questions should be shortened before deployment. This will reduce survey fatigue—a common issue in online surveys (Savage & Waldman, 2008). After the survey is shortened, it should be deployed through an online platform with a mobile-friendly design, such as Qualtrics. As with any human-subjects research, necessary approvals should be completed before data collection (e.g., Information Collection Request). This includes creating a consent form and a process to obtain consent, such as a question in the survey.

Next, the sampling strategy must be selected. Common sampling strategies are shown in Figure 3.1. For the survey, the research team recommends following a stratified purposive sampling approach to ensure a representative sample of utilities. This may be done across geography and region, system size and complexity, severity and frequency of noncompliance, among other factors deemed important for the research objective. For example, the percentage of respondents from each state could be based on the number of publicly owned treatment works in that specific state. The goal is to construct a heterogeneous sample that represents different issues with noncompliance based on pre-specified criteria or strata (Flick, 2018).

Figure 3.1. Common Sampling Strategies for Surveys and Interviews

In terms of recruitment workflow, an initial invitation email should be sent from the U.S. Environmental Protection Agency Office of Enforcement and Compliance Assurance, the

research team, or both, with clear branding. This email should include a brief description of purpose, confidentiality, and approximate completion time for the survey. There should also be a clear distinction between Clean Water Act enforcement and the research objectives. Surveys also necessitate a reminder strategy, typically by scheduling one or two reminders for non-respondents that consist of short, respectful messages emphasizing voluntary participation and the value of their insight.

The survey should remain open for a set amount of time, such as two to three months. Once closed, the data should be aggregated from the online platform and checked for quality. This might include removing responses that are incomplete or that were completed in a very short amount of time. After the data are cleaned, the U.S. Environmental Protection Agency can use descriptive statistics or statistical modeling to link survey responses to compliance outcomes. Survey data can be linked to outcomes based on utility name/location (Q2).

3.2.2. Semi-Structured Interviews

The interview guide was designed to be used for semi-structured interviews, meaning the questions are used to guide conversations, but there is flexibility to expand the conversation based on emergent ideas. As with the survey, it is imperative to make sure all human-subjects research approvals are in place and a consent form is developed.

The appropriate sampling strategy will also need to be determined for interviews—see Section 3.2.1. for more details. This decision is based on the desired generalizability of the results. One way to recruit interview participants is to include a supplemental question in the survey asking if the participant is willing to also participate in an interview. Such a convenience sampling approach can allow for more streamlined participant recruitment. Interviews should be conducted until no new information emerges in subsequent interviews, known as theoretical saturation (Strauss, 1998). Prior to starting interviews, the interviewer should conduct at least two practice interviews.

When reaching out to participants, it is important to include a clear explanation of the interview purpose, expected time duration, and confidentiality. The interview process should begin with rapport-building introductions and explanation of roles (i.e., research team vs. U.S. Environmental Protection Agency). The interviewer should provide interviewees with a plain-language description of the purpose of the study and the voluntary nature of the interview. It is essential to review informed consent, recording permission, and confidentiality. Explicit statements of the right to decline answering any question or to stop the interview at any time should be included. An example of this language is included at the start of the interview guide.

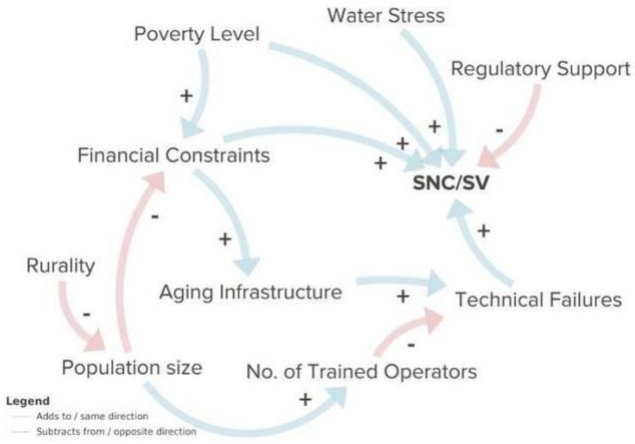
Interviews should be recorded, when possible, ensuring that procedures from approved research ethics applications are followed. Although many researchers have noted best practices in conducting interviews, best practices are summarized based on work by Mack and Woodsong (2005) below:

1. Build rapport and trust with a warm, respectful tone. Acknowledge the complexity and pressures utilities face. Start with easier, descriptive questions before moving into sensitive topics.

2. Maintain neutrality and a non-judgmental stance. Avoid leading questions or language implying blame. Use phrases like "What factors contributed…?" Allow respondents to frame issues in their own words.
3. Employ effective probing by using open-ended probes (e.g., "Can you tell me more about…?", "What happened next?"). Probe for connections and mechanisms (e.g., "How did that____affect day-to-day operations?").
4. When handling sensitive content, it is important to recognize that noncompliance events can be stressful and reputationally sensitive. It may be necessary to offer breaks and to remind participants they can skip questions if needed. Avoid sharing personal judgments and focus on understanding experiences.
5. Manage bias and reliability by being aware of social desirability (e.g., tendency to downplay internal shortcomings). Encourage discussion of both successes and failures. Ask for concrete examples rather than general statements.
6. Conduct post-interview debriefing immediately afterwards, by having the interviewer produce notes on main themes, surprises, and systems relationships. Flag emerging insights for iterative refinement of the interview guide or for analysis planning.

If the interviewee did not already complete the survey, they should be asked to do so. This allows for linking between the survey and interview data. After completion, the interview should be transcribed. If software is used, the transcript should be reviewed for quality control. Next, the data should be processed in line with social science research procedures to ensure bias is reduced and findings can be translated. The analysis should be validated based on the analysis technique selected. See Spearing et al., 2022 for more details about analysis and validation approaches.

Figure 3.2. Example Systems Map



Note: This figure is conceptual and not based on empirical data.

To create cognitive systems maps (Gray et al., 2014; Meadows, 2008) that outline how factors are interrelated and lead to noncompliance, the researchers can qualitatively code for connections (i.e., relationships). This means that each time an interviewee mentions a

relationship, it is captured through the analysis. Examples of such approaches can be found in the research team's prior work (Spearing et al., 2023; Tiedmann et al., 2023). An example of such a cognitive systems map is shown in Figure 3.2. Note that this figure is conceptual and not based on actual results or empirical data.

4. Recommendations and Conclusions

4.1. Evidence-Based Recommendations

The preliminary research findings presented throughout section two of this report are based on extensive quantitative analysis. The qualitative data collection and analysis to be conducted in phase two of this project is crucial to increasing understanding of utility personnels' perspectives on challenges to significant compliance. In the absence of qualitative findings, the section two results serve as the basis for these preliminary recommendations for enhancing Clean Water Act significant compliance among publicly owned treatment works:

Implement processes to improve data reporting by states of information about publicly owned treatment works that are required by the Clean Water Act. A major barrier to greater understanding of the factors correlated with significant noncompliance by publicly owned treatment works is lack of complete and reliable data that are publicly available and can be used for expert research analysis. The number of publicly owned treatment works throughout the U.S. is 17,085; however, only 13,548 (79.3 percent) could be matched to compliance, inspection, enforcement, and data reporting information. Further, the U.S. Environmental Protection Agency's Integrated Compliance Information System database presents data reported to the U.S. Environmental Protection Agency by states from National Pollutant Discharge Elimination System permit holders, as mandated by the Clean Water Act. However, there is considerable variation in how much information is reported, as this analysis found that missing data fields ranged from 11–71 percent of total. Similarly, the U.S. Environmental Protection Agency's National Sewershed Dataset is subject to limitations, including data and positional inaccuracies, reporting inconsistencies, and modeling artifacts, which may affect boundary delineation and endpoint location (U.S. Environmental Protection Agency, 2025). In addition, there are publicly owned treatment works with either known or suspected problems with their reported data. This study found that known data problems exist for about 15 percent of all publicly owned treatment works, and potential data problems have been identified for nearly 39 percent. Excluding these treatment works from analysis to ensure data accuracy reflects a significant amount of data loss, which has the potential to diminish the generalizability of the statistical results, not only for this study, but for all research utilizing these data.

Use the survey and interview data collection results to add or redesign the fields used for data collection to produce more varied descriptive information reported on publicly owned treatment works. In addition to creating limitations in the generalizability of statistical analyses to provide policy directions aimed at desired solutions, the significant amount of missing or nonexistent data fields diminishes the explanatory power of statistical models. Although the U.S. Environmental Protection Agency's Integrated Compliance Information System data on National Pollutant Discharge Elimination System contains various useful fields characterizing permits, facilities and operations. Much of these data fields are either missing information or contain largely the same information for all or nearly all publicly owned treatment works, significantly limiting their usefulness for analysis. In this study, the fully specified regression models with the largest sample sizes were only able to explain (according to the Pseudo R2 values) about 3.5–13 percent of the variation in significant

noncompliance. Adding additional plant-level characteristic control variables would help to enhance the explanatory power of the statistical models; however, doing so would either significantly reduce the sample size due to missing data in the additional control variables, thereby limiting generalizability of the results, or prove impossible due to the additional control variables getting dropped in model estimation because of a lack of variable in the observed values. By broadly implementing the survey and conducting semi-structured interviews using the protocols designed for this study, the data collection results can inform the U.S. Environmental Protection Agency on the utility of which additional information should be collected from publicly owned treatment works to better inform future research.

