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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 e ect of privatization on e -ciency and pro tability, its impact on quality remains underexplored. Understanding this relationship is particularly important in sectors where quality is essential for human health. This study investi-

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 Lopez-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, changes in quality outcomes for privatized systems to those for characteristically similar municipal systems stronger accountability for quality. As such, this type of ownership transfer may lead to di erent e ects

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 e ects and specify mandatory treatment techniques (Tiemann and Humphreys, 2021). The SDWA also requires periodic monitoring for contamination performed by state-certi ed 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).

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 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 necessary to for understanding this impact. The subsequent sections detail the data and methods used to estimate the e ect 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: rst, 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 le 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- ling systems. From nal orders summarizing these acquisition cases and the utility commission ruling, I have identi ed 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 ling 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 identi cation 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]

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

	Municipal Mean	Privatized Mean	Di erence in Means	t_stat	Normalized Di erence
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

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

$$\mathrm{RRMCL} = \frac{\mathrm{SampleResult}}{\;}$$

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 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 signi cant di erences in characteristics remain.[14]

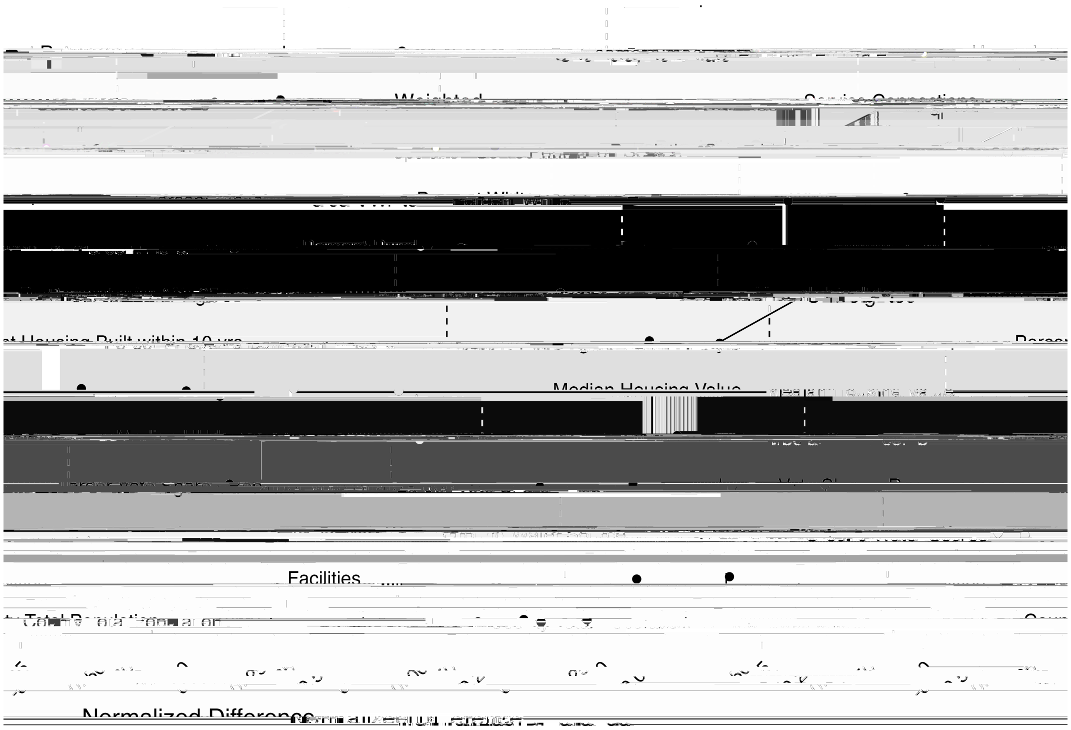
Table 2: Sale Logit Regression Estimates

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 rst year of the sample (1996).

[14] Normalized di erences exceeding 0.25 are considered to be signi cant (Imbens and Wooldridge, 2009).

