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Privatization and Quality: Evidence from U.S. Drinking Water Systems

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Abstract

While the existing economic literature has extensively examined the effect of privatization on efficiency and profitability, its impact on quality remains underexplored. Understanding this relationship is particularly important in sectors where quality is essential for human health. This study investigates how privatizing U.S. drinking water systems affects quality. Given the competing incentives and regulatory pressures that influence a firm's quality decisions, the ultimate impact of privatization is theoretically ambiguous. Using hand-collected data on municipal systems sold to private companies and employing a propensity-weighted difference-in-differences approach, I find that privatization leads to 1.4 fewer Safe Drinking Water Act violations, a 20% decrease in an index of regulated contaminant concentrations, and a 30% decrease in an index for contaminants that pose an immediate threat to human health. These findings indicate that privatization leads to an overall improvement in drinking water quality and back-of-the-envelope estimates suggest economically meaningful benefits to public health, averaging at least $12.6 million per state in the sample.

1 Introduction

The superiority of either public or private ownership has long been debated by economists and policymakers alike. A well-established economic literature has explored this question, with empirical evidence showing that privatization improves efficiency, productivity, and performance across various sectors (Boardman and Vining, 1989; Olley and Pakes, 1992; Megginson, Nash, and Van Randenborgh, 1994; La Porta and López-de Silanes, 1999; Li and Xu, 2004; Fabrizio, Rose, and Wolfram, 2007). Despite these findings, relatively little attention has been given to the impact of privatization on quality. It remains unclear whether the efficiency gains associated with privatization lead to improvements in product quality–a particularly important outcome in sectors that directly affect human health, such as healthcare, food production, and drinking water.

The relationship between privatization and quality is theoretically ambiguous. Relative to public firms, private firms have stronger incentives for cost reduction (Hart, Shleifer, and Vishny, 1997). On one hand, these stronger incentives could lead to quality improvements through the adoption of more efficient, cost-saving technologies that allow private firms to produce higher-quality goods at lower costs. On the other hand, the incentive to reduce costs could lead to reduced maintenance, the use of cheaper inputs, or other compromises that might harm quality. This relationship is further complicated by regulatory pressures, particularly from rate-of-return regulation which is commonly used in utility sectors, including drinking water. Such regulation can dampen private firms' cost-cutting incentives but may also give rise to the Averch-Johnson effect, where firms are incentivized to over-accumulate capital to increase their rate base (Averch and Johnson, 1962). If quality is capital-intensive, this could lead to improvements. However, over-investment in capital may divert resources from other crucial areas like maintenance and technological upgrades, potentially reducing overall quality. Ultimately, the impact of privatization on quality depends on a complex interplay of incentives and regulatory pressures, highlighting the need for empirical analysis to fully understand this relationship.

In this paper, I empirically estimate the effect of privatization on quality in the context of United States drinking water systems, a sector characterized by natural monopolies under rate-of-return regulation. This sector presents an interesting setting due to growing interest in privatization, driven by the need to address aging infrastructure. As privatization becomes more common in this sector, understanding its impact on quality is critical, yet there exist no empirical estimates of how privatization impacts drinking water quality in a developed country. Additionally, water quality is of crucial importance for public health, and any deterioration can lead to severe consequences, including adverse birth outcomes and increased illness and mortality (Currie et al., 2013; Marcus, 2022; DiSalvo and Hill, 2023; Keiser et al., 2023). Contaminated water is particularly harmful for infants whose early health is a strong predictor of future economic outcomes (Black, Devereux, and Salvanes, 2007; Oreopoulos et al., 2008; Almond and Currie, 2011). As such, changes in water quality may have far-reaching effects not only for public health, but also for human capital accumulation and broader economic outcomes.

To estimate the effect of water system privatization on quality, I combine hand-collected data of municipal systems sold to private companies in four U.S. states with panel data of water system characteristics, Safe Drinking Water Act (SDWA) violations, and contaminant sample results. Using a propensity-weighted difference-in-differences methodology, I estimate the causal impact of privatization by comparing changes in quality outcomes for privatized systems to those for characteristically similar municipal systems over time. I find that privatization leads to approximately 1.4 fewer SDWA violations, a large decrease given the sample mean of 1.17. Additionally, I show that privatization leads to a 20% decrease in an index of regulated contaminants and a 30% decrease in an index of contaminants that pose an immediate threat to human health. These results indicate that privatization improves regulatory compliance and product quality, with back-of-the-envelope estimates suggesting economically meaningful public health benefits. However, while privatization offers clear improvements in water quality, these gains may come with trade-offs in affordability, as results from a cross-sectional analysis suggest that private systems are associated with higher rates and lower affordability for low-income households. This emphasizes the need for a balanced approach to policymaking regarding water system privatization, with my findings providing important insights into the quality side of that balance.

These insights are particularly important in light of the growing trend toward privatization of U.S. drinking water systems. Since the latter half of the 19th century, these systems have largely been municipally owned and operated. However, interest in privatization has grown in recent years, coinciding with the aging of America's drinking water infrastructure, much of which was built in the first half of the 20th century. As this infrastructure approaches and surpasses its life expectancy, maintenance and upgrades are necessary for the continued provision of safe drinking water. Yet, historically, the level of investment necessary for such upkeep has not been met (EPA, 2023a). As municipalities struggle to meet these demands, selling water systems to private companies has become an increasingly attractive option, bolstered by policy initiatives encouraging privatization. In the last decade alone, fourteen states[1] have enacted fair market value legislation, making systems more attractive investments to private companies.[2] Beyond state legislation, the Biden Administration's National Infrastructure Advisory Council recommends that the federal government "remove barriers to privatization" of municipal water systems (NIAC, 2023), demonstrating that this growing interest extends to the national level. In this context, my results provide timely insights into how privatization impacts regulatory compliance and drinking water quality, with important consequences for both public health and future policymaking.

The main contribution of this paper is to the broader literature on the effects of privatization–see Vickers and Yarrow (1991) for a detailed discussion of the theory of privatization and Megginson and Netter (2001) for an overview of relevant empirical studies. While much of the existing literature has focused on efficiency and performance, relatively little empirical work addresses the effects of privatization on quality. The studies that do explore quality effects focus on mortality outcomes related to the contracting out of public healthcare services to private companies, yielding mixed results (Bedard and Frech III, 2009; Bergman et al., 2016; Wübker and Wuckel, 2019; Duggan et al., 2024; Zoorob, 2024). In contrast, I analyze a full transfer of ownership, where all assets and management responsibilities are transferred from the public sector to private companies. Unlike contracted services where quality outcomes are highly dependent on sector–specific characteristics and the completeness of contracts (Hart, Shleifer, and Vishny, 1997), a full transfer of ownership to a private entity may present different incentives and

[1]As of the writing of this paper, a total of fifteen states have enacted a form of fair market value legislation. California was first to do so in 1997.

[2]Traditionally, when a water system is acquired, it is valued at the cost of in-service capital less depreciation. This constitutes the buyer's rate base. With fair market value legislation, the seller and buyer of the system agree on a third-party appraisal of the value of the system's assets, with this appraised value taken as the buyer's rate base.

stronger accountability for quality. As such, this type of ownership transfer may lead to different effects on quality, yet this relationship remains underexplored in the existing literature.

This paper also contributes to the literature that analyzes ownership and quality in the drinking water sector. While previous studies show improvements in health outcomes due to drinking water privatization in developing countries, these improvements were largely due to increased access (Galiani, Gertler, and Schargrodsky, 2005; Barrera-Osorio, Olivera, and Ospino, 2009). It is unclear whether access is as relevant a mechanism in developed countries where infrastructure is established. I provide the first estimates of the effect of privatization on drinking water quality in a developed country, offering insights into how privatization influences quality in settings where infrastructure is not a limiting factor. By analyzing this relationship in a developed context, this paper addresses an important gap in the literature on privatization's role in maintaining essential public services.

I further contribute to this literature by analyzing quality directly and comprehensively. While health outcomes are certainly important, they can be influenced by a large number of external factors, making a more direct analysis of water quality itself necessary. Although recent studies have found correlations between private drinking water systems and fewer SDWA violations, they do not analyze a change in ownership (Wallsten and Kosec, 2008; Rahman et al., 2010; Allaire, Wu, and Lall, 2018; Fu, Liu, and Swallow, 2020). Inherent differences in water systems may be correlated with both ownership type and SDWA compliance, meaning that comparing systems that have always been privately owned to those that have always been municipally owned may not identify the effect of privatization on compliance with quality standards. Additionally, contamination at levels compliant with the SDWA can still lead to adverse health outcomes (DiSalvo and Hill, 2023). Thus, analyzing SDWA violations alone does not fully capture all dimensions of water quality.

To address these concerns, I exploit a panel of municipal water systems that were sold to a private company to analyze the effect of privatization on two outcomes: SDWA violations and contamination levels, capturing a more complete measure of quality. Using these data, I perform difference-in-differences regressions, weighting control units by their propensity to privatize. This approach accounts for pre-existing characteristics that may be correlated with both the likelihood to privatize and changes in quality, allowing me to construct a better counterfactual and identify the causal effect of privatization on quality.

As interest in the privatization of municipal drinking water systems grows, understanding its effect on quality is crucial for both municipalities and policymakers. I provide robust evidence that privatization improves both regulatory compliance and drinking water quality, with back-of-the-envelope estimates suggesting meaningful social benefits, averaging at least $12.6 million per state in the sample. This suggests that reducing barriers to privatization may be a viable way to address aging drinking water infrastructure and improve public health. However, these benefits may be partially offset by higher prices and lower affordability, as a cross-sectional analysis indicates that private systems are associated with both. While it is vital to approach privatization decisions with a nuanced understanding of the trade-offs between affordability and quality, I offer crucial insights into the quality implications of such ownership changes, contributing to the broader economic literature on the effects of privatization.

2 Background

The Safe Drinking Water Act (SDWA) was enacted in 1974. This act requires the EPA to set and enforce standards to ensure the safety of drinking water for the public. Under the SDWA, the EPA has established the National Primary Drinking Water Regulations which set maximum contaminant levels (MCLs) for over 90 contaminants that may cause adverse health effects and specify mandatory treatment techniques (Tiemann and Humphreys, 2021). The SDWA also requires periodic monitoring for contamination performed by state-certified laboratories using methods evaluated and approved by the EPA. Each public water system in the U.S., regardless of ownership type, must comply with the standards set under the SDWA and report all monitoring results to their primacy agency (typically the state government). These primacy agencies are then responsible for enforcing the requirements of the SDWA and reporting to the EPA.

Violations of the SDWA fall into two main categories: health-based violations and monitoring and reporting violations. Health-based violations consist of two types of violations: MCL violations and treatment technique violations. MCL violations occur when a water system exceeds the set MCL for any single contaminant.[3] Treatment technique violations occur when a system fails to follow required procedures for reducing contamination. Monitoring and reporting violations occur when a system does not conduct regular monitoring for contaminants, when a system fails to submit monitoring reports to their primacy agency or the EPA, or when a system fails to provide an annual water quality report (called a "Consumer Confidence Report") to its consumers. Given this definition, monitoring and reporting violations do not necessarily suggest a threat to human health. However, the failure to properly monitor drinking water, whether intentional or not, could mean that quality is falling and not being properly addressed. Violations are further categorized into three public notification tiers. I focus only the first tier which requires that notice be given to the public served by the system within 24 hours of the violation. Tier 1 violations consist of certain health-based MCL and treatment technique violations that present a significant chance for serious adverse health effects from short-term exposure.[4]

SDWA Violations are not rare, with over a quarter of all drinking systems committing a SDWA violation in 2022 (EPA, 2023b). There are no direct or immediate fines associated with a violation of the Safe Drinking Water Act. When a violation occurs, the primacy agency (the state) first takes informal actions such as "reminder letters, warning letters, notices of violation, field visits, and telephone calls" (EPA, 2023c). If compliance is not achieved following these informal actions, then the response from the state can escalate to citations, administrative orders, and criminal charges. Within the sample used in this paper, 90% of all violations result in a return to compliance. The median time between the compliance period start date and the return to compliance date is 364 days.

Costs of compliance across these types of violations differ. While compliance for health-based violations require the proper use and maintenance of equipment and disinfectants, monitoring and reporting compliance only requires periodic sampling and reporting. If a health-based violation occurs, a return to

[3]Instead of an MCL, disinfectants have a maximum residual disinfectant level and lead has an action level. All other contaminants have a MCL. Because violations for disinfectants and lead function in the same way as for other contaminants, I refer to all violations where the set limit is exceeded as "MCL violations".