Develop selection criteria to help states focus inspection efforts on those publicly owned treatment works that have had a prior significant noncompliance violation because they are at greatest risk of repeating significant noncompliance. This study found that publicly owned treatment works with at least one significant noncompliance violation in 2018-2022 were most likely (out of all variables analyzed) to have a significant noncompliance violation in 2023-2024 as well as to spend the greatest amount of time in significant noncompliance before resolving such violations. Treatment works that were persistently in significant noncompliance by having at least one such violation each year 2018-2024 were also among the smallest (measured by population served) and received the least compliance evaluation inspections yet received the most federal enforcement actions. Although this persistent significant noncompliance issue is fairly concentrated among just 2.5 percent of treatment works, more proactive oversight could help to overcome the challenges these treatment works face in resuming compliance. Phase two of this project would shed light on what these barriers are, e.g., lack of technical capacity or low staffing levels, and can help finetune broad recommendations. Nonetheless, broadly, the U.S. Environmental Protection Agency can (1) leverage federal funding programs to encourage investment in treatment works identified as at-risk based on the quantitative findings, and/or (2) provide monitoring related training for at-risk treatment works that can take the form of short courses or visits to exemplary compliant systems with similar characteristics. Such training should be informed by future results from the proposed interview guide and survey instrument.

Invest in human and financial support for wastewater operations. Quantitative results showed that an increase of 10 full-time employees in a local government (natural log increase of 2.3026) is correlated with 1.62 percentage points lower likelihood of having a significant noncompliance violation and 0.0741 quarters or about one week less time expected to remain in significant noncompliance. Results also found that publicly owned treatment works operating in more densely populated areas and those with wealthier residents are correlated with a lower likelihood of significant noncompliance as well as less time expected in significant noncompliance. This is likely reflecting these treatment works' ability to cover expenses with utility revenues, which helps to fund maintenance activities which are not eligible to be covered by the Clean Water State Revolving Funds. In turn, other treatment works that serve rural, lower-income areas may struggle to financially support their day-to-day operations. In turn, there should be a financial mechanism (e.g., loan fund) available for wastewater utilities to support operations and maintenance, including paying staff which was shown to improve compliance.

Use fiscal policy tools to enhance access to the municipal debt market for publicly owned treatment works. This study found that local government owned treatment works with higher debt service burdens are associated with less time in significant noncompliance. This likely stems from local governments with treatment works issuing debt for capital needs that help them to maintain compliance and avoid significant noncompliance. Of all the government fiscal capacity variables analyzed, this finding had the most meaningful potential impact on enhancing significant compliance. There are several ways the federal government can support and/or enhance municipal debt market access. Maintaining the tax-exempt status of municipal bonds reduces interest rates for water infrastructure, as it makes purchasing the debt more attractive to investors. The Federal Reserve could revive or expand the Municipal Liquidity Facility, established to help local governments better manage their cash flow pressures, to provide direct, short-term funding to municipalities and help to ensure market stability. State Revolving Funds, which operate alongside the U.S. Environmental Protection Agency's Water Infrastructure Finance and Innovation Act program, could be strengthened by increasing federal capitalization grants for the Clean Water State Revolving Fund to provide low- or zero-interest loans and grants directly to publicly owned treatment works with lower fiscal capacity. Finally, developing a federal national infrastructure bank could help pool smaller municipal securities, thereby improving their liquidity and making them more attractive to investors.

4.2. Conclusions and Next Steps

Publicly owned treatment works in the United States are facing a myriad of challenges including lack of funding, divided responsibilities, and aging infrastructure which has led some treatment works to receive significant violations to the Clean Water Act. Given that publicly owned treatment works provide wastewater services to more than 270 million people, it is critical to understand the causes of significant noncompliance in order to direct funding and interventions and, in turn, increase compliance (U.S. Environmental Protection Agency, April 2024).

This study used plant-level and sewershed characteristics, combined with local government finance data, to estimate both the probability of having any significant violation and the count of quarters in significant noncompliance. Quantitative results showed that publicly owned treatment works are less likely to have a significant noncompliance violation and/or spend less expected time in significant noncompliance if they have a larger population served, serve as an endpoint facility, or are owned by state governments, local governments, or municipal water districts. In terms of site visits or inspections, receiving a performance audit, follow-up inspection, or formal enforcement action makes a publicly owned treatment facility more likely to have a significant noncompliance violation and/or spend more time in significant noncompliance. Significant sewershed characteristics include population density and income of the population. Further, government finance data was modeled for locally owned treatment works, finding multiple variables significant including the number of full-time employees. Overall, the quantitative results, summarized in Section 2.6, help identify utilities that are at risk of noncompliance and inform actions that can be undertaken by the U.S. Environmental Protection Agency to achieve greater compliance, as outlined in the policy recommendations section.

Although results stemming from publicly available data are helpful to understand generalizable trends, it is not possible to capture contextual nuances in what contributes to noncompliance. In turn, it is imperative to capture perspectives of managers at wastewater utilities so they can share unique operational and managerial experiences. To do so, a survey and semi-structured interview guide were developed to collect data to capture this essential insight. These tools can be used by the U.S. Environmental Protection Agency to collect data directly from utilities. In parallel with the survey and interview guide, this report includes guidance and recommendations to implement these tools. Those findings could then be used in combination with the quantitative results of this study to inform future policy initiatives focused on increased resources and interventions for noncompliant treatment works, as well as operational guidance on risk management strategies.

References

Akpor, O. B., & Muchie, B. (2011). Environmental and public health implications of wastewater quality. *African journal of Biotechnology,* 10(13), 2379-2387.

Allaire, M., Wu, H., & Lall, U. (2018). National trends in drinking water quality violations. *Proceedings of the National Academy of Sciences, 115*(9), 2078–2083. https://doi.org/10.1073/pnas.1719805115

American Society of Civil Engineers (ASCE). (2026). 2025 Infrastructure Report Card. https://infrastructurereportcard.org/wp-content/uploads/2025/03/Wastewater.pdf

Baxter, G., & Sommerville, I. (2011). Socio-technical systems: From design methods to systems engineering. *Interacting with Computers, 23*(1), 4–17. https://doi.org/10.1016/j.intcom.2010.07.003

Bhujbal, P. (2025). Sewage treatment plant maintenance. My Waste Solution. Retrieved February 4, 2026, from https://blog.mywastesolution.com/sewage-treatment-plant-maintenance/

Bradford, L. E., Idowu, B., Zagozewski, R., & Bharadwaj, L. A. (2017). There is no publicity like word of mouth: Lessons for communicating drinking water risks in the urban setting. *Sustainable Cities and Society, 29*, 23–40. https://doi.org/10.1016/j.scs.2016.11.003

Brown, D. M., & Baxter, R. J. (1993). Planning and management failures cause Clean Water Act violations (Final report, LMI-CE211R3). Logistics Management Institute.

Cameron, A. C., & Trivedi, P. K. (2013). *Regression analysis of count data* (No. 53). Cambridge university press.

Centers for Disease Control and Prevention. (2024). *Waterborne disease outbreaks correlated with drinking water—United States, 2015–2020*. *Morbidity and Mortality Weekly Report*. https://www.cdc.gov/mmwr/volumes/73/ss/ss7301a1.htm

Center for Sustainable Systems, University of Michigan. (2025). *U.S. Wastewater Treatment Factsheet.*https://css.umich.edu/publications/factsheets/water/us-wastewater-treatment-factsheet

Choudhury, S. H., Yu, S. L., & Haimes, Y. Y. (1992). Assessing the risk of noncompliance in wastewater treatment. *Water Science and Technology,* 26(5–6), 1411–1420. https://doi.org/10.2166/wst.1992.0584

Choudhury, M., Choudhary, R., Sharma, D., Bhattacharjee, B., Majumdar, S., Chegini, S., ... & van Hullebusch, E. D. (2025). Building resilience in wastewater management: disaster preparedness and emergency response strategies, in *Smart Wastewater Systems and Climate Change Innovations Through Spatial Intelligence*, ed. M. Choudhury, S. Majumdar, S. Goswami, and M. Sillanpää, Royal Society of Chemistry, 2025, vol. 15, ch. 11, pp. 155-169. https://doi.org/10.1039/9781837676880-00155.

Code of Federal Regulations, Definitions. 40 CFR § 403.3 *et seq.* (2026)

Demaris, A. (1992). *Logit modeling: Practical applications* (Vol. 86). Sage.

District of Columbia Water and Sewer Authority (DC Water). (2026). Potomac Interceptor Collapse: News Releases and Updates. https://www.dcwater.com/about-dc-water /media/potomac-interceptor-collapse

Earnhart, D. (2004a). Regulatory factors shaping environmental performance at publicly-owned treatment plants. *Journal of Environmental Economics and Management, 48(1)*, 655-681.

Earnhart, D. (2004b). The effects of community characteristics on polluter compliance levels. *Land Economics*, 80(3), 408–432. https://doi.org/10.2307/3654729

Earnhart, D. (2007). Effects of permitted effluent limits on environmental compliance levels. *Ecological Economics*, 61(1), 178–193. https://doi.org/10.1016/j.ecolecon.2006.07.031

Earnhart, D., & Jacobson, S. (2025). How does the deterrence effect of regulatory enforcement differ between privately and government-owned facilities?. *Environmental and Resource Economics, 88(3)*, 553-588.