Figure 1: Characteristic Balance Before and After Propensity Weighting



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

5.2 Di erence-in-Di erences (DiD) Model

I estimate the following two-way xed-e ects (TWFE) DiD model:

$$Y_{it} = D_{it} + X_{it} + {}_{i} + {}_{t} + {}_{it} \tag{4}$$

where Y_{it} represents the water quality outcome of interest in year t for water system i. This variable takes two main forms: rst, 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 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:

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

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

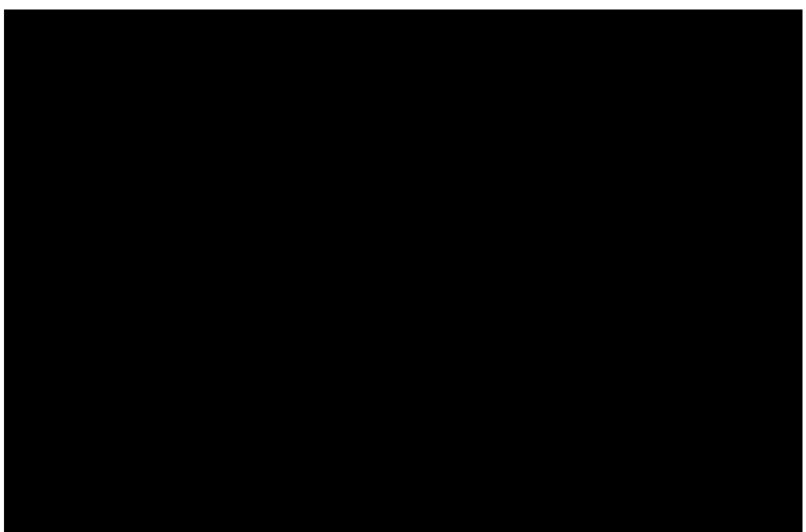
6.1 SDWA Violation Results

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.

Figure 2: Event Study: E ect of Privatization on Total SDWA Violations

This gure shows event-study di erence-in-di erences estimates of the e ect 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: E ect of Privatization on SDWA Violations by Type



This gure shows event-study di erence-in-di erences estimates of the e ect 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 e ect of privatization on violations by type show statistically signi cant 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 di erent speci cations, 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 privatelyowned 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 e ect of privatization on general drinking water quality shown in Table 4 and Figures 4 and 5 further support this nding.

Table 3: E ect 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 speci cation for the analysis of the e ect 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 signi cant e ect of privatization.

Figure 4: Event Study: E ect of Privatization on General Water Quality

This gure shows event-study di erence-in-di erences estimates of the e ect 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 Noti cation 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: E ect of Privatization on Secondary Drinking Water Standards Contaminants

This gure shows event-study di erence-in-di erences estimates of the e ect 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 e ects. 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 e ect on the RRMCL measure constructed only for regulated contaminants that pose an immediate health threat (Tier 1 contaminants), and column 3 shows the e ect on the RRMCL measure constructed for contaminants in the

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

Privatization has a statistically signi cant negative e ect on the RRMCL measure for the Primary Standards and Tier 1 contaminants, with coe cients of -0.032 (20% decrease) and -0.09 (30% decrease), respectively. These negative e ects 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 coe cients on privatization for secondary standards are not signi cant, though I cannot rule out an increase.

The sample used for estimating the e ect on the general water quality measure is signi cantly 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 e ects 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: E ect 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	0219.8d [(Meand [(Men)-13411(0219.8d [(8en)-13411(02193411(3briT5934268esu		

Table 5: E ect 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 e ect 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-

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.