[4]MCL violations that fall under tier 1 are for the following contaminants: nitrate, nitrite, fecal coliform, *E. coli*, and chlorine dioxide. Tier 1 violations also consist of treatment technique violations of the Interim Enhanced Surface Water Treatment Rule which specifies processes required for treating certain microbial contaminants.

compliance can include replacement of pipes or treatment systems or the implementation of new technology, all of which can be costly. In contrast, returning to compliance for a monitoring and reporting violation involves submitting missed reports and adhering to the mandated reporting schedule.

While SDWA violations are certainly a measure of drinking water quality, they do not offer a complete picture of water quality. This is due to two main reasons: first, contamination below regulatory limits can impact human health; second, there may be strategic behavior regarding violations. By intentionally committing monitoring and reporting violations, a water system could avoid a more costly health-based violation. To analyze a more complete picture of quality, I construct measures of general water quality using data on individual contaminant sample results. These data and construction of the general water quality measures are described in Section 4.3.

3 Privatization and Quality

To contextualize the empirical findings, I begin by discussing the incentives faced by privatized water systems that influence quality. Consider first a simple setting in which a drinking water system, defined as a natural monopoly, is either owned and operated by a municipality or by an unregulated private firm. In this setting, the municipality maximizes social welfare, while the private firm seeks to maximize profits. These divergent objectives can lead to variations in quality between ownership types; whether privatization leads to higher or lower quality depends on the relative strength of these forces.

Consider the private system's choice of quality. Assuming that quantity is appropriately set, the private system will choose the level of quality for which the private marginal benefits (here, the increase in revenue from the quality increase) equal the private marginal costs (e.g., the cost of equipment and maintenance necessary for achieving that level of quality). Because many waterborne illnesses are contagious, clean drinking water has positive externalities. Because the private system does not internalize these positive externalities, it chooses a level of quality below the social optimum (i.e., the municipal firm's quality level).

The private system also has stronger incentives for cost reduction and innovation compared to the municipal firm, as agents in the municipal system typically do not directly benefit from these efforts (Laffont and Tirole, 1993). A common argument against privatization is that this incentive to reduce costs might come at the expense of quality. Yet, as Hart, Shleifer, and Vishny (1997) show, quality can improve under private ownership if innovation is quality-improving and cost reductions do not significantly deteriorate quality. For illustrative purposes, imagine that, in effort to reduce costs, the private firm changes filters less frequently or performs less maintenance. Such cost-reducing efforts could negatively impact quality. However, if the private system's cost-reducing efforts involve the implementation of more efficient water treatment technologies, then quality may increase.

Additionally, because private water companies are often larger entities than individual municipal systems, private systems may have access to a broader network of experts.[5] This network can facilitate the adoption of advanced technologies or practices that improve both cost efficiency and quality. Therefore, while certain cost-reducing measures may pose risks to quality, the firm's stronger incentive to innovate

[5]Documents and city council minutes related to the sales of the systems in my sample show that this is often an argument presented by both the municipalities seeking to privatize and the private companies looking to purchase.

and ability to leverage economies of scale through its network of experts could ultimately lead to better quality outcomes.

It is unclear which of the incentives described above is strongest, making it uncertain whether privatization would lead to an improvement or a reduction in quality. Regardless of whether the unregulated private monopolist provides higher or lower quality, Spence (1975) and Sheshinski (1976) show that it will invariably provide a level of quality that deviates from the social optimum. In such scenarios, regulation can move the monopolist's decision closer to the socially optimal level of quality.

There are two key forms of regulation in the drinking water industry: quality regulation and rate-of-return regulation. Both private and municipal systems in the U.S. are subject to the Safe Drinking Water Act (SDWA) which sets enforceable standards for drinking water quality. In addition, private drinking water systems are often subject to rate-of-return regulation, as is the case for all privatized systems in my sample. These regulatory frameworks can induce new incentives and alter existing ones, which can affect quality in either direction. As with the simple scenario outlined above, the impact of privatization on quality under these regulatory conditions depends on the relative strength of these competing forces.

First, consider the impact of the SDWA regulation. In theory, this regulation mitigates the private firm's failure to account for the externalities of drinking water contamination, thereby reducing the downward pressure on quality. However, as evidenced by DiSalvo and Hill (2023), there are still negative health consequences of drinking water that is SDWA-compliant. If the municipal firm recognizes this, then it will seek to maximize the benefits of reduced contamination, even below regulatory limits, while the private firm, motivated by profits, may fail to account for the benefits of quality that exceeds regulatory standards, potentially resulting in lower quality. Moreover, if the standards are not strictly enforced and the costs of violating are lower than the costs of compliance, the private firm may opt to provide a quality level below the standard. In contrast, the municipal firm, facing higher costs for violations due to its commitment to social welfare, may be less likely to compromise on quality. On the other hand, the private system's enhanced knowledge and resources might enable it to more efficiently provide a level of quality that meets or surpasses regulatory standards, which could result in higher quality compared to a municipal system that may lack similar technological and operational advantages.

Now consider the effect of rate-of-return regulation, which regulates prices to ensure that privatized systems earn no more than a fair rate of return on their capital investment. The rate-of-return-regulated system can pass costs on to customers, reducing its incentive to cut costs and essentially reversing the intuition presented above: if cost-reductions harm quality, then rate-of-regulation could potentially improve the private system's quality. Conversely, if cost reductions improve quality, rate-of-return regulation might lead to a reduction in quality, as the firm is limited in its ability to capitalize on the savings from such improvements.

As shown in the Averch and Johnson (1962) model, rate-of-return regulation creates an incentive for the over-accumulation of capital. Because the regulation allows the private system to earn a fixed percentage return on its capital investment, the system can increase its profits by investing in additional capital. Spence (1975) demonstrates that rate-of-return regulation can improve quality when quality is a capital-intensive attribute, as is likely the case with drinking water systems.

Given this complex interplay of incentives and regulatory pressures, the ultimate impact of privatization on quality cannot be determined by theoretical consideration alone. Thus, empirical analysis is necessary to for understanding this impact. The subsequent sections detail the data and methods used to estimate the effect of privatization on quality.

4 Data

4.1 Water System Sales

I have hand-collected data of municipal water systems that were sold to private companies from the public utility commissions of four states: Illinois, Indiana, Missouri, and Pennsylvania. These states were chosen for several reasons: first, each has adopted fair market value legislation, making the purchase of municipal systems more attractive to private companies. Second, municipal systems are being sold to private companies in these states, with two of the largest private water companies reporting either completed or pending acquisitions in each of the four states in their 2023 investor reports.

In these states, the sale of a municipal system to a private company must be approved by the public utilities commission. Water systems file an application for approval of acquisition which is then reviewed by the public utility commission and a decision is reached. The documents and proceedings related to these applications are publicly available through the states' e-filing systems. From final orders summarizing these acquisition cases and the utility commission ruling, I have identified 49 municipal water systems that were sold to private companies between the years 2001-2022 in these four states.[6] These 49 systems represent all documented sales of entire municipal systems to private companies during the sample period. Documentation of these sales provides the name and location of the purchased system and purchasing company, the initial filing date of the application for acquisition, the utility commission approval date, and the date of closing of each sale.[7]

Using the Safe Drinking Water Information System (SDWIS) from the U.S. Environmental Protection Agency (EPA), I match each privatized system to its public water system identification number (henceforth referred to as 'system ID') using the system's name. I then use the system ID to match each privatized system to water system characteristic data and water quality data that are described in the following sections. Column 3 of Table 1 shows summary statistics for these 49 systems.

4.2 Water System Characteristics and Demographic Data

Summary statistics of system characteristics and demographic data by treatment status are shown in Table 1. System characteristic data come from the EPA's SDWIS and demographic data come from the U.S. Census and American Community Survey.

The SDWIS contains information pertaining to public water systems characteristics and SDWA violation history.[8] For each public water system in its borders, a state reports the following information to the EPA: the system's name, the system ID, the county in which the system operates, total population

[6] Sales by state are as follows: Illinois, 21, Indiana, 13, Missouri, 6, and Pennsylvania, 9.

[7] There is one water system for which no closing date is listed within the sale documentation nor within the public utilities commission files. For this system, I impute the closing date as 104 days from the commission approval date, which is the average length of time between approval and closure for the other 49 systems.

[8] Note: the use of the word "public" in the phrase "public water system" refers to the consumers that are served, rather than to the ownership type of a system.

served, number of service connections, number of facilities, the primary type of source water (ground water or surface water), whether that source water is protected, ownership type, and system type.

I collect this information for all municipally-owned community water systems within Illinois, Indiana, Missouri, and Pennsylvania, including those that are later sold to a private company. A community water system is defined as a water system that supplies water to the same population year-round. I match the identified privatized systems to their respective characteristic data by system ID; this constitutes the treatment group. The set of municipal water systems which were not sold to a private company within the sample period comprise the control group. I further limit the sample of controls to water systems that serve populations below 100,000. Privatized systems tend to be smaller systems, with a maximum population served of approximately 49,000. Limiting the sample of control systems to systems with smaller served populations improves balance between treated and control systems. This results in an initial sample of 3,179 water systems, 49 of which are privatized over the sample period.

Combining the data on treated and control systems results in a yearly panel of observations of water system characteristics. The EPA publicly provides the system characteristic data for 2013-2023 in the SDWIS database. I obtained these data for years 2008-2012 via a Freedom of Information Act request to the EPA. Earlier years of these data are not available and are linearly interpolated based on each respective water system's later-year characteristics. Water system characteristics are generally stable over time and results are robust to instead starting the sample in 2008.

I match this data set of water systems and their characteristics to demographic and voting record data by the county in which each system operates. Demographic data are taken from the U.S. Census and the American Community Survey. These data include county-level measures of the total number of housing units, the percent of housing units in rural areas, median housing value, the percent of housing units built within the previous 10 years, total population, median household income, and the percent of the population by age and race. Demographic survey data are not available for every year of the sample, so water-system-years are matched to demographic data from the nearest year in which a survey was conducted (i.e., demographic data for a water system in year 2001 comes from the 2000 Census and American Community Survey).

The approval of the public utility commission in each of the four sample states is required for the sale of a municipal water system to a private company. Because public utility commissioners are appointed by each state's governor, and because a municipality's political leanings may shape its stance on privatization as well as their approach to environmental standards, it is important to account for the political ideology of the county in which each water system operates. To do so, I use county-level election results for gubernatorial, senate, and presidential elections from Amlani and Algara (2021). Using these data, I construct a biennial indicator equal to one if the Republican nominee received a larger share of votes, and zero otherwise. In constructing this variable, gubernatorial voting data is prioritized due to the governor's influence on the public utility commission. For county-years without a gubernatorial election, Senate voting data is used, and any remaining missing county-years are filled in using presidential voting data.[9] As with the demographic data, water-system-years are matched to voting data from the most-recent year in which an election was held.

[9] For county-years in which both a gubernatorial and Senate election or both a gubernatorial and presidential election were held, the indicator that equals 1 if the Republican nominee received a larger share of votes aligns in ≈80% of the observations.

Table 1: Descriptive Statistics for Privatized and Non-Privatized Water Systems - Unweighted

	Municipal Mean	***Privatized*** Mean	Difference in Means	t_stat	Normalized Difference
Population Served	4901	4349	-552	-2.664	-0.063
Service Connections	1807	1516	-291	-4.371	-0.099
Facilities	9.8	9.0	-0.8	-6.328	-0.139
Ground Water Source	0.656	0.681	0.024	1.924	0.052
Percent Rural	47.672	33.837	-13.836	-19.917	-0.500
Percent over Age 65	16.210	14.992	-1.218	-14.100	-0.367
Median Housing Value	118929	131948	13019	8.115	0.222
Percent Housing Built within 10 yrs	9.825	11.146	1.320	5.854	0.173
County Total Population	344672	279546	-65126	-3.190	-0.072
Percent White	89.242	86.802	-2.440	-8.441	-0.229
Median HH Income	50533	55153	4620	10.441	0.294
Larger Vote Share - Rep.	0.669	0.599	-0.069	-5.212	-0.145
Unemployment rate	6.134	6.002	-0.132	-2.249	-0.061

This table shows the means for municipal systems (control) and privatized systems (treated) before propensity-score weighting. The sample includes observations of water systems for the years 1996-2023. The first 4 rows are characteristics of the individual water systems and the remaining rows are demographic characteristics of the counties in which the water systems operate. Normalized differences exceeding 0.25 are considered significant.

4.3 Water Quality Data

Water quality data comes from two sources: the EPA SDWIS and each individual state's environmental protection agency (or equivalent agency).[10] From the SDWIS, I take records of all SDWA violations committed by any water system in the sample between 1996-2023. The SDWIS maintains records of violation type, date the violation was first reported, if and when the systems returned to compliance, and details regarding the contaminant and/or rule that was violated.