Effective Utility Management. (2024). *A primer for water sector utilities*. https://www.watereum.org/wp-content/uploads/2025/01/FINAL-2024-EUM-PRIMER.pdf

Elbakidze, L., & Beeson, Q. (2021). State regulatory heterogeneity and compliance with the Clean Water and Safe Drinking Water Acts. *Water Resources Research, 57*(4), e2020WR028980. https://doi.org/10.1029/2020WR028980

Fachhochschule Nordwestschweiz, F. H. N. W. (2016). Standard operating procedures and health/safety procedures relative to the wastewater treatment and irrigation technologies.
Ferraro, P. J., & Shimshack, J. P. (2025). The effect of compliance assistance on pollution discharges and violations of environmental regulations. *Journal of Policy Analysis and Management,* 44(4), 901–924.
Flick, U. (2018). *The SAGE handbook of qualitative data collection*. SAGE Publications. https://doi.org/10.4135/9781526416070
Friedman, M. B., Hughes, S., Kirchhoff, C. J., Rauh, E., McOmber, C., Manshardt, D. J., & Prout, J. M. (2024). Broadening resilience: An evaluation of policy and planning for drinking water resilience in 100 U.S. cities. *Global Environmental Change, 84*, 102798. https://doi.org/10.1016/j.gloenvcha.2023.102798
Fu, G., Liu, P., & Swallow, S. (2020). Effectiveness of public versus private ownership: Violations of the Safe Drinking Water Act. *Agricultural and Resource Economics Review, 49*(1), 1–26. https://doi.org/10.1017/age.2019.15
Government Accountability Office. (2018). *Water and wastewater workforce*. https://www.gao.gov/assets/gao-18-102.pdf
Grant, L. E., & Grooms, K. K. (2017). Do nonprofits encourage environmental compliance? *Journal of the Association of Environmental and Resource Economists, 4(S1),* S261-S288.
Gray, S. A., Zanre, E., & Gray, S. R. J. (2014). Fuzzy cognitive maps as representations of mental models and group beliefs. In E. I. Papageorgiou (Ed.), *Fuzzy cognitive maps for applied sciences and engineering* (pp. 29–48). Springer. https://doi.org/10.1007/978-3-642-39739-4
Gray, W. B., & Shimshack, J. P. (2011). The effectiveness of environmental monitoring and enforcement: A review of the empirical evidence. Review of Environmental Economics and Policy, 5(1), 3–24. https://doi.org/10.1093/reep/req017
Hansen, K., & Mullin, M. (2022). Barriers to water infrastructure investment: Findings from a survey of U.S. local elected officials. *PLOS Water, 1*(8), e0000039. https://doi.org/10.1371/journal.pwat.0000039
Heberling, M. T., Price, J. I., Nietch, C. T., Elovitz, M., Smucker, N. J., & Schupp, D. A. (2022). Linking water quality to drinking water treatment costs using time series analysis. *Water Resources Research, 58*(4), e2021WR031257. https://doi.org/10.1029/2021WR031257
Hendren, K., Newcomer, K., Pandey, S. K., Smith, M., & Sumner, N. (2023). How qualitative research methods can be leveraged to strengthen mixed methods research. *Public Administration Review, 83*(3), 468–485. https://doi.org/10.1111/puar.13528
Jaishankar, M., Tseten, T., Anbalagan, N., Mathew, B. B., & Beeregowda, K. N. (2014). Toxicity, mechanism and health effects of some heavy metals. *Interdisciplinary Toxicology*, **7**(2), 60–72.
Josset, L., Allaire, M., Hayek, C., Rising, J., Thomas, C., & Lall, U. (2019). The U.S. water data gap—A survey of state-level water data platforms. *Earth's Future, 7*(4), 433–449. https://doi.org/10.1029/2018EF001069
Keiser, D. A., Mazumder, B., Molitor, D., & Shapiro, J. S. (2023). *Water works: Causes and consequences of safe drinking water in America*. National Center for Environmental Economics.
Khalaf, C., Carroll, D. A., Iuorio, A., Toland, J. C., & Spearing, L.A. (2026). A Systems Perspective on Contributing Factors to Safe Drinking Water Act Noncompliance. Chicago, IL: Government Finance Research Center.
Konisky, D. M., & Teodoro, M. P. (2016). When governments regulate governments. *American Journal of Political Science, 60*(3), 559–574. https://doi.org/10.1111/ajps.12207
Kryston, A., Woods, C. G., & Manga, M. (2024). Social barriers to safe sanitation access among housed populations in the United States: A systematic review. *International Journal of Hygiene and Environmental Health*, 257, 114326.
Lee, S. G. (1991). Regulatory enforcement and compliance: Industrial wastewater pretreatment programs. University of Rhode Island.
Lee, M. J., Lee, G., & Choi, J. Y. (2025). Linear probability model revisited: Why it works and how it should be specified. *Sociological Methods & Research, 54*(1), 173–186.

Linder, K. D., & Brewer, T. F. (2022). Develop standard operating procedures for routine practice and what-if scenarios. *Opflow, 48*(5), 6–7.
Mack, N., & Woodsong, C. (2005). *Qualitative research methods: A data collector's field guide*. FHI 360.
Marcillo, C., & Krometis, L. (2019). Small towns, big challenges: Does rurality influence Safe Drinking Water Act compliance? *AWWA Water Science, 1*(2), e1121
Maxcy-Brown, J., Capone, D., & Elliott, M. A. (2023). Characterizing the nature and extent of access to unsafely managed sanitation in the United States. *Nature Water, 1(11),* 915-928.
Meadows, D. (2008). *Thinking in systems: A primer* (D. Wright, Ed.). Earthscan.
Mele, V., & Belardinelli, P. (2019). Mixed methods in public administration research. *Journal of Public Administration Research and Theory, 29*(2), 334–347. https://doi.org/10.1093/jopart/muy046
Michigan Department of Environment, Great Lakes, and Energy. (2026). *IPP PFAS Initiative,* https://www.michigan.gov/egle/about/organization/water-resources/industrial-pretreatment/pfas-initiative
Muga, H. E., & Mihelcic, J. R. (2008). Sustainability of wastewater treatment technologies. *Journal of environmental management, 88(3),* 437-447.
Ottens, M., Franssen, M., Kroes, P., & van de Poel, I. (2006). Modelling infrastructures as socio-technical systems. *International Journal of Critical Infrastructures, 2*(2–3), 133–145.
Pennsylvania Department of Environmental Protection, Bureau of Clean Water. (2021, June). *Discharge monitoring reports: A guide to electronic and paper DMR reporting* (3800-BK-DEP3047). https://files.dep.state.pa.us/water/wastewater%20management/WastewaterPortalFiles/NutrientTrading/3800-BK-DEP3047.pdf
Pierce, G., Landes, L., Harrison, G., Schlichting, L., & Dunlap, L. (2023). *Considerations for a national drinking water quality compliance assessment*.
Raftelis Financial Consulting, 2004. Water and Wastewater Rate Survey, Pennsylvania; CRC Press/Lewis Publishers: Pennsylvania.
Ramalho, R. S. (2013). Introduction to wastewater treatment processes. Academic press.
Ramseur, J. L., Normand, A. E., Cowan, T., Humphreys, E. H., Stern, C. V., Stubbs, M., & Lawhorn, J. M. (2020). *Federally supported projects and programs for wastewater, drinking water, and water supply infrastructure*. Congressional Research Service.
Reibel, M. (2018). *Estimating median household income for community water agencies: A case study of Los Angeles County*.
Saha, N., Mollah, M. Z. I., Alam, M. F., & Rahman, M. S. (2016). Seasonal investigation of heavy metals in marine fishes captured from the Bay of Bengal and the implications for human health risk assessment. *Food control*, 70, 110-118.
Savage, S., & Waldman, D. (2008). Learning and fatigue during choice experiments. *Journal of Applied Econometrics, 23*(3), 351–371.
Scanlon, B. R., Fakhreddine, S., Reedy, R. C., Yang, Q., & Malito, J. G. (2022). Drivers of spatiotemporal variability in drinking water quality in the United States. *Environmental Science & Technology, 56*(18), 12965–12974. https://doi.org/10.1021/acs.est.2c03178
Sowby, R. B. (2023). The Safe Drinking Water Act at 50. *Water Resources Research, 59*(9), e2023WR035172. https://doi.org/10.1029/2023WR035172
Spearing, L. A., & Faust, K. M. (2020). Cascading system impacts of the 2018 Camp Fire in California. *International Journal of Disaster Risk Reduction, 47*, 101822. https://doi.org/10.1016/j.ijdrr.2020.101822
Spearing, L. A., Bakchan, A., Hamlet, L. C., Stephens, K. K., Kaminsky, J. A., & Faust, K. M. (2022). Comparing qualitative analysis techniques. *Journal of Construction Engineering and Management, 148*(7), 04022055. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002313
Spearing, L. A., Tariq, M., Safarpour, H., Abia, T., Mallory, M., Guild, J., Katz, L. E., & Faust, K. M. (2023). Moving beyond techno-economic considerations. *Current Opinion in Chemical Engineering, 42*, 100950. https://doi.org/10.1016/j.coche.2023.100950
Strauss, A. L. 1998. *Basics of qualitative research: Techniques and procedures for developing grounded theory*. Thousand Oaks, CA: SAGE.

Suchetana, B., Rajagopalan, B., & Silverstein, J. (2019). Modeling risk attributes of wastewater treatment plant violations of total ammonia nitrogen discharge limits in the United States. Stochastic Environmental Research and Risk Assessment, 33, 879–889. https://doi.org/10.1007/s00477-019-01654-6

Tiedmann, H. R., Spearing, L. A., Castellanos, S., Stephens, K. K., Sela, L., & Faust, K. M. (2023). Tracking the post-disaster evolution of water infrastructure resilience. *Sustainable Cities and Society, 91*, 104417. https://doi.org/10.1016/j.scs.2023.104417

U.S. Census Bureau. "ACS Demographic and Housing Estimates." *American Community Survey, ACS 1-Year Estimates Data Profiles, Table DP05,* https://data.census.gov/table/ACSDP1Y2024.DP05?q=us+population. Accessed on 10 Feb 2026.

