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Characteristics of 'early adopters' of water treatment capacity needed to remove PFAS and other emerging contaminants in the United States

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Past work shows exposures to drinking water contaminants can differ among regions with varying sociodemographic composition, in part due to disparities in siting of pollution sources. Drinking water treatment by reverse osmosis, ion exchange, or activated carbon has been recommended by United States (US) regulatory agencies for community water systems (CWS) with elevated concentrations of emerging chemical toxicants such as per- and polyfluoroalkyl substances (PFAS). However, barriers faced by CWS in implementing such technologies are not well understood. Here we used a national scale (n = 36 611 CWS) Kaplan–Meier "survival" analysis, as well as adjusted piecewise logistic regression models, to retrospectively examine characteristics of CWS that were "early adopters" of these treatment technologies between 2004–2022. Results showed the largest CWS serving >100 000 customers adopted the treatment technologies considered here 7–8 times faster than small and very small CWS serving <3300 customers from 2004–2022. Nationally and for a case study of CWS with elevated PFAS concentrations, the odds of CWS adopting the treatment technologies considered in this study between 2004–2022 were significantly lower (10–25%) for each 10% higher proportion of non-Hispanic Black residents. Results were generally consistent when focusing on CWS with prior MCL violations and in CWS across different US regions, system sizes, and source water types. The proportion of American Indian and Alaskan Native residents was also inversely associated with adoption of the treatment technologies for certain groups of CWS. These results suggest managerial and financial barriers to removal of high levels of emerging contaminants in drinking water may be most pronounced for some small CWS and those serving selected historically marginalized communities.

Environmental significance

In the US, marginalized communities more frequently receive drinking water with elevated levels of drinking water toxicants. However, little is understood about how treatment infrastructure differs across community water systems (CWS) with varying characteristics and customer sociodemographic composition. Here we used a national-scale time-to-event analysis to examine characteristics of CWS that were "early adopters" of reverse osmosis, ion exchange, and activated carbon between 2004–2022. Results showed the largest CWS serving >100 000 customers adopted these treatment technologies 7–8 times faster than smaller CWS. The proportions of Black and American Indian and Alaskan Native residents were associated with reduced likelihood of adopting these technologies. Our analysis offers insights into which CWS may face the greatest barriers to implementing effective drinking water treatment for emerging contaminants.

Introduction

Past work shows that historically disadvantaged populations are often exposed to drinking water with higher concentrations of regulated[1–3] and unregulated contaminants.[4–6] In the United States (US), drinking water quality is regulated federally under the Safe Drinking Water Act but marginalized communities more frequently consume drinking water that violates these standards than the rest of the country.[7–9] Higher contaminant exposures for marginalized groups reflect both disparities in the siting of pollution sources and regional differences in the technical, managerial, and financial capacities of community water systems (CWS) to supply drinking water.[10,11] However, much less is understood about how adoption of treatment infrastructure varies nationwide and whether this is related to the sociodemographic composition of communities served.[10,12]

Physical infrastructure for water treatment, management of treatment systems, and funding for infrastructure investments and maintenance are essential components of US public water

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systems (PWS).[10,13,14] PWS are defined as those that provide drinking water to greater than 25 people for at least 60 days per year. CWS are defined as the subset of PWS that serve the same population year-round.[15] Conventional drinking water treatment processes used by CWS include coagulation/flocculation, sedimentation, filtration of particulates, and disinfection. However, these treatment processes are not effective for removing emerging contaminants such as per- and polyfluoroalkyl substances (PFAS).[16,17] US regulatory agencies have therefore recommended reverse osmosis, ion exchange, or activated carbon processes for removal of PFAS and other emerging contaminants from drinking water supplies.[16,18–20] Delays in adopting treatment technology by CWS can prolong exposures of communities with contaminated drinking water. However, treatment technologies are costly and sometimes difficult to implement and maintain, posing a barrier to implementation and affordability for some CWS.[21]