SDWA violations likely do not fully reflect water quality. Recent studies have shown that drinking water contamination at levels below current regulatory limits can cause adverse birth outcomes (Hill and Ma, 2022; DiSalvo and Hill, 2023), meaning quality may be poor enough to negatively impact health, but not so poor as to trigger a SDWA violation. To analyze a more complete measure of quality, I have obtained records of all monitoring sample results for the four states in the sample through a combination of Freedom of Information Act Requests, direct provision by state environmental protection agencies, and scraping publicly available online water quality dashboards. These data include the system ID, sample date, the contaminant tested, and the result of the sample (typically given in parts per million). These sample result data come from the periodic, required monitoring of specific contaminants. Given the prevalence of monitoring and reporting violations, this may pose a threat to identification. If water systems strategically fail to monitor due to knowledge of high contaminant levels and if private companies are more likely to behave in this strategic manner, then my results could be biased towards finding a positive effect of privatization on water quality. Because I find that private companies commit fewer MR violations and also have higher water quality, I argue that this bias, if it exists, is small.

Following DiSalvo and Hill (2023), I use these sample result data to construct a main index of water

[10] These agencies are: Illinois Environmental Protection Agency, Indiana Department of Environmental Management, Missouri Division of Environmental Quality, Pennsylvania Department of Environmental Protection.

quality. For each water system, contaminant (other than total coliform), and sample, I construct a measure of the "result relative to MCL" (RRMCL):[11]

$$RRMCL = \frac{SampleResult}{MCL} \tag{1}$$

In general, states adopt the federal MCLs established by the SDWA but can implement more stringent regulations. The four states in the sample adhere to the federal MCLs for nearly all contaminants. However, Illinois imposes stricter MCLs for three contaminants, and Pennsylvania does so for one. When constructing the RRMCL for water systems in these states, the state MCLs are used as the denominator. Figures 6 and 8 show that results are robust to constructing the RRMCL with only the contaminants that have common regulation between all four states.

For samples with results that register below the reporting level, meaning they cannot be accurately distinguished from zero, I set the result to half of the given reporting level. Additionally, I exclude 340 outliers with RRMCLs exceeding 100. These outliers make up less than 0.0002% of all samples.

While nearly all of the contaminants regulated by the SDWA have a fixed MCL (for example, the MCL for nitrate is set at 10mg/L), the MCL for total coliform is dependent on the number of samples collected. For systems collecting more than 40 samples per month, no more than 5% of those samples can test positive for total coliform. For systems collecting fewer than 40 samples per month, no more than one sample can test positive. Again following DiSalvo and Hill (2023), I construct the total coliform RRMCL for each water system-month as follows:

$$RRMCL = \frac{\text{Share of Positive Tests}}{\max\left\{0.05, \frac{2}{\text{number of tests}}\right\}} \tag{2}$$

For each water system and year, I average the RRMCL over all contaminants (including total coliform), weighting contaminants equally. This creates an aggregate measure of overall water quality where each sample of various contaminants with distinct health effects is normalized by its regulatory limit. Because MCLs are set for the purpose of protecting public health, this measure reflects water quality in terms of its safety for human consumption. A higher annual RRMCL indicates poorer water quality, with RRMCLs exceeding one signifying that the water system exceeded the MCL for one or more contaminant.

Because the main concern of poor water quality is the potential impact on health, I also construct the average RRMCL for each water system-year using only samples of contaminants that fall under Tier 1 of the public notification rules, and thus pose an immediate threat to human health. To determine how privatization impacts levels of contaminants that are not regulated, I construct an index analogous to the RRMCL using the National Secondary Drinking Water Regulations which are non-enforceable standards for contaminants that may cause aesthetic or cosmetic effects, such as water odor or tooth discoloration, but do not present any known public health risk.[12] Because Pennsylvania has adopted the National Secondary Drinking Water Regulations as enforceable, all observations of Pennsylvania water systems are excluded from analysis of this quality measure. Additionally, Illinois adopts the secondary standards for three contaminants (zinc, manganese, and iron). These three contaminants are dropped when constructing the RRMCL of secondary standards for water systems in Illinois.

[11]Table A1 provides a list of contaminants included in this measure.
[12]Table A2 provides a list of contaminants included in this measure.

5 Methodology

5.1 Propensity-score weighting

A threat to identification exists if water systems that privatize differ from water systems that do not in ways that also affect drinking water quality. Of particular concern is the fact that aging infrastructure appears to motivate privatization, potentially introducing bias. While aging infrastructure is a common problem among U.S. drinking water systems, it may still be the case that older systems are more likely to privatize and are also more prone to high levels of contamination and frequent SDWA violations due to aging infrastructure. On the other hand, it may be that private companies intentionally acquire only newer systems that may be less prone to poor quality. This could result in an estimate of the effect of privatization on quality that also (or entirely) reflects the effect of aging infrastructure on quality. Because the SDWIS system characteristic data do not include information on system age, I use a measure of the percent of the housing stock built within the past 10 years as a proxy for system age. This measure serves as an indirect indicator of the likelihood that drinking water infrastructure has been upgraded. I assume areas experiencing residential construction are likely to have simultaneous improvements to the drinking water infrastructure. Table 1 shows that, while there are significant differences in certain characteristics between treatment and control systems, the difference in this age proxy variable is not statistically significant according to the normalized difference. Nevertheless, it is important to account for the potential selection bias from age and other characteristics. To do so, I use a propensity-weighted difference-in-differences approach. I use *logit* regression to estimate the following probability:

$$Pr(D_i = 1|X_i, \gamma_s) \tag{3}$$

where D_i is an indicator equal to 1 if water system i was sold to a private company. X_i contains water system characteristics and demographic characteristics of the county in which the water system operates. All characteristic variables are measured in 1996, the first year of the sample.[13] Included water system characteristics are: population served, number of service connections, number of facilities, and whether the primary source water of the water system is ground water. County-level demographic characteristics included are: the percent of housing units in a rural area, the median housing value, the percent of homes built within the previous 10 years, the total population, the percent of the population over 65, the percent of the population that is white, median household income, the unemployment rate, an indicator for if the Republican presidential nominee received the larger vote share in the 1996 presidential election, and 2nd order polynomials of the following variables: population served by the water system, total county population, median household income, and median housing value. State fixed effects, γ_s, are included to control for statewide characteristics that may affect privatization and drinking water quality. Results of this *logit* regression are shown in Table 2.

To ensure appropriate comparisons, I identify the region of common support by determining the range of overlapping propensity scores between the treatment and control groups and then drop any water system with a propensity score outside of this range. Through this process, all treated water system are retained and 54 control water system are dropped. I then weight untreated water systems by $\frac{\hat{p}}{1-\hat{p}}$

[13] For the water system characteristics, these variables are linearly interpolated from observations in years 2008-2023, the years for which system characteristic data are available. Results are robust to beginning the sample in 2008 and using characteristic data from 2008 for the propensity score estimation, as shown in Figures 6-8.

where $\hat{p}$ is the propensity score estimated by Equation 3. Figure 1 shows that this weighting process improves the balance between treated and control water systems; no statistically significant differences in characteristics remain.[14]

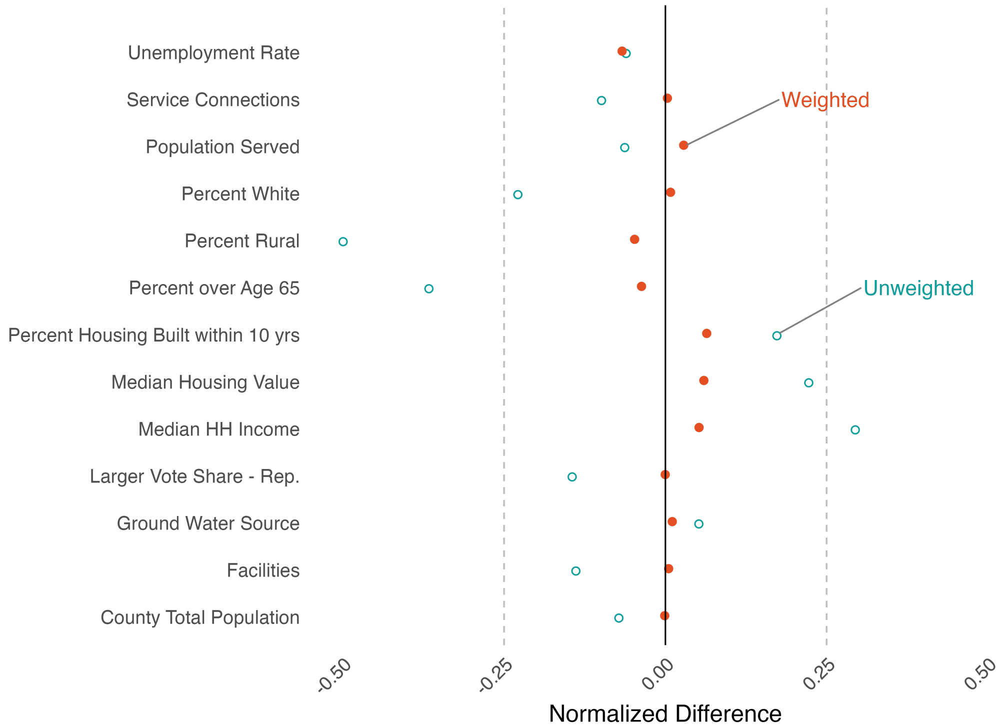
Table 2: Sale Logit Regression Estimates

Population Served	0.00008***
	(0.00001)
Groundwater Source	$-$0.000002***
	(0.0000003)
Number Facilities	$-$0.00028***
	(0.00004)
Service Connections	0.00010***
	(0.00001)
Perc. Rural	$-$0.03887
	(0.06771)
Perc. Over 65	$-$0.03284***
	(0.00775)
Median Housing Value	$-$0.00024***
	(0.00003)
Perc. Housing Built within 10 yrs	$-$0.00984***
	(0.00206)
County Total Population	$-$0.00246
	(0.02239)
Perc. White	$-$0.02980***
	(0.00898)
HH Median Income	$-$0.03970***
	(0.00590)
Larger Vote Share - Republican	$-$0.38460***
	(0.07045)
Unemployment	0.15852***
	(0.02979)
$PopulationServed^2$	$-$0.0000000005**
	(0.00000)
$CountyTotalPopulation^2$	0.0000000000003***
	(0.00000)
$HHMedianIncome^2$	0.000000005***
	(0.00000)
$MedianHousingValue^2$	$-$0000000006***
	(0.00000)
psuedo R2	0.906
Observations	87,500
Note:	*p<0.1; **p<0.05; ***p<0.01

Estimates shown are from a cross-sectional logit regression. The outcome is an indicator equal to one if the water system was ever sold to a private company, and zero otherwise. Regressors are water system and county characteristics, measured in first year of the sample (1996).

[14]Normalized differences exceeding 0.25 are considered to be significant (Imbens and Wooldridge, 2009).

Figure 1: Characteristic Balance Before and After Propensity Weighting



This figure shows the normalized difference in means between the treatment and control group for the corresponding characteristic shown on the horizontal axis. Blue outlined points show the normalized difference before propensity matching is performed, while red filled points represent the difference after propensity score weighting is performed.

5.2 Difference-in-Differences (DiD) Model

I estimate the following two-way fixed-effects (TWFE) DiD model:

$$Y_{it} = \beta D_{it} + \gamma X_{it} + \alpha_i + \alpha_t + \epsilon_{it} \tag{4}$$

where Y_{it} represents the water quality outcome of interest in year t for water system i. This variable takes two main forms: first, the number of EPA Safe Drinking Water Act violations committed and, second, the average annual RRMCL as described in Section 4.3. D_{it} is an indicator equal to 1 if the water system was under private ownership in year t and is equal to 0 otherwise. X_{it} contains a similar set of characteristic variables used in the propensity-score estimation, but measured at the water system-year level. α_i and α_t are water system and year fixed effects, respectively. Standard errors are clustered at the water system level.

For analysis of the effect of privatization on SDWA violations, I perform this regression first with Y_{ict} denoting the total number of violations committed by a water system in a year. I then break the violations down into the two main categories: health-based and monitoring and reporting.

For analysis of the effect of privatization on general water quality, Y_{ict} takes the following forms: the RRMCL, the RRMCL constructed for only Tier 1 public notification contaminants, and the measure constructed analogously to the RRMCL for the National Secondary Drinking Water Regulations which are non-enforceable guidelines for contaminants that affect water appearance or may cause cosmetic issues for consumers.