U.S. Environmental Protection Agency. (2005). Guide for evaluating capacity, management, operation, and maintenance (CMOM) programs at sanitary sewer collection systems (EPA 305-B-05-002). https://www.epa.gov/sites/default/files/2015-10/documents/cmom_guide_for_collection_systems.pdf

U.S. Environmental Protection Agency. (2011a). *Introduction to the national pretreatment program* (EPA-833-B-11-001) [PDF]. https://www.epa.gov/sites/default/files/2015-10/documents/pretreatment_program_intro_2011.pdf

U.S. Environmental Protection Agency. (2012). *Assessing water system managerial capacity* (EPA 816-K-12-004). U.S. Environmental Protection Agency. https://www.epa.gov/sites/default/files/2015-07/documents/epa816k12004.pdf

U.S. Environmental Protection Agency. (2017a). *Asset management for water and wastewater utilities*. EPA Sustainable Water Infrastructure. https://19january2017snapshot.epa.gov/sustainable-water-infrastructure/asset-management-water-and-wastewater-utilities_.html

U.S. Environmental Protection Agency. (2017b). NPDES Compliance Inspection Manual (EPA 305-K-17-001). U.S. Environmental Protection Agency. https://www.epa.gov/compliance/compliance-inspection-manual-national-pollutant-discharge-elimination-system

U.S. Environmental Protection Agency. (2017, May 15). *Learn About Water System Partnerships.* U.S. EPA. https://www.epa.gov/dwcapacity/learn-about-water-system-partnerships

U.S. Environmental Protection Agency. (2018). *Preventive Maintenance for Small Public Water Systems Using Ground Water: An Interactive PDF with Suggested Preventive Maintenance Tasks and Logs Guidebook.* U.S. EPA. Retrieved from: https://www.epa.gov/sites/default/files/2018-03/documents/o_and_m_guidebook.pdf

U.S. Environmental Protection Agency (2022). *Clean Water Act 50th Anniversary.* https://storymaps.arcgis.com/stories/fdba46ff085747308e2f7c324a22f793

U.S. Environmental Protection Agency. (2023, March). *ECHO Training.* https://echo.epa.gov/help/training

U.S. Environmental Protection Agency. (2024, April). *2022 Clean Watersheds Needs Survey summary* (EPA Publication No. 832-F-24-005). U.S. EPA. https://www.epa.gov/system/files/documents/2024-05/2022-cwns-summary.pdf

U.S. Environmental Protection Agency. (2024, October 8). *Water Affordability Resources for Utilities.* U.S. EPA. https://www.epa.gov/waterfinancecenter/water-affordability-resources-utilities

U.S. Environmental Protection Agency. (2024). *Interagency Water Workforce Working Group report to Congress* (EPA 810-R-24-004). https://www.epa.gov/system/files/documents/2024-09/interagency-water-workforce-working-group-report-to-congress_august-2024-508-compliant.pdf

U.S. Environmental Protection Agency. (2025, May 22). *Summary of the Clean Water Act*. U.S. EPA. https://www.epa.gov/laws-regulations/summary-clean-water-act

U.S. Environmental Protection Agency. (2025, June 5). *Regulatory and guidance information by topic: Water*. https://www.epa.gov/regulatory-information-topic/regulatory-and-guidance-information-topic-water

U.S. Environmental Protection Agency. (2025, June 25). *Enforcement and Compliance History Online (ECHO)*. https://echo.epa.gov/

U.S. Environmental Protection Agency. (2025, September 26). *Basic information about sewage sludge and biosolids*. U.S. EPA. https://www.epa.gov/biosolids/basic-information-about-sewage-sludge-and-biosolids/
U.S. Environmental Protection Agency. (2025, December 29). *NPDES permits around the nation*. https://www.epa.gov/npdes-permits
U.S. Environmental Protection Agency. (2025). U.S. EPA national sewershed dataset & model documentation. https://www.epa.gov/cwns/sewersheds
U.S. Environmental Protection Agency. (2026, January). *Known data problems*. https://echo.epa.gov/resources/echo-data/known-data-problems
U.S. Environmental Protection Agency. (2026, February 20). *Safe Drinking Water Act (SDWA) resources and FAQs*. https://echo.epa.gov/help/sdwa-faqs
Van Thiel, S. (2014). *Research methods in public administration and public management* (1st ed.). Routledge. https://doi.org/10.4324/9780203078525
Wallerstein, N., Muhammad, M., Sanchez-Youngman, S., Rodriguez Espinosa, P., Avila, M., Baker, E. A., & Duran, B. (2019). Power dynamics in community-based participatory research. *Health Education & Behavior, 46*(1_suppl), 19S–32S. https://doi.org/10.1177/1090198119852998
Wallsten, S., & Kosec, K. (2008). The effects of ownership and benchmark competition. *International Journal of Industrial Organization, 26*(1), 186–205. https://doi.org/10.1016/j.ijindorg.2006.09.003
Wang, Y., Sobien, D., Kulkarni, A., & Batarseh, F. A. (2024). Quantifying water effluent violations and enforcement impacts using causal AI. *Policy & Internet,* 16(2), 227–249. https://doi.org/10.1002/poi3.402
Wells, E. C., Vidmar, A. M., Webb, W. A., Ferguson, A. C., Verbyla, M. E., de los Reyes III, F. L., ... & Mihelcic, J. R. (2022). Meeting the water and sanitation challenges of underbounded communities in the U.S. *Environmental Science & Technology*, *56*(16), 11180-11188.
Younis, R., & Knight, M. A. (2014). Development and implementation of an asset management framework for wastewater collection networks. *Tunnelling and Underground Space Technology, 39*, 130-143.

Appendix A: Clean Water Act Data and Robustness Checks

The dataset for quantitative analysis was constructed by combining the U.S. Environmental Protection Agency's 2025 Sewershed Boundaries Dataset containing information for 17,272 unique publicly owned treatment works with permit information and treatment works characteristics from the U.S. Environmental Protection Agency's Clean Watershed Needs Survey (Table A.1) and the U.S. Environmental Protection Agency's Enforcement and Compliance History Online database for 2025 Q2 (Table A.2).

Table A.1. Dataset Construction: Sewershed Area

	Number of Observations
U.S. EPA's 2025 Sewershed Dataset publicly owned treatment works	17,272
Exclude observations with missing or duplicate CWNS_ID	17,085
Publicly owned treatment works matched with Permit Number	14,561
Publicly owned treatment works matched with ICIS-NPDES Permit Information	**13,548**

Data source: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets obtained from https://echo.epa.gov/tools/data-downloads#downloads.

Table A.2. Dataset Construction: Quarterly Noncompliance Reporting

	Number of Observations
U.S. Environmental Protection Agency Clean Water Act Quarterly Noncompliance Reporting	7,502,127
Keep information for relevant NPDES_IDs matched to Publicly Owned Treatment Works	1,007,863
Exclude noncompliance that began prior to Q1 2018	246,101
Exclude noncompliance that began prior to Q1 2023	64,294
Removed rows with missing historical noncompliance data	59,494
Count of rows containing Significant Noncompliance status	**10,537**

Data source: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets obtained from https://echo.epa.gov/tools/data-downloads#downloads.

Characteristics of each publicly owned treatment works' sewershed were obtained from the U.S. Census Bureau's American Community Survey, 2018-2022 5-year estimates (Table A.3).[17] These data were collected at the census tract level, using a crosswalk to match census tracts to community water system sewersheds.

This process began by intersecting the 2025 publicly owned treatment works' sewershed boundaries with 2022 U.S. census tract boundaries, both projected using the *USA Contiguous Albers Equal Area Conic* coordinate system and then calculating the overlap area in square meters followed by the percentage overlap relative to sewershed. The higher the number of overlapping areas, the more the rounding error compounds. In addition, the

[17] For additional information about the U.S. Census Bureau's American Community Survey data, please see https://www.census.gov/programs-surveys/acs.html.

sewershed shapefile overlaps bodies of water while the census tract shapefile does not. Adjusting for the rounding errors, water overlap, and minor overlaps of polygons in the sewershed shapefile was accomplished by rescaling the calculated proportions so that the sum of the adjusted proportions is equal to one. Using areal interpolation to estimate characteristics of treatment works' sewersheds is a common approach used in prior research on this topic (Pierce et al., 2023; Reibel, 2018).

The full dataset combines information from the 2025 U.S. Environmental Protection Agency's Sewershed Boundaries Dataset, the U.S. Environmental Protection Agency's Enforcement and Compliance History Online data for Q2 of 2025, and American Community Survey 5-year estimates from 2018 to 2022.

Table A.3. Dataset Construction: Sewershed Characteristics

	Number of Observations
Sewershed and Census tracts data[18]	105,632
Separating out sewersheds with multiple CWNS_IDs	115,235
Aggregate by creating areal weighted means of variables so each system appears only once	**17,085**

Data sources: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets obtained from https://echo.epa.gov/tools/data-downloads#downloads, and U.S. Census Bureau's American Community Survey 2018-2022 5-year estimates obtained from https://www.census.gov/programs-surveys/acs.html.

For a subset of publicly owned treatment works, those owned by local governments, data were collected to assess fiscal capacity, obtained from the U.S. Census Bureau's Census of Governments Finance Survey data for 2022 (Table A.4). These data are available at the municipality, municipal water district, and county level for every government in the U.S..[19]

Fiscal information was matched to publicly owned treatment works by intersecting the 2025 Sewershed Boundaries Map with the U.S. Census Bureau's 2022 Place and County Boundary files, both projected using the *USA Contiguous Albers Equal Area Conic* coordinate system. For treatment works that intersected with multiple geographies, the name of the treatment works was used to finalize the matching. When treatment works names were not conclusive, data were inspected on a case-by-case basis to ensure the appropriate one-to-one match.

For the 12,969 publicly owned treatment works included in the subset analysis, 75.43 percent were matched to municipal water districts, 22.85 percent to municipal governments, and 1.72 percent to county governments. Robustness checks assess the

[18] These data reflect the overlap between sewershed and census tract polygons, calculated in ArcGIS Pro. Before calculating the overlap, the sewershed shapefile geometry was repaired to address self-intersection issues.

[19] For additional information about the US Census Bureau's Census of Governments Finance Survey data, please see: https://www.census.gov/programs-surveys/cog.html.

sensitivity of the regression results by excluding observations for which 1) full-time employees, and 2) government finance data are unavailable.