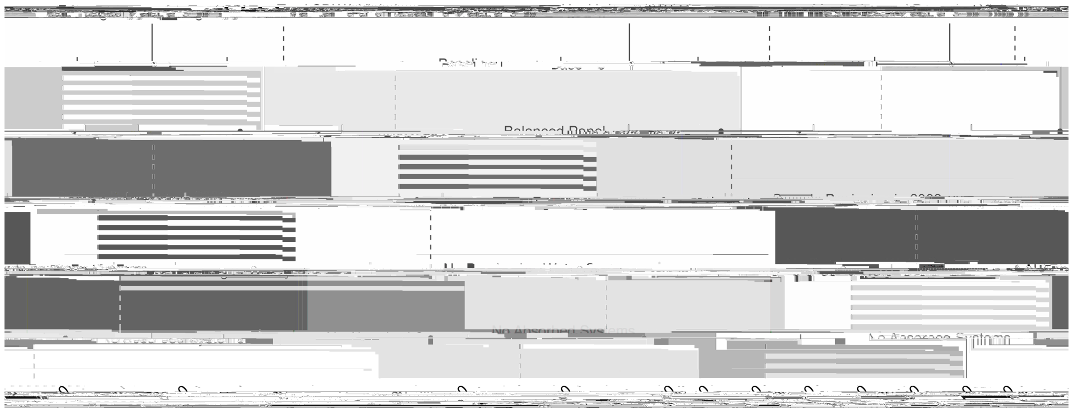
Even without such errors, absorbed systems may introduce selection bias if private companies intentionally acquire under-performing systems that are in close proximity to their existing systems. This seems like a likely strategy for private companies. To address this potential bias, I conduct the main 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

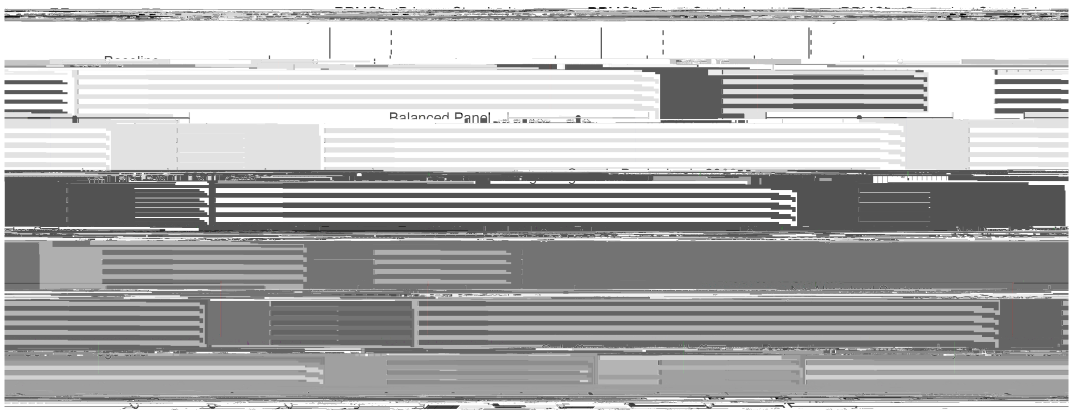
As discussed in Section 4.3, states generally adopt the federal MCLs established by the SDWA but can implement more stringent regulations. Within the sample, there are only four contaminants for which a stricter MCL is set by the state. These contaminants are regulated by the National Primary Drinking 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 Di erence-in-Di erences Results



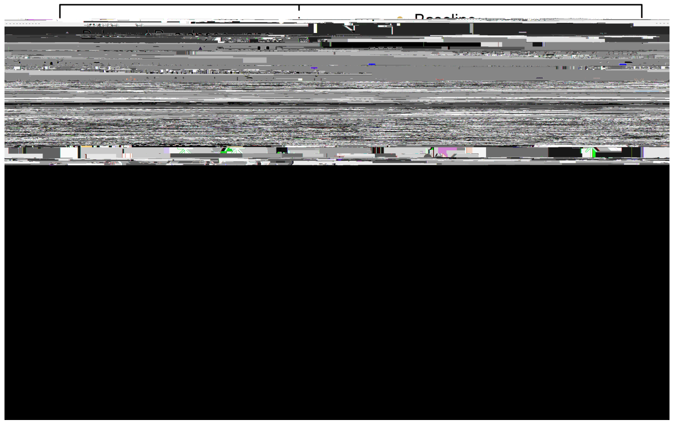
(a) SDWA Violations



(b) General Water Quality Measures

This gure shows alternate speci cations of the di erence-in-di erences estimation of the e ect of privatization on Safe Drinking Water Act violations in Panel (a) and general water quality measures in Panel (b). Black circles represent the coe cient of the corresponding speci cation shown on the vertical axis, horizontal black bars represent the 95% con dence intervals constructed using standard errors clustered at the water system level, the red vertical line represents the coe cient 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