The coefficient of interest is β which gives the estimated effect of privatization on each of the water quality measures. This specification restricts the effect of privatization to be constant over time. To explore the potential of dynamic treatment effects, I also perform the following DiD event study regression:

$$Y_{it} = \sum_{j=-5}^{5} \beta^j D_{it}^j + \gamma Xit + \alpha_i + \alpha_t + \epsilon_{it} \tag{5}$$

where D_{it}^j is an indicator variable equal to 1 if water system i is j years away from from being sold to a private company in year t, with $j \in [-5, 5]$.[15] The remaining variables and subscripts are analogous to Equation 4. Standard errors are again clustered at the water system level.

The β^j are the coefficients of interest and capture the difference in the water quality outcome Y between treated and control water systems at j years to treatment. The main identifying assumption behind this estimations strategy is that water quality in treated systems would have followed the same trend as control systems had they not been privatized. Figures 2-5 show that the β^j are only rarely statistically different from zero for $j < 0$, providing support for this assumption. The parallel trends prior to privatization also lessen concerns regarding the potential selection bias due to system age.

Standard DiD estimators may introduce bias when treatment roll out is staggered, as it is in this setting (De Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021). When treatment roll out is staggered, the standard DiD estimate is a weighted average of individual treatment effects, where those effects come from both "clean comparisons" of newly treated units to not-yet-treated units and "forbidden comparisons" of newly treated unites to earlier treated units. Given the large never-treated group in my sample, the standard TWFE approach estimates are unlikely to be biased. To support this statement, I perform the decomposition proposed by (Goodman-Bacon, 2021) and find that more than 92% of the variation used in the difference-in-differences estimation comes from "clean comparisons" of treated and never-treated water systems. Figure A1 shows the results of this decomposition. For further support, I estimate the main results of the paper using the Sun and Abraham (2021) estimator. Results are similar across the two estimation methods (shown in Figures A2 and A3), suggesting that my estimates are unlikely biased by the variation in treatment timing.

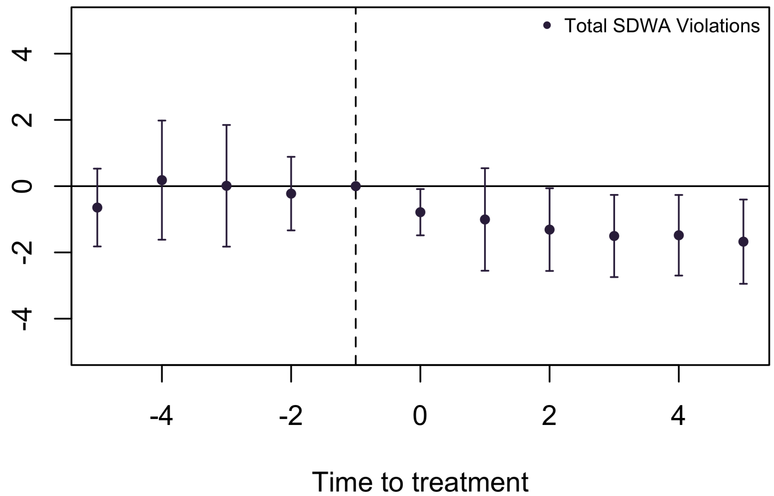
6 Results

6.1 SDWA Violation Results

Figures 2 and 3 show the event-study versions of the analyses shown in Table 3. These figures provide support for the parallel trends assumption and show a decrease in the number of total SDWA violations and monitoring and reporting violations, but are less conclusive for health-based violations.

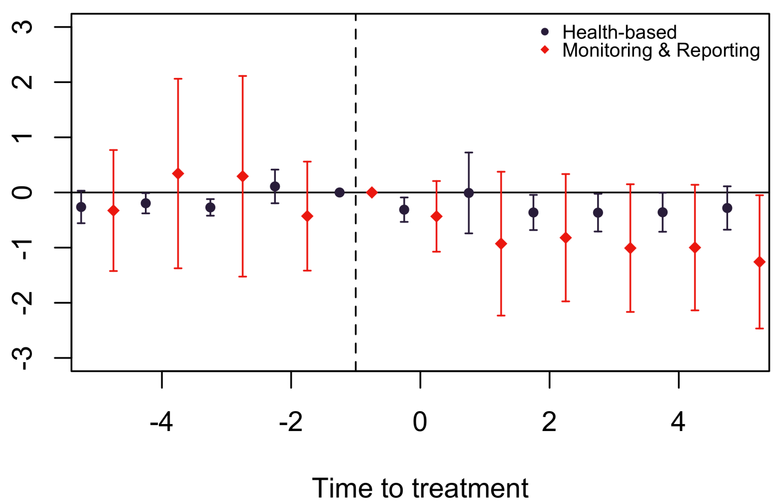
[15]This panel is not balanced as water quality data is available only through 2023 and some systems were sold after 2018. Figures 6-8 show that results are robust to limiting the sample to only those systems with a balanced panel.

Figure 2: Event Study: Effect of Privatization on Total SDWA Violations



This figure shows event-study difference-in-differences estimates of the effect of privatization on total Safe Drinking Water Act violations for the 5 years before and after privatization. Standard errors clustered at the water system level. Control units are weighted by the propensity to be sold to a private company.

Figure 3: Event Study: Effect of Privatization on SDWA Violations by Type



This figure shows event-study difference-in-differences estimates of the effect of privatization on health-based and monitoring and reporting violations of the Safe Drinking Water Act for the 5 years before and after privatization. Standard errors clustered at the water system level. Control units are weighted by the propensity to be sold to a private company.

Table 3 shows the TWFE DiD estimates from Equation 4. Following a sale to a private company, water systems commit approximately 1.4 fewer total SDWA violations, this represents a large decrease over the sample mean of 1.17. Estimates of the effect of privatization on violations by type show statistically significant reductions of 0.12 and 1.1 in health-based and monitoring and reporting violations, respectively. The estimates on total SDWA violations and monitoring and reporting violations are robust to many different specifications, but the estimates for health-based violations are less so. Robustness of the results is discussed in more detail in Section 7. Together, these results provide strong evidence that privately-owned water systems better comply with the monitoring and reporting schedules mandated by the SDWA than their municipal counterparts. These results also provide weak evidence that privatized water systems provide higher quality drinking water. Analyses of the effect of privatization on general drinking water quality shown in Table 4 and Figures 4 and 5 further support this finding.

Table 3: Effect of Privatization on SDWA Violations

	Violation Type		
	Total	Health-based	Monitoring and Reporting
	(1)	(2)	(3)
Sold to Private Company	-1.357^{***}	-0.124^{*}	-1.100^{***}
	(0.339)	(0.073)	(0.320)
Mean	1.171	0.143	0.929
Observations	87,500	87,500	87,500
R^2	0.134	0.267	0.123

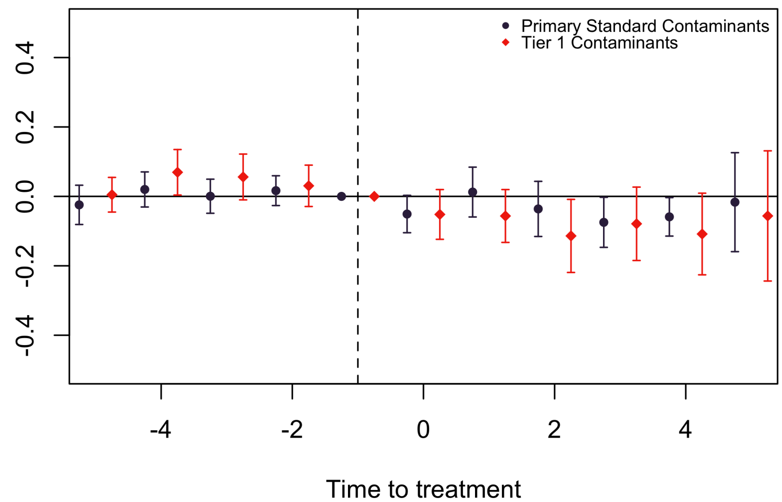
Note: *p<0.1; **p<0.05; ***p<0.01

Standard errors in parentheses are clustered at the water system level. Control units are weighted by the propensity to be sold to a private company.

6.2 General Water Quality Results

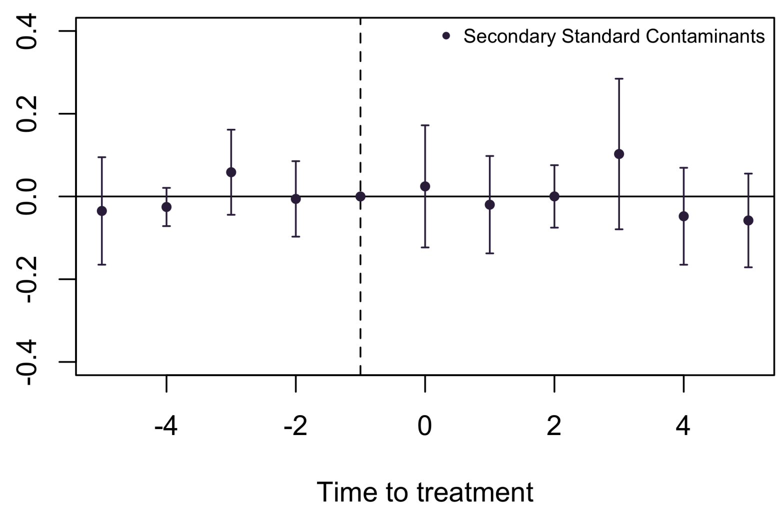
Figures 4-5 show the event study specification for the analysis of the effect of privatization on the general water quality measures. The pre-privatization estimates support the parallel trend assumption estimates of following privatization show decreases in the RRMCL measure for all regulated contaminants and the analogous measure for Tier 1 contaminants. Estimates for the secondary standard contaminants show no significant effect of privatization.

Figure 4: Event Study: Effect of Privatization on General Water Quality



This figure shows event-study difference-in-differences estimates of the effect of privatization on the Result Relative to Maximum Contaminant Level for all contaminants regulated under the Safe Drinking Water Act and all regulated contaminants that fall under the Public Notification Tier 1, meaning they pose and immediate threat to human health. Standard errors clustered at the water system level. Control units are weighted by the propensity to be sold to a private company.

Figure 5: Event Study: Effect of Privatization on Secondary Drinking Water Standards Contaminants



This figure shows event-study difference-in-differences estimates of the effect of privatization on the Result Relative to Maximum Contaminant Level for all contaminants that fall under the National Secondary Drinking Water Standards, which are non-enforceable standards for contaminants that may cause aesthetic or cosmetic effects. Standard errors clustered at the water system level. Control units are weighted by the propensity to be sold to a private company.

Table 4 shows the TWFE DiD estimates for the general water quality measures. Column 1 shows the TWFE DiD estimate on the RRMCL measure constructed using all contaminants regulated by the National Primary Drinking Water Regulations of the SDWA, column 2 shows the effect on the RRMCL measure constructed only for regulated contaminants that pose an immediate health threat (Tier 1 contaminants), and column 3 shows the effect on the RRMCL measure constructed for contaminants in the

National Secondary Drinking Water Regulations.[16] The event study specification of these general water quality analyses are shown in Figures 4-5 and provide for support the parallel trends assumption.

Privatization has a statistically significant negative effect on the RRMCL measure for the Primary Standards and Tier 1 contaminants, with coefficients of -0.032 (20% decrease) and -0.09 (30% decrease), respectively. These negative effects mean that the concentration of contaminants regulated by the primary standard and the concentration Tier 1 contaminants move further below the regulatory threshold following privatization, suggesting an improvement in drinking water quality. The coefficients on privatization for secondary standards are not significant, though I cannot rule out an increase.

The sample used for estimating the effect on the general water quality measure is significantly smaller than for SDWA violations and does not represent a balanced panel. This is due to a lack of sample data in every year for each water system. This could present an issue if privatized systems have higher contaminant concentrations and also submit fewer monitoring samples to their state's environmental protection department. Given the result that privatized systems commit fewer monitoring and reporting violations, this seems unlikely to be the case. Table 5 shows that this smaller sample exhibits the same effects on total SDWA violations and monitoring and reporting violations. Figures 6 and 8 further show that these results are robust when limiting the sample to a balanced panel.

Table 4: Effect of Privatization on General Water Quality

	Quality Measure (RRMCL)		
	Primary Standards	Tier 1 Contaminants	Secondary Standards
	(1)	(2)	(3)
Sold to Private Company	-0.032^{**}	-0.090^{***}	-0.003
	(0.016)	(0.034)	(0.035)
Mean	0.157	0.303	0.268
Observations	28,502	28,502	21,329
R^2	0.750	0.839	0.474

Note: *p<0.1; **p<0.05; ***p<0.01

Standard errors in parentheses are clustered at the water system level. Control units are weighted by the propensity to be sold to a private company. "Result relative to maximum contaminant level" measures are constructed by dividing each contaminant sample result by the respective regulatory maximum contaminant level then averaging within each water system and year. Column 1 shows this measure for all contaminants regulated under the Safe Drinking Water Act. Column 2 shows this measure only for contaminants that fall under Tier 1 of the public notification regulations of the Safe Drinking Water Act. Column 3 shows this measure for standards that fall under the National Secondary Standards which are not enforceable. For the estimation of the result in column 3, all water systems in Pennsylvania are excluded as Pennsylvania has adopted the National Secondary Standards as enforceable.