Table A.4. Data Subset: Local Government Characteristics

	Number of Observations
Census of Governments Units	38,736
Merge Census of Government Employment Information	38,736
Merge facilities to municipal/township/county government crosswalk[20]	12,969
Merge Census of Government Financial Information	**12,969**

Data sources: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets obtained from https://echo.epa.gov/tools/data-downloads#downloads, U.S. Census Bureau's American Community Survey 2018-2022 5-year estimates obtained from https://www.census.gov/programs-surveys/acs.html, and U.S. Census Bureau's Census of Governments Finance Survey data for 2022 obtained from: https://www.census.gov/programs-surveys/cog.html.

[20] This crosswalk was created by first overlaying sewershed and municipal, township, and county polygons, in ArcGIS Pro. Before overlaying, the sewershed shapefile geometry was repaired to address self-intersection issues. When sewershed overlapped with multiple governmental units, the name of the system was used to finalize the matching. When system names were not conclusive, data were inspected on a case-by-case basis to ensure the appropriate one-to-one match.

Table A.5. Robustness Check: Functional Form for All Publicly Owned Treatment Works

	Probit		Logit		Linear Probability Model
Variables	Coefficient (Std. Error) (1)	Marginal Effect (2)	Coefficient (Std. Error) (3)	Marginal Effect (4)	Coefficient (Std. Error) (5)
Plant-Level Characteristics					
Ownership					
Federal Facility	0.0243	0.0070	0.0785	0.0132	0.0170
	(0.4710)		(0.7880)		(0.1420)
County Govt.	-0.2400	-0.0687	-0.4510*	-0.0757	-0.0602
	(0.1570)		(0.2570)		(0.0436)
Municipal Govt.	0.0963	0.0276	0.1330	0.0223	0.0176
	(0.1210)		(0.1940)		(0.0314)
Municipal Water District	0.0105	0.0030	-0.0053	-0.0009	0.0033
	(0.0918)		(0.1450)		(0.0266)
Mixed Ownership	-0.4920***	-0.1409	-0.8650***	-0.1453	-0.1370***
	(0.1610)		(0.2770)		(0.0367)
Tribal Govt.	0.0637	0.0183	0.0885	0.0149	0.0268
	(0.4040)		(0.6140)		(0.1360)
State Govt.	-0.2480	-0.0712	-0.4890	-0.0822	-0.0792
	(0.2120)		(0.3470)		(0.0599)
Privately Owned	-0.1520	-0.0435	-0.2760	-0.0464	-0.0417
	(0.1700)		(0.2860)		(0.0478)
Population Served (Ln)	-0.0214*	-0.0061	-0.0406*	-0.0068	-0.0070*
	(0.0129)		(0.0221)		(0.0037)
Part of Sewershed Network	-0.0343	-0.0098	-0.0643	-0.0108	-0.0076
	(0.0352)		(0.0610)		(0.0094)
Endpoint Facility	-0.2490***	-0.0713	-0.4490***	-0.0754	-0.0727***
	(0.0776)		(0.1310)		(0.0247)
Pretreatment Program	-0.0726	-0.0208	-0.1190	-0.0201	-0.0181
	(0.0534)		(0.0928)		(0.0146)
Compliance Evaluation Inspection	0.0208	0.0060	0.0305	0.0051	0.0061
	(0.0364)		(0.0619)		(0.0105)
Reconnaissance Inspection	0.0863	0.0247	0.1480	0.0248	0.0241
	(0.0640)		(0.1070)		(0.0215)
Performance Audit Inspection	0.1530**	0.0438	0.2740**	0.0461	0.0424*
	(0.0748)		(0.1330)		(0.0216)
Follow-Up Inspection	0.1070***	0.0307	0.1790***	0.0300	0.0276**
	(0.0350)		(0.0573)		(0.0130)
Formal Enforcement Action	0.3050***	0.0875	0.5130***	0.0861	0.0968***
	(0.0481)		(0.0812)		(0.0173)
Sig. Noncompliance 2018-2022	0.8840***	0.2533	1.5280***	0.2567	0.2700***
	(0.0414)		(0.0691)		(0.0148)
Proportion Unreported Data	0.3950	0.1133	0.6930	0.1163	0.1270
	(0.4940)		(0.8510)		(0.1420)
Known Data Problems	0.0676	0.0194	0.1010	0.0170	-0.0138
	(0.1130)		(0.2010)		(0.0254)
Potential Data Problems	0.4440***	-0.0326	0.7590***	0.1275	-0.0254
	(0.1050)		(0.1860)		(0.0208)
Sewershed Characteristics					
Population Density (per sq km) (Ln)	-0.0328***	-0.0094	-0.0598***	-0.0100	-0.0094***
	(0.0110)		(0.0192)		(0.0032)
Median Household Income (Ln)	-0.0905*	-0.0259	-0.1460	-0.0246	-0.0247
	(0.0539)		(0.0929)		(0.0160)
Median Age	-0.0039	-0.0011	-0.0074*	-0.0012	-0.0013*
	(0.0026)		(0.0043)		(0.0008)
Proportion of Housing Stock					
Built Before 1960	0.0832	0.0238	0.1490	0.0250	0.0207
	(0.1590)		(0.2650)		(0.0440)
Built 1960-1969	-0.4030	-0.1155	-0.6620	-0.1112	-0.1180
	(0.2830)		(0.4740)		(0.0831)
Built 1970-1979	0.1110	0.0319	0.1930	0.0323	0.0284
	(0.2360)		(0.4120)		(0.0698)
Built 1980-1989	0.0614	0.0176	0.0964	0.0162	0.0186
	(0.2960)		(0.5130)		(0.0831)
Mean	0.2702		0.2702		0.2702
Pseudo/Adjusted R2	0.1298		0.1307		0.1452
Number of Observations	13,547		13,547		13,548

Note: Columns (1)-(2) present results from a probit model, while Columns (3)-(4) present results from a negative binomial model, and Column (5) presents results from a linear probability model. Coefficients are presented in Column (1), (3), and (5), while mean marginal effects are presented in Columns (2) and (4). Ln indicates natural log values are used for analysis to reduce skewness in the data distribution and improve model fit. In the probit model, one observation from DC is excluded as the DC treatment plant had no significant noncompliance violations. In all columns, state fixed effects are included. Clustered standard errors are in parentheses. Statistical significance of each variable is determined by the relevant test statistic and corresponding p-value (not shown), and denoted as: * p < 0.1, ** p < 0.05, *** p < 0.01. Data sources: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets obtained from https://echo.epa.gov/tools/data-downloads#downloads and U.S. Census Bureau's American Community Survey 2018-2022 5-year estimates obtained from https://www.census.gov/programs-surveys/acs.html.

.

Table A.6. Robustness Check: Excluding Known Data Problems for All Treatment Works

	Any Sig. Noncompliance 2023-2024 All Treatment Works		Quarters in Sig. Noncompliance 2023-2024 All Treatment Works		Quarters in Sig. Noncompliance 2023-2024 Noncompliant Treatment Works	
Variables	Coefficient (Std. Error) (1)	Marginal Effect (2)	Coefficient (Std. Error) (3)	Marginal Effect (4)	Coefficient (Std. Error) (5)	Marginal Effect (6)
Plant-Level Characteristics						
Ownership						
Federal Facility	0.0955	0.0273	0.0306	0.0228	-0.1290	-0.3659
	(0.5140)		(0.7950)		(0.5820)	
County Govt.	-0.2390	-0.0682	-0.4040	-0.3006	-0.1670	-0.4730
	(0.2310)		(0.3420)		(0.1260)	
Municipal Govt.	0.1230	0.0351	-0.0764	-0.0569	**-0.3130*** **	-0.8878
	(0.1490)		(0.2320)		(0.0947)	
Municipal Water District	0.0210	0.0060	-0.1160	-0.0865	**-0.2180*** **	-0.6185
	(0.1270)		(0.1800)		(0.0511)	
Mixed Ownership	**-0.4600** **	-0.1312	**-1.0410** **	-0.7758	**-0.4060** **	-1.1520
	(0.1890)		(0.4510)		(0.1790)	
Tribal Govt.	0.0424	0.0121	0.1410	0.1048	**0.1710***	0.4851
	(0.4850)		(0.3810)		(0.1020)	
State Govt.	-0.2290	-0.0653	**-0.8750** **	-0.6516	**-0.7100*** **	-2.0158
	(0.2460)		(0.4190)		(0.2190)	
Privately Owned	-0.0855	-0.0244	0.0201	0.0150	0.0815	0.2313
	(0.2070)		(0.2410)		(0.1040)	
Population Served (Ln)	-0.0163	-0.0047	-0.0252	-0.0188	**-0.0270** **	-0.0766
	(0.0109)		(0.0211)		(0.0121)	
Part of Sewershed Network	-0.0228	-0.0065	-0.0451	-0.0336	0.0183	0.0518
	(0.0391)		(0.0563)		(0.0347)	
Endpoint Facility	**-0.2110** **	-0.0603	-0.2190	-0.1629	-0.0034	-0.0098
	(0.0832)		(0.1350)		(0.0839)	
Pretreatment Program	-0.0773	-0.0221	-0.0945	-0.0704	0.0108	0.0307
	(0.0564)		(0.0853)		(0.0561)	
Compliance Evaluation Inspection	0.0040	0.0011	0.0001	0.0001	-0.0135	-0.0384
	(0.0385)		(0.0584)		(0.0295)	
Reconnaissance Inspection	0.0094	0.0027	0.1190	0.0887	0.0612	0.1735
	(0.0377)		(0.1090)		(0.1090)	
Performance Audit Inspection	**0.2130** **	0.0608	**0.2890** **	0.2150	-0.0320	-0.0909
	(0.0905)		(0.1410)		(0.1220)	
Follow-Up Inspection	**0.1180*** **	0.0337	**0.3050*** **	0.2270	**0.0949*** **	0.2694
	(0.0349)		(0.0491)		(0.0367)	
Formal Enforcement Action	**0.3440*** **	0.0982	**0.3650*** **	0.2716	0.0717	0.2034
	(0.0636)		(0.0869)		(0.0485)	
Sig. Noncompliance 2018-2022	**0.8530*** **	0.2436	**1.5230*** **	1.1348	**0.4280*** **	1.2138
	(0.0434)		(0.0715)		(0.0433)	
Proportion Unreported Data	0.7650	0.2183	1.0800	0.8043	0.0191	0.0542
	(0.4700)		(0.7920)		(0.5790)	
Potential Data Problems	**0.3920*** **	0.1120	**0.8150** **	0.6068	0.2660	0.7561
	(0.1040)		(0.3500)		(0.1870)	
Sewershed Characteristics						
Population Density (per sq km) (Ln)	**-0.0250** **	-0.0071	**-0.0468** **	-0.0349	-0.0178	-0.0506
	(0.0116)		(0.0235)		(0.0110)	
Median Household Income (Ln)	**-0.1080***	-0.0307	**-0.2030** **	-0.1511	**-0.0894** **	-0.2537
	(0.0584)		(0.0855)		(0.0413)	
Median Age	-0.0035	-0.0010	-0.0043	-0.0032	**-0.0050** **	-0.0140
	(0.0028)		(0.0040)		(0.0022)	
Proportion of Housing Stock						
Built Before 1960	-0.0327	-0.0093	0.0483	0.0360	0.0932	0.2646
	(0.1610)		(0.2640)		(0.1380)	
Built 1960-1969	-0.2480	-0.0708	-0.1800	-0.1341	0.2320	0.6585
	(0.2930)		(0.4530)		(0.2400)	
Built 1970-1979	0.1080	0.0309	0.3810	0.2839	0.0905	0.2567
	(0.2380)		(0.3280)		(0.1970)	
Built 1980-1989	-0.1070	-0.0306	-0.0400	-0.0298	0.3360	0.9522
	(0.2880)		(0.5480)		(0.3330)	
Mean	0.2639		0.7484		2.8377	
Pseudo R2	0.1233		0.0647		0.0387	
Number of Observations	11,495		11,496		3,032	