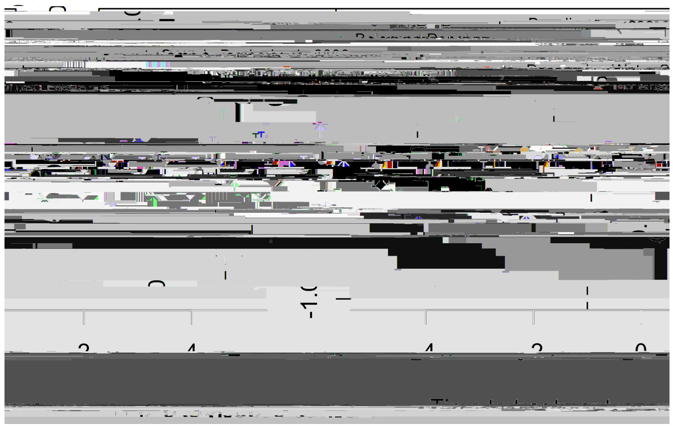
(b) Health-based Violations

(c) Monitoring and Reporting Violations

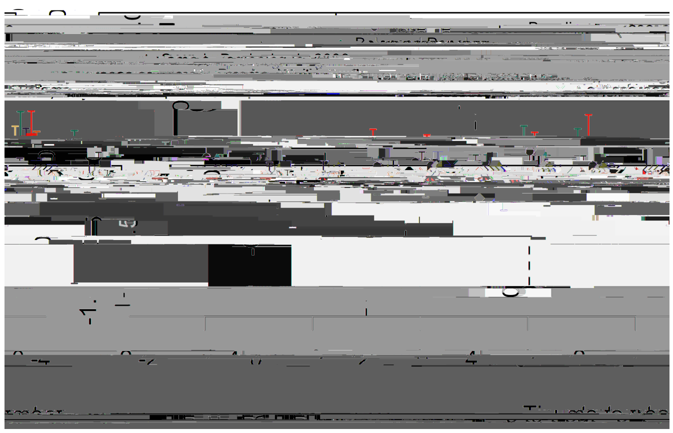
This gure shows alternate speci cations of the event-study di erence-in-di erences estimation of the e ect of privatization on Safe Drinking Water Act violations. Standard errors clustered at the water system level. Control units are weighted by the propensity to be sold to a private company.

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

(a) RRMCL - Primary Standards



(b) RRMCL - Tier 1 Contaminants



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

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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 associated with a higher Traditional A ordability Burden but still remain below the EPA's a ordability threshold.

The Low-Income A ordability Burden provides a more accurate measure of true a ordability issues, 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 drinking water quality.

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A Appendix

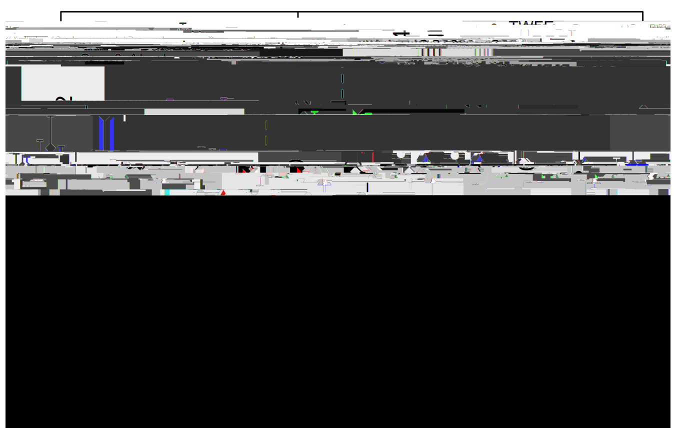
Figure A1: Goodman-Bacon Decomposition

This gure shows results of the Goodman-Bacon decomposition for the main di erence-in-di erences estimation. The horizontal dotted line depicts the full two-way xed-e ects estimate.

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

(a) Total SDWA Violations

(b) Health-based Violations



(c) Monitoring and Reporting Violations

This gure shows event-study di erence-in-di erences 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.

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)*y	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) y	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

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 identi er 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.