[16]Note: Pennsylvania has adopted the Secondary standards as enforceable and are thus excluded from the regression shown in column 3 of Table 4.

Table 5: Effect of Privatization on SDWA Violations - RRMCL Sample

	Violation Type		
	Total	Health-based	Monitoring and Reporting
	(1)	(2)	(3)
Sold to Private Company	-1.386^{**}	0.036	-1.353^{**}
	(0.575)	(0.069)	(0.592)
Mean	1.413	0.158	1.13
Observations	28,502	28,502	28,502
R^2	0.232	0.428	0.224

Note: *p<0.1; **p<0.05; ***p<0.01

Sample is limited to CWS for which sample result data is available. This is the sample used to estimate the effect of privatization on the general water quality measures. Standard errors in parentheses are clustered at the water system level. Control units are weighted by the propensity to be sold to a private company.

7 Robustness of Main Results

Figures 6-8 show various specifications of the main analyses. Results are generally robust to these different specifications. Figure 6 shows the point estimates of the DiD specification (Equation 4) for SDWA violations in panel (a) and the general water quality measures in panel (b). In this figure, black circles represent the coefficient of the corresponding specification shown on the vertical axis, horizontal black bars represent the 95% confidence intervals constructed using standard errors clustered at the water system level, the red vertical line represents the coefficient of the baseline analysis, and the black, dashed vertical line denotes zero. Figures 7 and 8 show the event study versions of these analyses (Equation 5.) These tables show results from the specifications where the sample is limited to beginning in 2008, where the sample is limited to a balanced panel, and several other specifications that are discussed in detail below.

7.1 Purchasing Water Systems

Some water systems purchase water from other systems rather than sourcing it themselves. Within the data, these systems are listed has having a primary water source of either "Groundwater - Purchased" or "Surface Water - Purchased". These purchasing systems represent 35% of all systems. Systems that purchase water from another may distribute that water as-is with no further treatment, or they may perform additional treatment. Within the SDWIS system characteristic data, there is no way to distinguish whether a system listed as purchasing water purchases 100% of the water they distribute, nor is there a way to distinguish whether a system that purchases water performs further treatment. As such, I include all systems regardless of purchasing status within the main analysis. This could bias results towards finding no effect if privatized systems that purchase water and perform no additional treatment continue to do so after privatization. Figures 6-8 show results when the sample excludes all systems listed as purchasing water, listing this specification as "No Purchasing Systems." As evident from these figures, results are robust to this specification suggesting that any existing bias is likely minimal.

7.2 Absorbed Systems

There are 11 privatized systems within the sample that are joined into ("absorbed" by) nearby, larger systems owned by the purchasing company following the sale. This absorption process appears in the SDWIS as a change in system activity status from "active" to "inactive" in the year of the sale.[17] For each absorbed, privatized system, I obtain the annual Consumer Confidence Reports by searching for the system's original name or town on the report lookup dashboard of the acquiring private company. In years leading up to privatization, this yields the report for the system listed under its original system ID and name. In years following privatization, this provides reports for the absorbing system, showing the new system ID and name. For absorbed systems, I use records of violations and contaminant sample results listed under the original system ID up to the point of privatization, and the violations and sample results attributed to the absorbing system afterward. This process may not be faultless and could introduce measurement error if I incorrectly identify the absorbing system and thus misattribute violations and sample results.

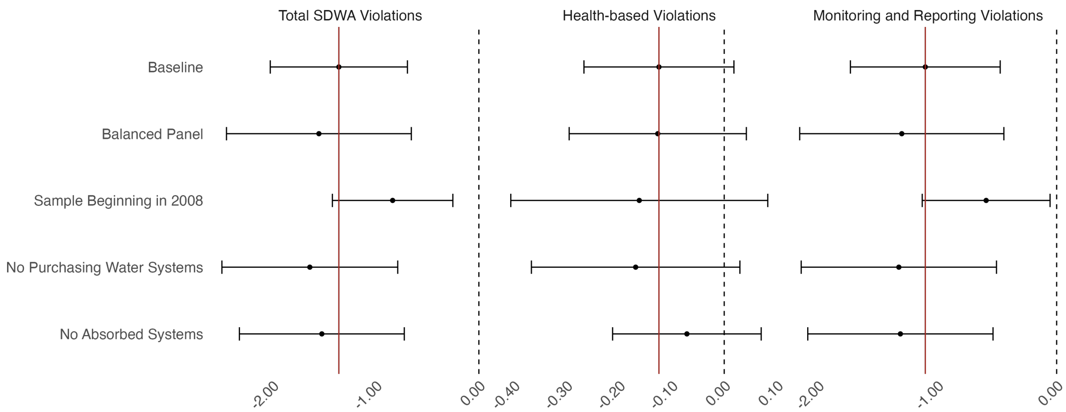
Even without such errors, absorbed systems may introduce selection bias if private companies intentionally acquire under-performing systems that are in close proximity to their existing systems. This seems like a likely strategy for private companies. To address this potential bias, I conduct the main analyses excluding all absorbed systems. As Figures 6-8 show, results are robust to this specification, suggesting that the absorbed systems are not driving the results.

7.3 Contaminants with Common Regulation

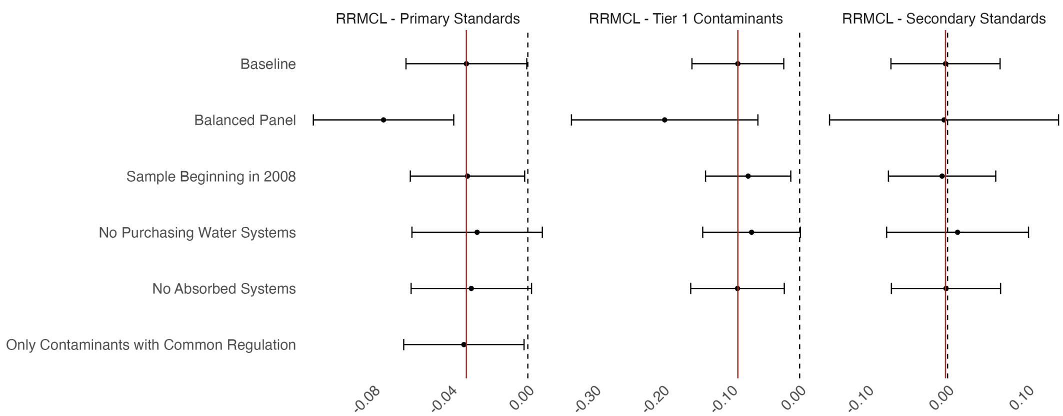
As discussed in Section 4.3, states generally adopt the federal MCLs established by the SDWA but can implement more stringent regulations. Within the sample, there are only four contaminants for which a stricter MCL is set by the state. These contaminants are regulated by the National Primary Drinking Water Standards, but are not Tier 1 contaminants, and thus do not affect the construction of the RRMCL for Tier 1 contaminants. Figure 8 shows that results are robust to constructing the RRMCL for primary standards with only the contaminants that have common regulation between all four states.

[17] Control systems are limited to only active systems, and thus absorption is not an issue for the control group.

Figure 6: Robustness of Main Difference-in-Differences Results



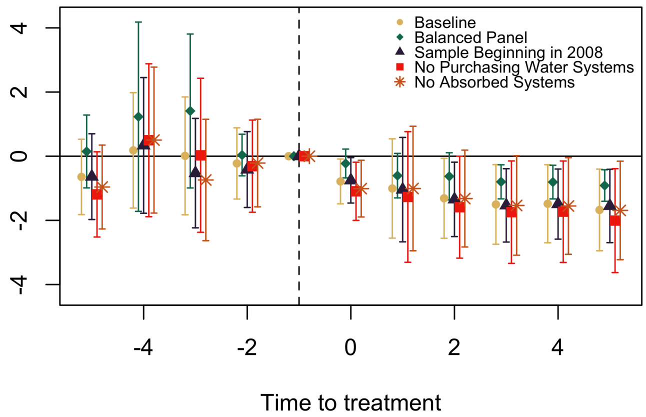
(a) SDWA Violations



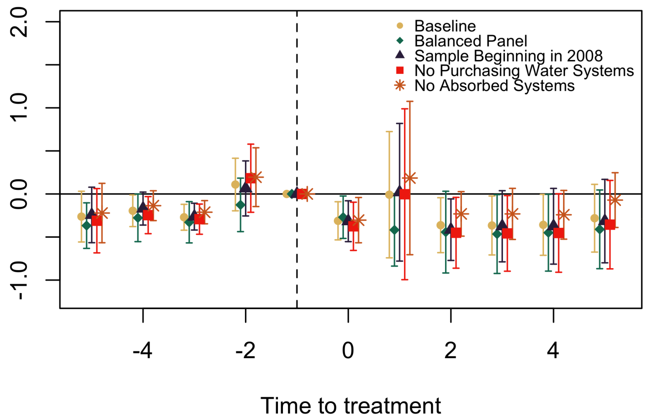
(b) General Water Quality Measures

This figure shows alternate specifications of the difference-in-differences estimation of the effect of privatization on Safe Drinking Water Act violations in Panel (a) and general water quality measures in Panel (b). Black circles represent the coefficient of the corresponding specification shown on the vertical axis, horizontal black bars represent the 95% confidence intervals constructed using standard errors clustered at the water system level, the red vertical line represents the coefficient of the baseline analysis, and the black, dashed vertical line denotes zero. Control units are weighted by the propensity to be sold to a private company.

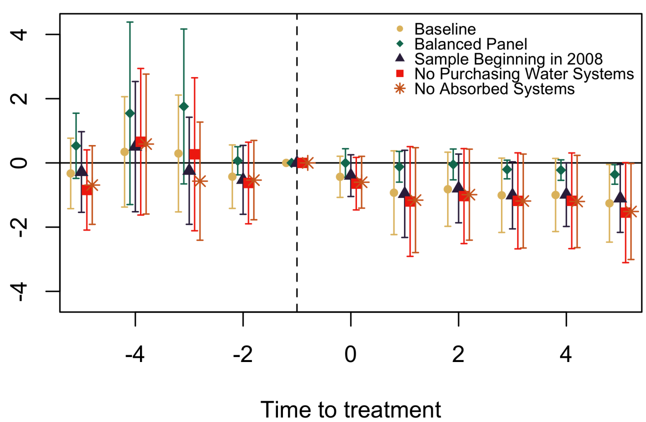
Figure 7: Robustness of SDWA Violation Results - Event Study



(a) Total SDWA Violations



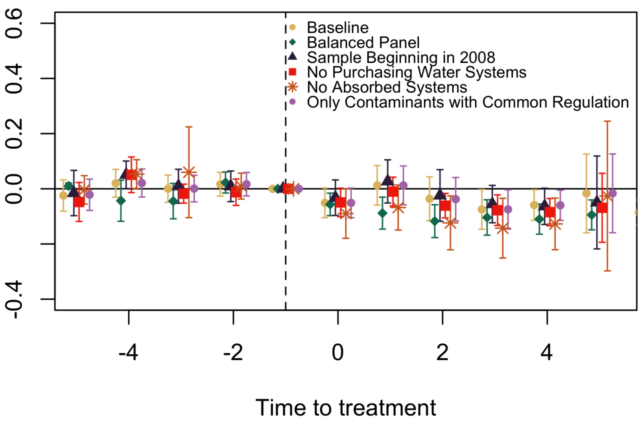
(b) Health-based Violations



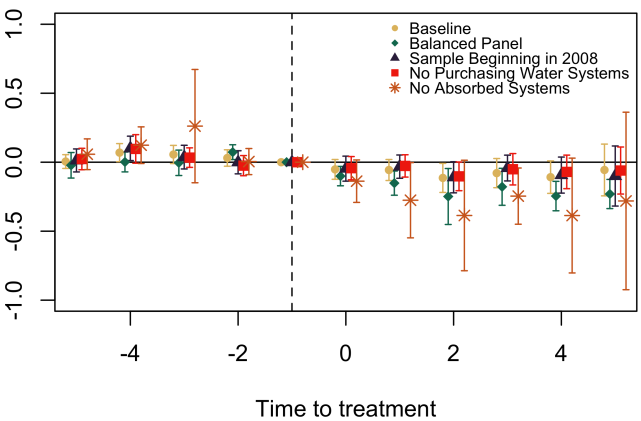
(c) Monitoring and Reporting Violations

This figure shows alternate specifications of the event-study difference-in-differences estimation of the effect of privatization on Safe Drinking Water Act violations. Standard errors clustered at the water system level. Control units are weighted by the propensity to be sold to a private company.