Note: Columns (1)-(2) present results from a probit model while Columns (3)-(6) present results from a negative binomial model. Coefficients are presented in Column (1), (3), and (5), while mean marginal effects are presented in Columns (2), (4), and (6). Ln indicates natural log values are used for analysis to reduce skewness in the data distribution and improve model fit. In the probit model, one observation from DC is excluded as the DC treatment plant had no significant noncompliance violations. In all columns, state fixed effects are included. Clustered standard errors are in parentheses. Statistical significance of each variable is determined by the relevant test statistic and corresponding p-value (not shown), and denoted as: * p < 0.1, ** p < 0.05, *** p < 0.01. Data sources: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets obtained from https://echo.epa.gov/tools/data-downloads#downloads and U.S. Census Bureau's American Community Survey 2018-2022 5-year estimates obtained from https://www.census.gov/programs-surveys/acs.html.

Table A.7. Robustness Check: Excluding Known and Potential Data Problems for All Treatment Works

	Any Sig. Noncompliance 2023-2024 All Treatment Works		Quarters in Sig. Noncompliance 2023-2024 All Treatment Works		Quarters in Sig. Noncompliance 2023-2024 Noncompliant Treatment Works	
Variables	Coefficient (Std. Error) (1)	Marginal Effect (2)	Coefficient (Std. Error) (3)	Marginal Effect (4)	Coefficient (Std. Error) (5)	Marginal Effect (6)
Plant-Level Characteristics						
Ownership						
Federal Facility	0.0930	0.0273	0.0514	0.0424	-0.1170	-0.3400
	(0.5290)		(0.7980)		(0.5840)	
County Govt.	-0.2880	-0.0844	-0.4230	-0.3482	-0.1470	-0.4255
	(0.2410)		(0.3640)		(0.1340)	
Municipal Govt.	0.0182	0.0053	-0.1450	-0.1192	**-0.2500****	-0.7245
	(0.1400)		(0.2470)		(0.1100)	
Municipal Water District	0.0352	0.0103	-0.0856	-0.0706	**-0.2030*****	-0.5900
	(0.1300)		(0.1830)		(0.0564)	
Mixed Ownership	-0.4530	-0.1328	-0.9920	-0.8174	**-0.4670*****	-1.3556
	(0.5920)		(0.8740)		(0.0504)	
Tribal Govt.	0.0843	0.0247	0.1810	0.1493	**0.1950***	0.5664
	(0.5000)		(0.3660)		(0.1070)	
State Govt.	-0.1910	-0.0560	**-0.8370***	-0.6900	**-0.7360*****	-2.1341
	(0.2580)		(0.4470)		(0.2310)	
Privately Owned	-0.0716	-0.0210	0.0188	0.0155	0.0588	0.1705
	(0.2170)		(0.2380)		(0.1140)	
Population Served (Ln)	**-0.0253****	-0.0074	**-0.0402***	-0.0331	**-0.0303****	-0.0878
	(0.0112)		(0.0225)		(0.0137)	
Part of Sewershed Network	-0.0297	-0.0087	-0.0851	-0.0702	-0.0079	-0.0228
	(0.0473)		(0.0613)		(0.0346)	
Endpoint Facility	**-0.2510*****	-0.0734	**-0.2970****	-0.2448	-0.0471	-0.1365
	(0.0930)		(0.1410)		(0.0873)	
Pretreatment Program	**-0.1190****	-0.0350	**-0.1540****	-0.1265	0.0135	0.0393
	(0.0590)		(0.0709)		(0.0509)	
Compliance Evaluation Inspection	-0.0187	-0.0055	-0.0264	-0.0217	-0.0221	-0.0640
	(0.0396)		(0.0589)		(0.0356)	
Reconnaissance Inspection	-0.0181	-0.0053	-0.0082	-0.0067	-0.0358	-0.1037
	(0.0431)		(0.0788)		(0.0905)	
Performance Audit Inspection	**0.2840****	0.0833	0.3160	0.2601	-0.0461	-0.1338
	(0.1440)		(0.2000)		(0.1450)	
Follow-Up Inspection	**0.1130*****	0.0331	**0.3130*****	0.2576	**0.1130*****	0.3269
	(0.0398)		(0.0462)		(0.0300)	
Formal Enforcement Action	**0.3180*****	0.0932	**0.2750*****	0.2264	0.0454	0.1316
	(0.0749)		(0.0919)		(0.0517)	
Sig. Noncompliance 2018-2022	**0.9130*****	0.2676	**1.6250*****	1.3390	**0.4740*****	1.3762
	(0.0437)		(0.0658)		(0.0505)	
Proportion Unreported Data	**1.0370***	0.3040	**1.5930****	1.3126	0.4480	1.2985
	(0.5490)		(0.7080)		(0.4700)	
Sewershed Characteristics						
Population Density (per sq km) (Ln)	-0.0180	-0.0053	-0.0246	-0.0203	-0.0084	-0.0243
	(0.0120)		(0.0246)		(0.0116)	
Median Household Income (Ln)	-0.0729	-0.0214	**-0.1840****	-0.1520	**-0.1130*****	-0.3265
	(0.0620)		(0.0864)		(0.0401)	
Median Age	-0.0037	-0.0011	-0.0051	-0.0042	**-0.0053****	-0.0154
	(0.0034)		(0.0047)		(0.0025)	
Proportion of Housing Stock						
Built Before 1960	0.0556	0.0163	0.2040	0.1677	0.0612	0.1774
	(0.1950)		(0.2980)		(0.1610)	
Built 1960-1969	-0.2840	-0.0833	-0.2020	-0.1666	0.1680	0.4866
	(0.2910)		(0.4300)		(0.2560)	
Built 1970-1979	0.2690	0.0787	0.3880	0.3194	-0.0050	-0.0142
	(0.2790)		(0.3810)		(0.2240)	
Built 1980-1989	-0.1420	-0.0415	0.0949	0.0782	0.4410	1.2797
	(0.3420)		(0.6600)		(0.3600)	
Mean	0.2857		0.8281		2.9012	
Pseudo R2	0.1338		0.0691		0.0399	
Number of Observations	8,319		8,320		2,375	

Note: Columns (1)-(2) present results from a probit model while Columns (3)-(6) present results from a negative binomial model. Coefficients are presented in Column (1), (3), and (5), while mean marginal effects are presented in Columns (2), (4), and (6). Ln indicates natural log values are used for analysis to reduce skewness in the data distribution and improve model fit. In the probit model, one observation from DC is excluded as the DC treatment plant had no significant noncompliance violations. In all columns, state fixed effects are included. Clustered standard errors are in parentheses. Statistical significance of each variable is determined by the relevant test statistic and corresponding p-value (not shown), and denoted as: * p < 0.1, ** p < 0.05, *** p < 0.01. Data sources: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets obtained from https://echo.epa.gov/tools/data-downloads#downloads and U.S. Census Bureau's American Community Survey 2018-2022 5-year estimates obtained from https://www.census.gov/programs-surveys/acs.html.