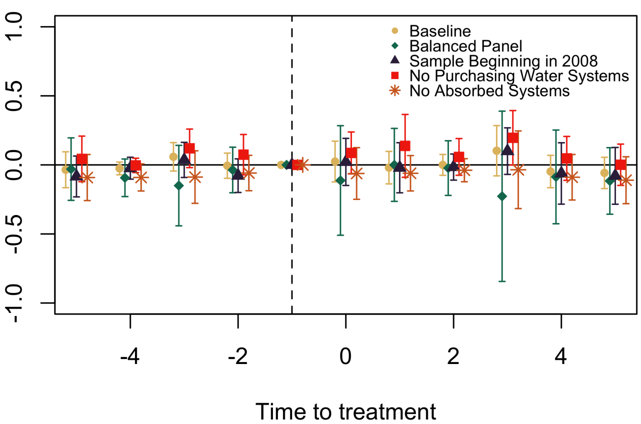
Figure 8: Robustness of General Water Quality Results - Event Study



(a) RRMCL - Primary Standards



(b) RRMCL - Tier 1 Contaminants



(c) RRMCL - Secondary Contaminants

This figure shows alternate specifications of the event-study difference-in-differences estimation of the effect of privatization on general water quality measures. Standard errors clustered at the water system level. Control units are weighted by the propensity to be sold to a private company.

8 Discussion

Due to a limited availability of drinking water rate data and the relatively underexplored health effects of drinking water contamination in developed countries, conducting a thorough welfare analysis is challenging. However, using the available data and drawing on the small but growing body of related literature, I am able to provide some insights into the potential consumer welfare implications of privatization of drinking water systems. I begin with a discussion of rates and then explore the potential public health implications of my findings, focusing on health outcomes and how improved drinking water quality may reduce healthcare expenditures and mitigate costs related to avoidance behavior.

8.1 Privatization and Water Rates

A primary concern with privatization is that the profit-maximizing incentives of private owners will result in essential services that are unaffordable. Although rate-of-return regulation is intended to limit excessive profit-taking and control price increases in privatized water systems, it may still result in rising costs for consumers. Private systems, driven by profit-maximization, may be incentivized to invest heavily in capital, as such investments can increase their allowed rate of return with costs subsequently passed on to customers (the Averch-Johnson effect). Additionally, rate-of-return regulation may reduce the private system's incentive to minimize costs, leading to higher prices. Consequently, even with government oversight, privatization may still result in unaffordable water, particularly for low-income households. However, I show that privatization results in improved drinking water quality. It may be that any increase in rates that occurs following privatization simply reflects the costs of providing higher-quality water. In contrast, municipal systems, managed by elected officials, may avoid necessary infrastructure investments and keep rates suppressed to maintain voter support, potentially compromising long-term water quality.

A rigorous empirical analysis of the effect of privatization on drinking water rates is challenging due to a lack of adequate rate data. While many private water systems publish current rates and service charges online, obtaining historic rate data involves combing through numerous public utility commission rate case documents, which are often fragmented and inconsistently formatted across different states. For municipal systems, which often do not require public utility commission approval for rate increases, finding rate data is even more difficult, as these records are often not centralized and are rarely publicly available. This makes it challenging to compile a dataset suitable for conducting an empirical analysis of the impact of privatization on rates that is consistent with the methodology presented in this paper. Instead, I present a cross-sectional analysis of Pennsylvania water rates by ownership type in Table 6. These data were compiled by the Nicholas Institute for Energy, Environment, and Sustainability to construct an online water affordability dashboard.[18] Because there is no publicly available database of water rates, the Institute hand-collected rates data for several states, including Pennsylvania. This is the only state in my sample for which rate data is readily available. However, these data do not cover every water system in Pennsylvania, resulting in information for only two of the treated systems in my sample. Additionally, the data lack complete panels for the systems, making a difference-in-differences analysis infeasible.

I follow methods presented in (Patterson and Doyle, 2021), linking system service boundaries with

[18] The dashboard can be accessed here: https://nicholasinstitute.duke.edu/water-affordability/.

rates data and census-tract level income data to construct the following measures at the system-level:

Monthly Water Cost: The sum of fixed service charges, variable usage charges, and any surcharges.

Traditional Affordability Burden: The percentage of household income spent on drinking water services annually, based on median household income.

Low-income Affordability Burden: The percentage of household income spent on drinking water services annually, based on household income at the 20th percentile.

Minimum Wage Labor Hours: The number of hours at minimum wage ($7.25 in PA) required to pay the monthly water cost.

I construct these measures for two different usage levels: essential and typical water use. I define essential water use as 50 gallons per-person day, following Teodoro (2018), Patterson and Doyle (2021), and Cardoso and Wichman (2022). Given an average U.S. household size of 2.5, this amounts to approximately 4,000 gallons per month (gpm). While essential use represents the minimum amount of water needed for basic consumption and hygiene, the typical household uses more than this amount. According to the EPA, the average American consumes around 82 gallons per day, amounting to approximately 6,000gpm for the average household. These two usage levels allow for a comparison between the minimum necessary consumption and the more common, higher levels of water use, providing a fuller picture of water affordability across households.

Table 6: Analysis of 2020 Water Rates & Affordability in Pennsylvania by Ownership Type

	4,000 gallons per month			**6,000 gallons per month**		
Variable	Municipal *n = 150*	Private *n = 57*	p-value	Municipal	Private	p-value
Monthly Water Cost	35.77	62.62	<0.01	48.15	85.44	<0.01
Traditional Affordability Burden	0.78	1.19	<0.01	1.05	1.63	<0.01
Low-Income Affordability Burden (20th perc.)	1.73	2.76	<0.01	2.32	3.78	<0.01
Min. Wage Labor Hours	4.91	8.64	<0.01	6.62	11.79	<0.01

Metrics shown are constructed using data from the Nicholas Institute for Energy, Environment, and Sustainability and following methods in (Patterson and Doyle, 2021). Data is for Pennsylvania in the year 2020. Monthly water cost is the sum of fixed service charges, variable usage charges, and surcharges at the specified usage level. Traditional affordability burden is calculated as the ratio of annual water costs to median household income and the low-income affordability burden is the ratio of annual water costs to household income at 20th percentile. Minimum wage labor hours reflects the number of hours at minimum wage ($7.25 in PA) required to pay the monthly water cost.

Table 6 shows that private systems are associated with higher water bills, consisten with anecdotal evidence of rate increases following privatization (Gregory, O'Connell, and Reyes, 2017; Miranda, 2021; Seidman, 2024). However, higher rates do not necessarily imply unaffordable water. The EPA defines an affordability threshold for drinking water costs using the Traditional Affordability Burden, setting the limit at 2.5% of household income. This threshold provides a benchmark for assessing when water costs become a financial burden for households. When focusing on essential use (4,000gpm), private systems are associated with a higher Traditional Affordability Burden but still remain below the EPA's affordability threshold.

The Low-Income Affordability Burden provides a more accurate measure of true affordability issues, as it reflects the financial strain on households at the 20th percentile of income who are more vulnerable to rising water costs. Using this measure, private systems are associated with affordability burdens that slightly exceed the EPA threshold, while municipal counterparts remain below it. A similar pattern is observed for typical use (6,000gpm), with low-income households allocating nearly 4% of their annual income solely on drinking water services. If we consider the number of minimum wage hours required to cover these costs, the pattern of financial strain for low-income households persists. Teodoro (2018) suggests a "rule of thumb" that monthly water bills should not exceed one day of minimum wage labor. For both essential and typical use, private systems are associated with water costs that exceed this threshold.

Although private systems are associated with higher rates and lower affordability, it is important to note that this association is not necessarily causal. Privatization itself may not be the direct driver of increased rates; rather, it could reflect pre-existing conditions or necessary investments that private operators make to improve aging infrastructure and water quality. Municipal systems, which often face political pressure to keep rates low, may underinvest in infrastructure, leading to poorer long-term outcomes for water quality. Policymakers should consider these nuances when evaluating privatization, recognizing that while privatization can lead to higher costs, these increases may reflect efforts to ensure safer, cleaner water. Nonetheless, further analysis is essential to determine whether this relationship between private systems and higher rates is causal and, if so, to disentangle the factors contributing to these increased water bills. Such research will enable more informed policy decisions regarding the balance of affordability and quality in drinking water provision.

8.2 Public Health Implications

A direct assessment of the health benefits of privatization is beyond the scope of this paper and represents a promising avenue for future research. I instead explore the public health implications of the results of this study by drawing on existing economic literature that examines the effects of drinking water contamination on infant health, health care expenditures, and avoidance behavior costs.

The majority of economic studies analyzing the health impacts of drinking water contamination focus on birth outcomes. This focus stems from the availability of data and fewer confounding variables as compared to other health outcomes. In their paper, DiSalvo and Hill (2023) examine the effect of SDWA-compliant contamination on birth outcomes and utilize the RRMCL measure for all contaminants, finding that moving from the 10th to the 90th percentile increases the likelihood of low birth weight (LBW) and preterm births by 12% and 17%, respectively. Extrapolating from my results and assuming that a movement in the opposite direction (from the 90th to the 10th percentile of the RRMCL measure) would result in similarly sized decreases in these adverse birth outcomes, this suggests that privatization could reduce LBW births by 1.29% and preterm births by 1.83%. For each of the four states in my sample, this translates to an average of approximately 200 fewer preterm births and 115 fewer LBW births. Given the estimated social cost of preterm birth of $64,815 (Waitzman, Jalali, and Grosse, 2021), this reduction in preterm births alone suggests a potential social benefit of privatization averaging around $12.6 million for each state in my sample.

This back-of-the-envelope estimate likely represents a lower bound of the true public health benefits due to the quality improvements from privatization, as drinking water contamination poses adverse effects that extend beyond preterm birth. Although, to my knowledge, there is no comprehensive estimate of the social cost of LBW birth, existing studies indicated that lower birth weight negatively impacts adult education and earnings and increases the likelihood of childhood mortality and later-life welfare take-up (Black, Devereux, and Salvanes, 2007; Oreopoulos et al., 2008; Currie et al., 2010). Additionally, many SDWA-regulated contaminants are suspected or known carcinogens, while others cause gastrointestinal illness. While contamination below regulatory thresholds may not be salient to consumers, public notification is required for violations of standards that pose an immediate threat to human health. These more salient contamination issues may prompt consumers to adopt avoidance behaviors, such as purchasing bottled water or investing in filtration systems, leading to additional costs. Existing studies have analyzed the effect of drinking water contamination on these other health-related outcomes, finding that SDWA violations increase emergency room admissions and school absences (Marcus, 2022), as well as spending on bottled water (Zivin, Neidell, and Schlenker, 2011). Further, reductions in the percent of the population exposed to health-based SDWA violations leads to reductions in health care expenditures (Alzahrani, Collins, and Erfanian, 2020). As such, the true benefits of reduced contamination and SDWA violations are likely higher than the estimated social benefits calculated from reduced preterm births alone.

Although the available data are limited, I use them alongside estimates from the economic literature to provide insights into the consumer welfare implications of privatization. I present suggestive evidence that private systems are associated with higher prices and reduced affordability for low-income households. However, I show that privatization leads to improved drinking water quality, with back-of-the-envelope estimates suggesting that these improvements generate public health benefits averaging at least \$12.6 million per state. It is also worth noting that contamination may disproportionately affect low-income households, who may be less able to engage in avoidance behaviors and face greater financial strain from healthcare costs. As such, the estimated improvements in water quality may be particularly advantageous for low-income households. While further analysis of the effect of privatization on rates and health outcomes is necessary to determine whether privatization ultimately benefits consumers overall, I show that the effects of privatization on quality are economically meaningful.

9 Conclusion

The past decade has seen growing interest in the privatization of U.S. drinking water systems. As this trend continues, understanding the effects of private ownership on drinking water quality is crucial for public health. While the previous empirical literature shows that privatization improves productivity and profitability under competition, less is understood about its effect on quality.

Using a propensity-weighted difference-in-differences methodology, I show that privatization leads to a decrease in total SDWA violations of 1.4 violations, with reductions in both health-based and monitoring and reporting violations. Using contaminant sample results to construct a measure of general water quality, I further show that privatization leads to a 20% reduction in an index of regulated contaminant concentrations and a 30% reduction in an index of contaminants that pose an immediate threat to human health. Collectively, these findings suggest that privatization improves both regulatory compliance and drinking water quality.

The results of this paper shed light on several key arguments of the debate regarding privatization. Opponents often argue that private owners, driven by profit, may neglect the externalities of drinking water contamination and implement cost-cutting measures that reduce quality. Contrary to this argument, I find that quality improves following privatization. While cross-sectional data suggest that private systems are associated with higher rates and lower affordability for low-income households, the estimated quality improvements are economically meaningful, with back-of-the-envelope estimates showing large public health benefits.

Access to high-quality drinking water is a key component of public health. As interest in privatizing municipal drinking water systems grows, understanding how this change in ownership impacts water quality becomes increasingly important. While municipalities and policy makers should carefully consider the potential effects of privatization on rates and affordability, the results of this paper provide valuable insights, showing that privatization may be a meaningful way to address aging infrastructure and improve drinking water quality.

References

Allaire, Maura, Haowei Wu, and Upmanu Lall. 2018. "National trends in drinking water quality violations." *Proceedings of the National Academy of Sciences* 115 (9):2078–2083.

Almond, Douglas and Janet Currie. 2011. "Killing me softly: The fetal origins hypothesis." *Journal of Economic Perspectives* 25 (3):153–72.

Alzahrani, Fahad, Alan R Collins, and Elham Erfanian. 2020. "Drinking water quality impacts on health care expenditures in the United States." *Water Resources and Economics* 32:100162.

Amlani, Sharif and Carlos Algara. 2021. "Partisanship & nationalization in American elections: Evidence from presidential, senatorial, & gubernatorial elections in the US counties, 1872–2020." *Electoral Studies* 73:102387.

Averch, Harvey and Leland L Johnson. 1962. "Behavior of the firm under regulatory constraint." *American Economic Review* 52 (5):1052–1069.

Barrera-Osorio, Felipe, Mauricio Olivera, and Carlos Ospino. 2009. "Does society win or lose as a result of privatization? The case of water sector privatization in Colombia." *Economica* 76 (304):649–674.

Bedard, Kelly and HE Frech III. 2009. "Prison health care: is contracting out healthy?" *Health Economics* 18 (11):1248–1260.

Bergman, Mats A, Per Johansson, Sofia Lundberg, and Giancarlo Spagnolo. 2016. "Privatization and quality: Evidence from elderly care in Sweden." *Journal of Health Economics* 49:109–119.

Black, Sandra E, Paul J Devereux, and Kjell G Salvanes. 2007. "From the cradle to the labor market? The effect of birth weight on adult outcomes." *The Quarterly Journal of Economics* 122 (1):409–439.

Boardman, Anthony E and Aidan R Vining. 1989. "Ownership and performance in competitive environments: A comparison of the performance of private, mixed, and state-owned enterprises." *The Journal of Law and Economics* 32 (1):1–33.

Callaway, Brantly and Pedro HC Sant'Anna. 2021. "Difference-in-differences with multiple time periods." *Journal of Econometrics* 225 (2):200–230.

Cardoso, Diego S and Casey J Wichman. 2022. "Water affordability in the United States." *Water Resources Research* 58 (12):e2022WR032206.

Currie, Janet, Joshua Graff Zivin, Katherine Meckel, Matthew Neidell, and Wolfram Schlenker. 2013. "Something in the water: Contaminated drinking water and infant health." *Canadian Journal of Economics/Revue canadienne d'économique* 46 (3):791–810.

Currie, Janet, Mark Stabile, Phongsack Manivong, and Leslie L Roos. 2010. "Child health and young adult outcomes." *Journal of Human Resources* 45 (3):517–548.

De Chaisemartin, Clément and Xavier d'Haultfoeuille. 2020. "Two-way fixed effects estimators with heterogeneous treatment effects." *American Economic Review* 110 (9):2964–2996.

DiSalvo, Richard W and Elaine L Hill. 2023. "Drinking water contaminant concentrations and birth outcomes." *Journal of Policy Analysis and Management* .

Duggan, Mark, Atul Gupta, Emilie Jackon, and Zachary S. Templeton. 2024. "The Impact of Privatization: Evidence from the Hospital Sector." Working Paper Working Paper No. 30824, National Bureau of Economic Research. URL https://www.nber.org/papers/w30824. NBER Working Ppaer No. 30824.

EPA. 2023a. "Building Sustainable Water Infrastructure." URL https://www.epa.gov/sustainable-water-infrastructure/building-sustainable-water-infrastructure. Accessed: April 11, 2024.

———. 2023b. "Providing Safe Drinking Water in America: National Public Water Systems Compliance Report." URL https://www.epa.gov/compliance/providing-safe-drinking-water-america-national-public-water-systems-compliance-report. Accessed: July 2, 2024.

———. 2023c. "Safe Drinking Water Act (SDWA) Resources and FAQs." URL https://echo.epa.gov/help/sdwa-faqs. Accessed: April 11, 2024.

Fabrizio, Kira R, Nancy L Rose, and Catherine D Wolfram. 2007. "Do markets reduce costs? Assessing the impact of regulatory restructuring on US electric generation efficiency." *American Economic Review* 97 (4):1250–1277.

Fu, Guanlong, Pengfei Liu, and Stephen K Swallow. 2020. "Effectiveness of public versus private ownership: violations of the safe drinking water act (SDWA)." *Agricultural and Resource Economics Review* 49 (2):291–320.

Galiani, Sebastian, Paul Gertler, and Ernesto Schargrodsky. 2005. "Water for life: The impact of the privatization of water services on child mortality." *Journal of Political Economy* 113 (1):83–120.

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics* 225 (2):254–277.

Gregory, Ted, Patrick M. O'Connell, and Cecilia Reyes. 2017. "Tribune Investigation: The Water Drain Precious Resource, Private Profits." URL https://graphics.chicagotribune.com/news/lake-michigan-drinking-water-rates/privatization.html. Accessed: 2023-08.

Hart, Oliver, Andrei Shleifer, and Robert W Vishny. 1997. "The proper scope of government: theory and an application to prisons." *The Quarterly Journal of Economics* 112 (4):1127–1161.

Hill, Elaine L and Lala Ma. 2022. "Drinking water, fracking, and infant health." *Journal of Health Economics* 82:102595.

Imbens, Guido W and Jeffrey M Wooldridge. 2009. "Recent developments in the econometrics of program evaluation." *Journal of Economic Literature* 47 (1):5–86.

Keiser, David A, Bhash Mazumder, David Molitor, and Joseph S Shapiro. 2023. "Water works: Causes and consequences of safe drinking water in America." In *National Center for Environmental Economics Seminar, Washington, DC, April*, vol. 13.

La Porta, Rafael and Florencio López-de Silanes. 1999. "The benefits of privatization: Evidence from Mexico." *The Quarterly Journal of Economics* 114 (4):1193–1242.

Laffont, Jean-Jacques and Jean Tirole. 1993. *A theory of incentives in procurement and regulation*. MIT press.

Li, Wei and Lixin Colin Xu. 2004. "The impact of privatization and competition in the telecommunications sector around the world." *The Journal of Law and Economics* 47 (2):395–430.

Marcus, Michelle. 2022. "Testing the water: Drinking water quality, public notification, and child outcomes." *Review of Economics and Statistics* 104 (6):1289–1303.

Megginson, William L, Robert C Nash, and Matthias Van Randenborgh. 1994. "The financial and operating performance of newly privatized firms: An international empirical analysis." *The Journal of Finance* 49 (2):403–452.

Megginson, William L and Jeffry M Netter. 2001. "From state to market: A survey of empirical studies on privatization." *Journal of Economic Literature* 39 (2):321–389.

Miranda, Leticia. 2021. "Residents push back at high sewage and water bills from private companies." URL https://www.nbcnews.com/business/consumer/residents-push-back-high-sewage-water-bills-private-companies-n1271228. Accessed: 2023-08.

NIAC. 2023. "Preparing United States Critical Infrastructure for Today's Evolving Water Crises." Tech. rep., The Presiden't National Infrastucture Advisory Council.

Olley, Steven and Ariel Pakes. 1992. "The dynamics of productivity in the telecommunications equipment industry."

Oreopoulos, Philip, Mark Stabile, Randy Walld, and Leslie L Roos. 2008. "Short-, medium-, and long-term consequences of poor infant health: An analysis using siblings and twins." *Journal of Human Resources* 43 (1):88–138.

Patterson, Lauren A and Martin W Doyle. 2021. "Measuring water affordability and the financial capability of utilities." *AWWA Water Science* 3 (6):e1260.

Rahman, Tauhidur, Mini Kohli, Sharon Megdal, Satheesh Aradhyula, and Jackie Moxley. 2010. "Determinants of environmental noncompliance by public water systems." *Contemporary Economic Policy* 28 (2):264–274.

Seidman, Andrew. 2024. "Water privatization is coming under renewed scrutiny from Pa. lawmakers and regulators as consumers sour on rate increases." URL https://www.inquirer.com/business/pennsylvania-water-privatization-act-12-20240407.html. Accessed: 2024-10.

Sheshinski, Eytan. 1976. "Price, quality and quantity regulation in monopoly situations." *Economica* 43 (170):127–137.

Spence, A Michael. 1975. "Monopoly, quality, and regulation." *The Bell Journal of Economics* :417–429.

Sun, Liyang and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics* 225 (2):175–199.

Teodoro, Manuel P. 2018. "Measuring household affordability for water and sewer utilities." *Journal-American Water Works Association* 110 (1):13–24.

Tiemann, Mary and Elena H. Humphreys. 2021. "Safe Drinking Water Act (SDWA): A Summary of the Act and Its Major Requirements." Tech. rep., Congressional Research Service.

Vickers, John and George Yarrow. 1991. "Economic perspectives on privatization." *Journal of Economic Perspectives* 5 (2):111–132.

Waitzman, Norman J, Ali Jalali, and Scott D Grosse. 2021. "Preterm birth lifetime costs in the United States in 2016: An update." In *Seminars in Perinatology*, vol. 45. Elsevier, 151390.

Wallsten, Scott and Katrina Kosec. 2008. "The effects of ownership and benchmark competition: An empirical analysis of US water systems." *International Journal of Industrial Organization* 26 (1):186–205.

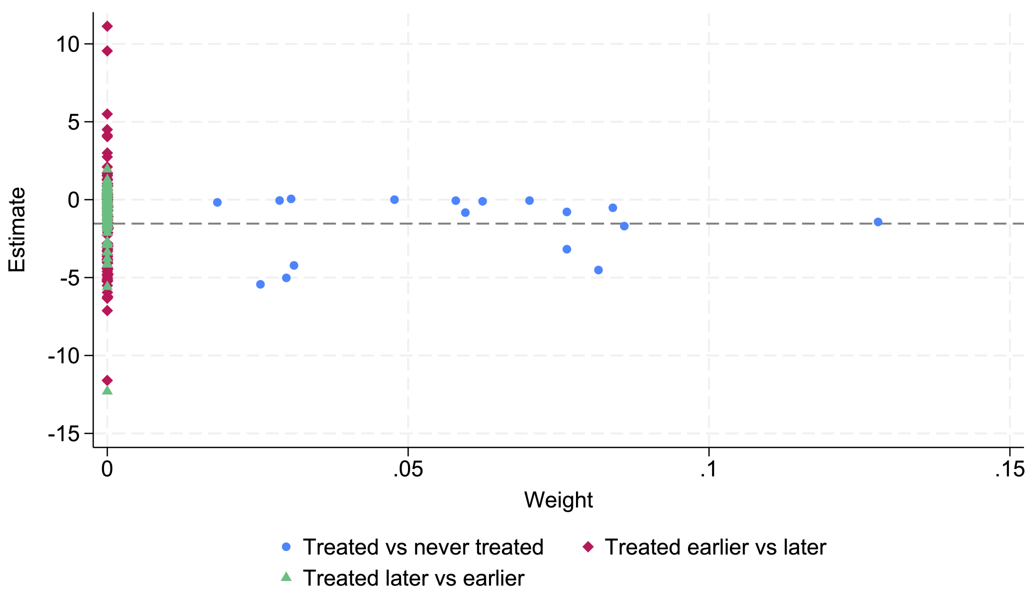
Wübker, Ansgar and Christiane Wuckel. 2019. "The impact of private for-profit hospital ownership on costs and quality of care–evidence from Germany." *CESifo Economic Studies* 65 (4):373–401.

Zivin, Joshua Graff, Matthew Neidell, and Wolfram Schlenker. 2011. "Water quality violations and avoidance behavior: Evidence from bottled water consumption." *American Economic Review* 101 (3):448–453.

Zoorob, Michael James. 2024. "Privatization and quality of carceral healthcare: A difference-in-differences analysis of jails in the United States, 2008-2019." *International Journal of Public Administration* 47 (1):14–25.