Table A.8. Robustness Check: Excluding Known Data Problems for Govt. Owned Treatment Works

	Any Sig. Noncompliance 2023-2024 All Treatment Works		Quarters in Sig. Noncompliance 2023-2024 All Treatment Works		Quarters in Sig. Noncompliance 2023-2024 Noncompliant Treatment Works	
Variables	Coefficient (Std. Error) (1)	Marginal Effect (2)	Coefficient (Std. Error) (3)	Marginal Effect (4)	Coefficient (Std. Error) (5)	Marginal Effect (6)
Plant-Level Characteristics						
Ownership						
Municipal Govt.	**0.3350***	0.0955	0.2870	0.2116	-0.1450	-0.4041
	(0.1870)		(0.2780)		(0.1030)	
Municipal Water District	0.2100	0.0599	0.1820	0.1339	-0.0808	-0.2258
	(0.1920)		(0.3060)		(0.1340)	
Population Served (Ln)	-0.0121	-0.0035	-0.0146	-0.0108	**-0.0230***	-0.0642
	(0.0115)		(0.0226)		(0.0121)	
Part of Sewershed Network	-0.0060	-0.0017	-0.0172	-0.0127	0.0238	0.0665
	(0.0367)		(0.0551)		(0.0340)	
Endpoint Facility	**-0.2240****	-0.0640	**-0.2320***	-0.1707	0.00001	0.0000
	(0.0919)		(0.1410)		(0.0855)	
Pretreatment Program	-0.0500	-0.0143	-0.0698	-0.0514	-0.0066	-0.0183
	(0.0614)		(0.0898)		(0.0576)	
Compliance Evaluation Inspection	0.0112	0.0032	0.0157	0.0116	-0.0056	-0.0157
	(0.0386)		(0.0581)		(0.0293)	
Reconnaissance Inspection	-0.0147	-0.0042	0.0812	0.0598	0.0542	0.1514
	(0.0358)		(0.1050)		(0.1020)	
Performance Audit Inspection	**0.2470*****	0.0705	**0.3890*****	0.2864	0.0243	0.0678
	(0.0849)		(0.1320)		(0.1300)	
Follow-Up Inspection	**0.1140*****	0.0326	**0.2960*****	0.2179	**0.0906****	0.2531
	(0.0365)		(0.0467)		(0.0361)	
Formal Enforcement Action	**0.3480*****	0.0992	**0.3790*****	0.2788	0.0750	0.2095
	(0.0646)		(0.0918)		(0.0490)	
Sig. Noncompliance 2018-2022	**0.8330*****	0.2374	**1.4850*****	1.0930	**0.4190*****	1.1694
	(0.0438)		(0.0714)		(0.0418)	
Proportion Unreported Data	**1.0950****	0.3124	1.4190	1.0447	-0.2600	-0.7257
	(0.5260)		(0.8630)		(0.5960)	
Potential Data Problems	0.0771	0.0220	-0.0163	-0.0120	0.0014	0.0040
	(0.1030)		(0.2140)		(0.1760)	
Sewershed Characteristics						
Population Density (per sq km) (Ln)	-0.0179	-0.0051	-0.0344	-0.0253	-0.0146	-0.0407
	(0.0111)		(0.0212)		(0.0111)	
Median Household Income (Ln)	**-0.0901***	-0.0257	**-0.1530***	-0.1127	-0.0662	-0.1851
	(0.0514)		(0.0854)		(0.0416)	
Median Age	-0.0028	-0.0008	-0.0031	-0.0023	**-0.0045***	-0.0125
	(0.0028)		(0.0042)		(0.0023)	
Proportion of Housing Stock						
Built Before 1960	-0.0644	-0.0184	-0.0104	-0.0077	0.0782	0.2186
	(0.1560)		(0.2680)		(0.1430)	
Built 1960-1969	-0.2190	-0.0624	-0.1150	-0.0846	0.2160	0.6022
	(0.2830)		(0.448)		(0.2590)	
Built 1970-1979	0.1260	0.0360	0.2720	0.2002	-0.0517	-0.1444
	(0.2460)		(0.3450)		(0.1860)	
Built 1980-1989	-0.0831	-0.0237	0.0366	0.0269	0.3720	1.0383
	(0.2620)		(0.5360)		(0.3550)	
Government Finance						
Debt Service Burden	-0.0913	-0.0260	**-0.1830***	-0.1350	**-0.0537***	-0.1502
	(0.0775)		(0.0941)		(0.0307)	
Risk Exposure Factor	**-0.0255****	-0.0073	-0.0702	-0.0517	0.0672	0.1878
	(0.0110)		(0.1120)		(0.1360)	
Operating Expenditure Ratio	0.0077	0.0022	0.0164	0.0121	0.0047	0.0132
	(0.0157)		(0.0247)		(0.0134)	
Water Revenue Expenditure Ratio	0.0044	0.0013	-0.0182	-0.0134	-0.0017	-0.0047
	(0.0451)		(0.0505)		(0.0235)	
Full Time Employees (Ln)	**-0.0251*****	-0.0072	**-0.0465*****	-0.0342	-0.0105	-0.0294
	(0.0067)		(0.0114)		(0.0076)	
Mean	0.2633		0.7359		2.7945	
Pseudo R2	0.1228		0.0642		0.0337	
Number of Observations	11,012		11,013		2,900	

Note: Columns (1)-(2) present results from a probit model while Columns (3)-(6) present results from a negative binomial model. Coefficients are presented in Column (1), (3), and (5), while mean marginal effects are presented in Columns (2), (4), and (6). Ln indicates natural log values are used for analysis to reduce skewness in the data distribution and improve model fit. In the probit model, one observation from DC is excluded as the DC treatment plant had no significant noncompliance violations. In all columns, state fixed effects are included. Clustered standard errors are in parentheses. Statistical significance of each variable is determined by the relevant test statistic and corresponding p-value (not shown), and denoted as: * p < 0.1, ** p < 0.05, *** p < 0.01. Data sources: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets obtained from https://echo.epa.gov/tools/data-downloads#downloads, U.S. Census Bureau's American Community Survey 2018-2022 5-year estimates obtained from https://www.census.gov/programs-surveys/acs.html, and U.S. Census Bureau's Census of Governments Finance Survey data for 2022 obtained from: https://www.census.gov/programs-surveys/cog.html.

Table A.9. Robustness Check: Excluding Known and Potential Data Problems for Govt. Owned Treatment Works

	Any Sig. Noncompliance 2023-2024 All Treatment Works		Quarters in Sig. Noncompliance 2023-2024 All Treatment Works		Quarters in Sig. Noncompliance 2023-2024 Noncompliant Treatment Works	
Variables	Coefficient (Std. Error) (1)	Marginal Effect (2)	Coefficient (Std. Error) (3)	Marginal Effect (4)	Coefficient (Std. Error) (5)	Marginal Effect (6)
Plant-Level Characteristics						
Ownership						
Municipal Govt.	0.2880	0.0844	0.2280	0.1859	-0.1310	-0.3742
	(0.1990)		(0.2930)		(0.1130)	
Municipal Water District	0.2800	0.0820	0.2330	0.1903	-0.1000	-0.2864
	(0.2070)		(0.3380)		(0.1410)	
Population Served (Ln)	**-0.0196***	-0.0057	-0.0269	-0.0220	**-0.0242***	-0.0690
	(0.0118)		(0.0239)		(0.0138)	
Part of Sewershed Network	-0.0229	-0.0067	-0.0781	-0.0637	-0.0077	-0.0220
	(0.0440)		(0.0592)		(0.0326)	
Endpoint Facility	**-0.2830****	-0.0830	**-0.3330****	-0.2721	-0.0474	-0.1354
	(0.1040)		(0.1450)		(0.0857)	
Pretreatment Program	-0.0871	-0.0255	-0.1110	-0.0907	0.0123	0.0350
	(0.0671)		(0.0763)		(0.0548)	
Compliance Evaluation Inspection	-0.0161	-0.0047	-0.0195	-0.0159	-0.0172	-0.0490
	(0.0401)		(0.0575)		(0.0360)	
Reconnaissance Inspection	-0.0294	-0.0086	-0.0180	-0.0147	-0.0265	-0.0756
	(0.0439)		(0.0920)		(0.0899)	
Performance Audit Inspection	**0.2860****	0.0838	**0.3360***	0.2740	-0.0410	-0.1171
	(0.1350)		(0.1950)		(0.1450)	
Follow-Up Inspection	**0.1140*****	0.0333	**0.3120*****	0.2544	**0.1080*****	0.3085
	(0.0403)		(0.0437)		(0.0315)	
Formal Enforcement Action	**0.3210*****	0.0941	**0.2820*****	0.2301	0.0476	0.1358
	(0.0757)		(0.0950)		(0.0520)	
Sig. Noncompliance 2018-2022	**0.8880*****	0.2603	**1.5850*****	1.2930	**0.4680*****	1.3352
	(0.0443)		(0.0660)		(0.0483)	
Proportion Unreported Data	**1.5690****	0.4598	**2.2320*****	1.8214	0.2580	0.7376
	(0.6330)		(0.7880)		(0.5010)	
Sewershed Characteristics						
Population Density (per sq km) (Ln)	-0.0131	-0.0038	-0.0149	-0.0122	-0.0045	-0.0128
	(0.0118)		(0.0215)		(0.0110)	
Median Household Income (Ln)	-0.0669	-0.0196	-0.1320	-0.1080	**-0.0742***	-0.2118
	(0.0561)		(0.0834)		(0.0416)	
Median Age	-0.0029	-0.0009	-0.00401	-0.0033	**-0.0050***	-0.0143
	(0.0035)		(0.0050)		(0.0026)	
Proportion of Housing Stock						
Built Before 1960	0.0118	0.0035	0.1250	0.1017	0.0357	0.1019
	(0.1890)		(0.3030)		(0.1700)	
Built 1960-1969	-0.2990	-0.0877	-0.2440	-0.1993	0.0805	0.2297
	(0.2730)		(0.4370)		(0.2800)	
Built 1970-1979	0.3150	0.0923	0.3580	0.2925	-0.0966	-0.2756
	(0.2840)		(0.4050)		(0.2180)	
Built 1980-1989	-0.1580	-0.0463	0.0496	0.0405	0.3890	1.1098
	(0.3070)		(0.6400)		(0.3860)	
Government Finance						
Debt Service Burden	-0.0492	-0.0144	**-0.1250***	-0.1017	**-0.0604*****	-0.1723
	(0.0436)		(0.0668)		(0.0233)	
Risk Exposure Factor	**-0.0224*****	-0.0066	**-0.0450****	-0.0368	0.0739	0.2109
	(0.0055)		(0.0176)		(0.1320)	
Operating Expenditure Ratio	0.0114	0.0033	0.0339	0.0276	0.0159	0.0453
	(0.0232)		(0.0311)		(0.0141)	
Water Revenue Expenditure Ratio	0.0018	0.0005	-0.0226	-0.0185	-0.0086	-0.0244
	(0.0477)		(0.0572)		(0.0192)	
Full Time Employees (Ln)	**-0.0212****	-0.0062	**-0.0456*****	-0.0372	**-0.0167****	-0.0478
	(0.0084)		(0.0133)		(0.0081)	
Mean	0.2855		0.8149		2.8545	
Pseudo R2	0.1331		0.0686		0.0344	
Number of Observations	7,944		7,945		2,268	