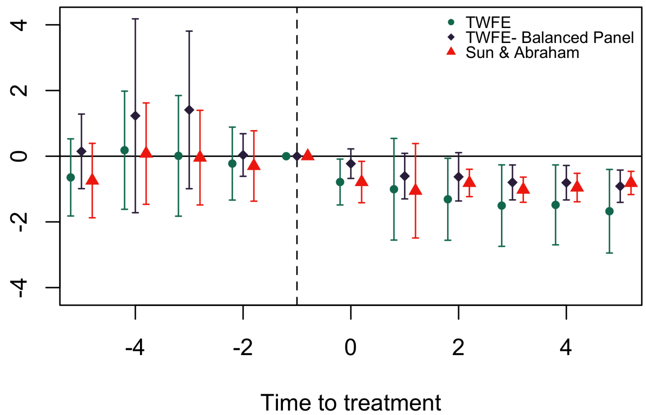
A Appendix

Figure A1: Goodman-Bacon Decomposition

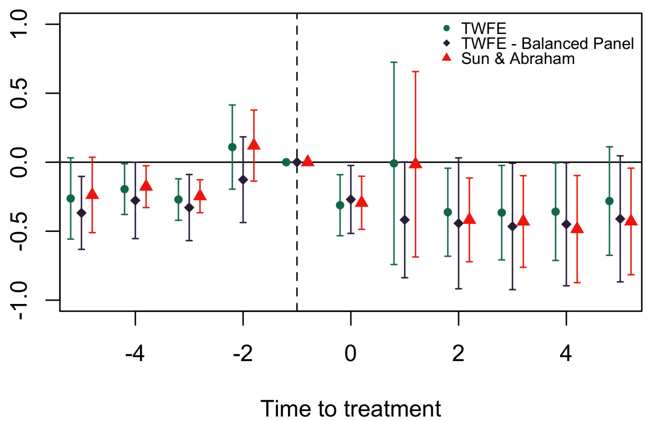


This figure shows results of the Goodman-Bacon decomposition for the main difference-in-differences estimation. The horizontal dotted line depicts the full two-way fixed-effects estimate.

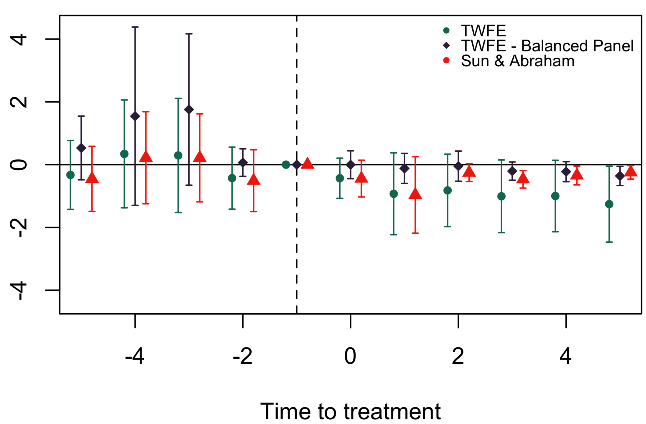
Figure A2: Event Study: Effect of Privatization on SDWA Violations - Sun & Abraham Estimator



(a) Total SDWA Violations



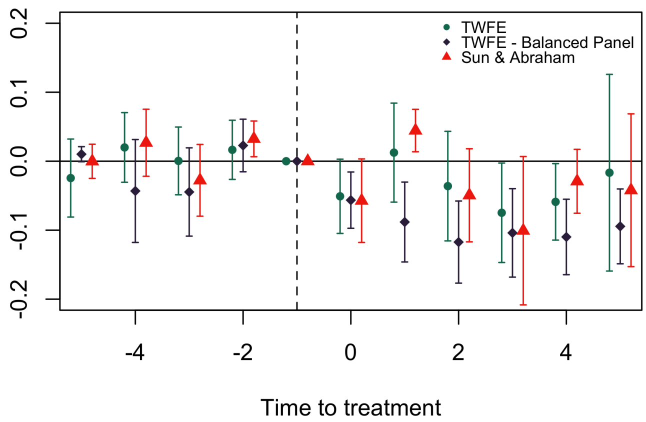
(b) Health-based Violations



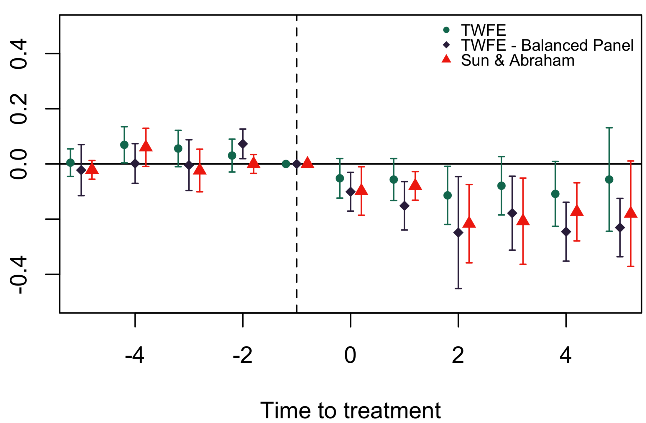
(c) Monitoring and Reporting Violations

This figure shows event-study difference-in-differences results estimated using the (Sun and Abraham, 2021) estimator. Panel (a) shows results for total Safe Drinking Water Act violations, (b) for health-based violations, and (c) for monitoring and reporting violations. Standard errors clustered at the water system level. Control units are weighted by the propensity to be sold to a private company.

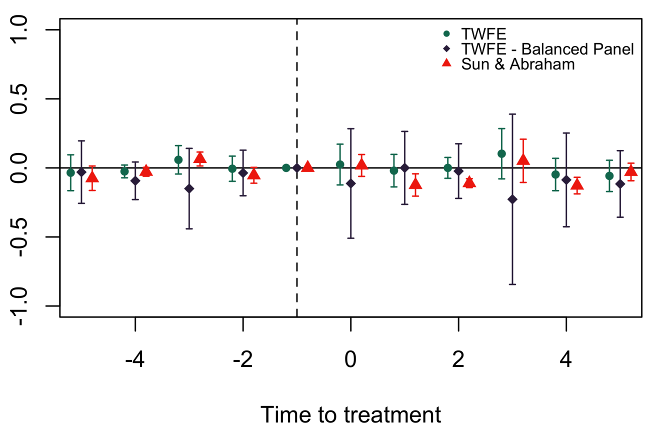
Figure A3: Event Study: Effect of Privatization on SDWA Violations - Sun & Abraham Estimator



(a) Total SDWA Violations



(b) Health-based Violations



(c) Monitoring and Reporting Violations

This figure shows event-study difference-in-differences results estimated using the (Sun and Abraham, 2021) estimator. Panel (a) shows results for the 'Result Relative to Maximum Contaminant Level' (RRMCL) measure constructed for contaminants regulated by the National Primary Drinking Water Standards, panel (b) shows results for the RRMCL constructed for only Tier 1 contaminants that pose an immediate threat to human health, and panel (c) shows results for the RRMCL constructed for contaminants under the National Secondary Drinking Water Standards. Standard errors clustered at the water system level. Control units are weighted by the propensity to be sold to a private company.

Table A1: Contaminants Included in Result Relative to Maximum Contaminant Level Measure

Contaminant Code	Contaminant	MCL (mg/L)	Observations
2977	1,1-ichloroethylene	0.007	74543
2981	1,1,1-Trichloroethane	0.2	74734
2985	1,1,2-Trichloroethane	0.005	74488
2931	1,2-Dibromo-3-chloropropane	0.0002	49864
2980	1,2-Dichlorotehane	0.005	74525
2983	1,2-Dichloropropane	0.005	74483
2378	1,2,4-Trichlorobenzene	0.07	74530
2105	2,4-D	0.07	44915
2110	2,4,5-TP (Silvex)	0.05	43097
1074	Antimony, total	0.006	41920
1005	Arsenic	0.01	71533
1094	Asbestos	7	6125
2050	Atrazine	0.003	54309
1010	Barium	2	50667
2990	Benzene	0.005	74588
2306	Benzo(a)pyrene	0.0002	40808
1075	Beryllium, total	0.004	41830
4100	Beta photon emitters	4	1525
1011	Bromate	0.01	2944
1015	Cadmium	0.005	42120
2046	Carbofuran	0.04	42097
2982	Carbon tetrachloride	0.005	74561
1006	Chloramines (as CL2)*	4	56661
2959	Chlordane	0.002	46209
999	Chlorine (as Cl2)	4	7151603
1008	Chlorine Dioxide (as ClO2)*†	0.8	32965
1009	Chlorite	1	43224
2989	Chlorobenzene	0.1	74481
1020	Chromium	0.1	44278
2380	cis-1,2-Dichloroethylene	0.07	74973
3100	Coliform (TCR)†	5	6313895
4010	Combined Radium (-226 & -228)	5	19727
1024	Cyanide (as free cyanide)	0.2	36492
2031	Dalapon	0.2	43415
2035	Di(2-ethylhexyl) Adipate	0.4	40812
2039	Di(2-ethylhexyl) Phthalate	0.006	43830
2964	Dichloromethane	0.005	74678
2041	Dinoseb	0.007	42972
2063	Dioxin (2,3,7,8-TCDD)	0.00000003	19346
2032	Diquat	0.02	35333
2033	Endothall	0.1	35951
2005	Endrin	0.002	45294
2992	Ethylbenzene	0.7	74671
2946	Ethylene dibromide	0.00005	50133
1025	Fluoride	4	75776
2034	Glyphosate	0.7	27431

Continued on next page

Contaminant Code	Contaminant	MCL (mg/L)	Observations
2065	Heptachlor	0.0004	45332
2067	Heptachlor epoxide	0.0002	45394
2042	Hexachloro-cyclopentadiene	0.05	47073
2274	Hexachlorobenzene	0.001	45471
2051	LASSO	0.002	48831
2010	Lindane	0.0002	46337
1035	Mercury	0.002	41547
2015	Methoxychlor	0.04	46517
1040	Nitrate†	10	139244
1038	Nitrate-Nitrite†	10	83099
1041	Nitrite†	1	90360
2968	o-Dichlorobenzene	0.6	74466
2036	Oxamyl (Vydate)	0.2	42067
2969	P-Dichlorobenzen	0.075	74615
2326	Pentachlorophenol	0.001	44581
2040	Picloram	0.5	43923
2383	Polychlorinated biphenyls (PCBs)	0.0005	37493
1045	Selenium	0.05	42215
2037	Simazine	0.004	50392
2996	Styrene	0.1	74646
2987	Tetrachloroethylene	0.005	75095
1085	Thallium, total	0.002	41780
2991	Toluene	1	74879
2456	Total Haloacetic Acids (HAA5)	0.06	253774
2020	Toxaphene	0.003	44956
2979	trans-1,2-Dichloroethylene	0.1	74651
2984	Trichloroethylene	0.005	75336
2950	Total Trihalomethanes (TTHM)	0.08	256303
4006	Uranium	30	9797
2976	Vinyl chloride	0.002	66637
2955	Xylenes (total)	10	75041

This table shows all contaminants included in the construction of the Result Relative to Maximum Contaminant Level (RRMCL) measure. Contaminant identifier codes and names are given in columns 1 and 2, the Maximum Contaminant Level set by the EPA is shown in column 3, and column 4 provides the number of observations for each contaminant in the raw data.

† Tier 1 Contaminant, poses immediate threat to human health. Violations require notice to customers within 24 hours.

*Signifies that the regulatory standard for the contaminant is considered a Maximum Residual Disinfectant Level, rather than a Maximum Contaminant Level.

Table A2: Contaminants Included in Secondary Standards Result Relative to Maximum Contaminant Level Measure

Contaminant Code	Contaminant	MCL (mg/L)	Observations
1002	Aluminum	0.2 mg/L	17267
1017	Chloride	250 mg/L	25914
1022	Copper	1 mg/L	460626
1025	Fluoride	2 mg/L	75776
1028	Iron	0.3 mg/L	41965
1032	Manganese	0.05 mg/L	42886
1050	Silver	0.1 mg/L	16935
1055	Sulfate	250 mg/L	34033
1089	Foaming Agents	0.5 mg/L	5
1095	Zinc	5 mg/L	28399
1905	Color	15 (color units)	2648
1920	Odor	3 threshold odor number	2489
1925	pH	8.5	181216
1930	Total Dissolved Solids	500 mg/L	21566

This table shows all contaminants included in the construction of the Secondary Standards Result Relative to Maximum Contaminant Level (RRMCL) measure. Contaminant identifier codes and names are given in columns 1 and 2, the non-enforceable Secondary Maximum Contaminant Level set by the EPA is shown in column 3, and column 4 provides the number of observations for each contaminant in the raw data.