Note: Columns (1)-(2) present results from a probit model while Columns (3)-(6) present results from a negative binomial model. Coefficients are presented in Column (1), (3), and (5), while mean marginal effects are presented in Columns (2), (4), and (6). Ln indicates natural log values are used for analysis to reduce skewness in the data distribution and improve model fit. In the probit model, one observation from DC is excluded as the DC treatment plant had no significant noncompliance violations. In all columns, state fixed effects are included. Clustered standard errors are in parentheses. Statistical significance of each variable is determined by the relevant test statistic and corresponding p-value (not shown), and denoted as: * p < 0.1, ** p < 0.05, *** p < 0.01. Data sources: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets obtained from https://echo.epa.gov/tools/data-downloads#downloads, U.S. Census Bureau's American Community Survey 2018-2022 5-year estimates obtained from https://www.census.gov/programs-surveys/acs.html, and U.S. Census Bureau's Census of Governments Finance Survey data for 2022 obtained from: https://www.census.gov/programs-surveys/cog.html.

Table A.10. Robustness Check: Local Government Owned Treatment Works Excluding Govt. Finance

	Any Sig. Noncompliance 2023-2024 All Treatment Works		Quarters in Sig. Noncompliance 2023-2024 All Treatment Works		Quarters in Sig. Noncompliance 2023-2024 Noncompliant Treatment Works	
Variables	Coefficient (Std. Error) (1)	Marginal Effect (2)	Coefficient (Std. Error) (3)	Marginal Effect (4)	Coefficient (Std. Error) (5)	Marginal Effect (6)
Plant-Level Characteristics						
Ownership						
Municipal Govt.	0.3460**	0.0993	0.2380	0.1851	-0.2170**	-0.6252
	(0.1380)		(0.2040)		(0.0977)	
Municipal Water District	0.2400*	0.0689	0.1250	0.0969	-0.2070**	-0.5964
	(0.1240)		(0.2030)		(0.0915)	
Population Served (Ln)	-0.0245*	-0.0070	-0.0366*	-0.0285	-0.0243**	-0.0699
	(0.0136)		(0.0216)		(0.0114)	
Part of Sewershed Network	-0.0241	-0.0069	-0.0446	-0.0347	0.0184	0.0528
	(0.0349)		(0.0514)		(0.0314)	
Endpoint Facility	-0.2510***	-0.0722	-0.2970**	-0.2306	-0.0607	-0.1748
	(0.0847)		(0.1300)		(0.0736)	
Pretreatment Program	-0.0612	-0.0176	-0.0945	-0.0735	-0.0236	-0.0679
	(0.0567)		(0.0816)		(0.0498)	
Compliance Evaluation Inspection	0.0219	0.0063	0.0193	0.0150	-0.0090	-0.0258
	(0.0358)		(0.0531)		(0.0289)	
Reconnaissance Inspection	0.0640	0.0184	0.0956	0.0744	-0.00008	-0.0002
	(0.0611)		(0.0781)		(0.0651)	
Performance Audit Inspection	0.1680**	0.0482	0.1990	0.1549	-0.0759	-0.2184
	(0.0747)		(0.1320)		(0.1100)	
Follow-Up Inspection	0.1250***	0.0358	0.3160***	0.2456	0.0978***	0.2814
	(0.0352)		(0.0492)		(0.0353)	
Formal Enforcement Action	0.3090***	0.0888	0.3260***	0.2532	0.0903***	0.2597
	(0.0485)		(0.0547)		(0.0208)	
Sig. Noncompliance 2018-2022	0.8630***	0.2480	1.5360***	1.1946	0.4280***	1.2324
	(0.0394)		(0.0648)		(0.0381)	
Proportion Unreported Data	0.5700	0.1637	0.8340	0.6487	-0.1210	-0.3480
	(0.5760)		(0.8290)		(0.5340)	
Known Data Problems	0.3040**	0.0874	0.5770***	0.4486	0.2500*	0.7182
	(0.1270)		(0.2100)		(0.1500)	
Potential Data Problems	0.2160*	0.0621	0.1950	0.1516	0.0301	0.0867
	(0.1120)		(0.1960)		(0.1440)	
Sewershed Characteristics						
Population Density (per sq km) (Ln)	-0.0343***	-0.0099	-0.0565***	-0.0440	-0.0169	-0.0487
	(0.0110)		(0.0205)		(0.0104)	
Median Household Income (Ln)	-0.1010**	-0.0290	-0.1720**	-0.1339	-0.0533	-0.1533
	(0.0494)		(0.0790)		(0.0373)	
Median Age	-0.0034	-0.0010	-0.0036	-0.0028	-0.0023	-0.0066
	(0.0027)		(0.0042)		(0.0025)	
Proportion of Housing Stock						
Built Before 1960	0.0901	0.0259	0.1610	0.1252	0.0430	0.1238
	(0.1540)		(0.2410)		(0.1110)	
Built 1960-1969	-0.3880	-0.1114	-0.2740	-0.2128	0.2610	0.7523
	(0.2660)		(0.4140)		(0.2480)	
Built 1970-1979	0.0936	0.0269	0.2620	0.2034	-0.0683	-0.1966
	(0.2420)		(0.3360)		(0.2070)	
Built 1980-1989	0.0608	0.0175	0.2800	0.2177	0.4080	1.1752
	(0.2820)		(0.5220)		(0.3000)	
Mean	0.2703		0.7779		2.8782	
Pseudo R2	0.1272		0.0661		0.0347	
Number of Observations	12,968		12,969		3,505	

Note: Columns (1)-(2) present results from a probit model while Columns (3)-(6) present results from a negative binomial model. Coefficients are presented in Column (1), (3), and (5), while mean marginal effects are presented in Columns (2), (4), and (6). Ln indicates natural log values are used for analysis to reduce skewness in the data distribution and improve model fit. In the probit model, one observation from DC is excluded as the DC treatment plant had no significant noncompliance violations. In all columns, state fixed effects are included. Clustered standard errors are in parentheses. Statistical significance of each variable is determined by the relevant test statistic and corresponding p-value (not shown), and denoted as: * p < 0.1, ** p < 0.05, *** p < 0.01. Data sources: U.S. Environmental Protection Agency, Enforcement and Compliance History Online datasets obtained from https://echo.epa.gov/tools/data-downloads#downloads and U.S. Census Bureau's American Community Survey 2018-2022 5-year estimates obtained from https://www.census.gov/programs-surveys/acs.html.

The Research Team

Deborah A. Carroll, Ph.D.
Deborah A. Carroll is Professor and Director of the Government Finance Research Center at the University of Illinois Chicago. Her research focuses on financial management and fiscal policy of state and local governments, particularly related to taxation, revenue diversification, and water pricing and affordability, as well as the interconnectedness of the public and nonprofit sectors and the implications for tax policy, tax burden, and public service provision. Dr. Carroll has produced more than 75 scholarly publications and 25 white papers and technical reports reflecting more than $2.75 million in research funding. She has been invited to share her research and expertise with academic and practitioner audiences across the U.S. and in several other countries. Dr. Carroll began her career in public service as a budget and policy analyst for the City of Milwaukee, Wisconsin. Email: deborahc@uic.edu.

Lauryn A. Spearing, Ph.D.
Lauryn Spearing is an Assistant Professor in the Civil and Environmental Engineering Department at Tufts University. She received her PhD in Civil Engineering from the University of Texas at Austin. Dr. Spearing uses a systems thinking approach, involving both qualitative and quantitative methods, to understand complex problems at the intersection of technical, social, and natural systems. Her research focuses on three broad areas: 1) infrastructure management during uncertain contexts; 2) understanding public perceptions towards the built environment; and 3) sustainable water systems. She has worked on various complex engineering problems such as managing infrastructure interdependencies in rural Alaska, understanding community impacts after the East Palestine, Ohio train derailment, and exploring how population dynamics impact the built environment. Email: lauryn.spearing@tufts.edu.

Christelle Khalaf, Ph.D.
Christelle Khalaf is an economist and the associate director of the Government Finance Research Center at the University of Illinois Chicago. Her research uses applied economic and data-driven methods to analyze regional economies, labor markets, and public systems. Khalaf is author or co-author of 25 technical reports and has been quoted in several news media outlets, including NPR, HuffPost, and Energy News Network. She has published peer-reviewed papers in Economic Development Quarterly, Utilities Policy, and Journal of Computational Social Science, among other journals. She holds a Ph.D. in Economics from North Carolina State University. Email: ckhalaf@uic.edu.

Abigail Iuorio
Abby Iuorio is a PhD student working in the Spearing Lab at Tufts University in the Civil and Environmental Engineering Department. She has a BS in Civil Engineering from the University of Illinois Urbana-Champaign and an MS in Environmental Engineering from Stanford University. Her research focuses on the intersection of built, natural, and social systems, primarily in water infrastructure. Email: Abigail.Iuorio@tufts.edu.

Joseph C. Toland
Joseph Toland is a fourth-year PhD candidate in Civil and Environmental Engineering at Tufts University. His research investigates human-infrastructure interactions in disasters, aiming to improve infrastructure management, strengthen public policy and emergency management practices. His work draws on more than 20 years of practical experience in emergency management with FEMA and DHS, natural hazards research with the USGS, and supporting disaster relief efforts with the Red Cross to steer his research towards practical solutions that strengthen community resilience. Email: Joseph.Toland@tufts.edu.