Initial estimates suggested that 12–17% of all US CWS would need to comply with the 2024 nationwide maximum contaminant levels (MCLs) for PFAS.[22] Between 71–95 million US residents rely on groundwater containing detectable PFAS concentrations.[23] When surface water is also considered, the estimated affected population served increases to 200 million people.[24] PFAS have been associated with many adverse health outcomes, including increased risk of kidney and testicular cancer.[25,26] Since the federal PFAS rule was finalized in 2024 (ref. 27) and regulatory requirements are evolving as of 2025,[28] data are not yet fully available for isolating the time-course over which such CWS may adopt reverse osmosis, ion exchange, or activated carbon processes. However, nationwide longitudinal information on adoption of these treatment technologies by CWS between 2004–2022 are available and can assist with better understanding barriers to future technology adoption.

The main objective of this work was to better understand the characteristics of US CWS that were "early adopters" of reverse osmosis, ion exchange, or activated carbon processes suitable for removing emerging contaminants such as PFAS. To do this, we leveraged national data on treatment infrastructure used by 36 613 CWS between 2004–2022, in part obtained through a Freedom of Information Act (FOIA) request from the US government, representing approximately 74% of active systems. We also considered a case study of US CWS with elevated PFAS detections. Our statistical analysis employed a retrospective time-to-event study design to examine changes in the same CWS over 18 years of follow-up (Kaplan–Meier "survival" analysis) and quantify statistical associations with specific CWS characteristics. We considered associations between adoption of new treatment processes by CWS and the sociodemographic composition of residents served at two spatial scales (counties or service area boundaries) using adjusted piecewise logistic regressions. We stratified models by CWS size, source water type, prior MCL violations, and region, among other factors, to ensure the robustness of statistical results. Our analysis offers insights into the characteristics of CWS that may face the greatest technical, financial and managerial barriers to implementing drinking water treatment requirements for emerging contaminants such as PFAS.

Methods

Treatment process data

We focused our analysis on technologies identified by the US Environmental Protection Agency (EPA) as treatment processes effective for removing a variety of emerging toxicants in drinking water such as PFAS including: reverse osmosis, ion exchange, granulated activated carbon (GAC), and/or powdered activated carbon (PAC).[16,18,19,27] We obtained historical data (2004–2013) on PWS treatment infrastructure from a FOIA request to the US EPA in June 2020. More recent PWS infrastructure data (2013–2022) were downloaded from the Safe Drinking Water Information System (SDWIS).[29] The full, initial water treatment infrastructure dataset spanning 2004–2022 included 102 078 PWS (>70% of active PWS). Additional details on the data processing are provided in the (SI) Section 1 and Fig. S1 shows an overview of the data sources.

We merged the dataset on treatment infrastructure with SDWIS data[29] on facility characteristics using PWS identification numbers. SDWIS data archived for this analysis included: (a) water system type (transient non-community water system, non-transient non-community water system, and CWS), (b) population served, (c) source water type (groundwater or surface water), (d) ownership type, (e) water source protection measures (based on state policies), (f) county/counties served, and (g) maximum contaminant level (MCL) violations prior to the study window (before 2004).[29] Using reported dates of deactivation from SDWIS and status descriptions,[29] we identified systems that became inactive because they changed status to a non-public water system, merged with another system, or were otherwise listed as inactive over the study window.

Fig. S2 shows a flowchart of the determination of the analytic samples. We excluded all PWS that did not meet the definition of CWS (n = 59 066 PWS). Additional exclusions included any systems or treatment facilities that: (a) reported adoption of reverse osmosis, ion exchange, or activated carbon before the onset of the study window in 2004 (8.8% of CWS serving ∼77 million individuals [Fig. S3]), (b) became inactive prior to 2004 based on deactivation data from SDWIS, (c) had only one year of treatment records, (d) were missing corresponding census data (*e.g.*, missing county served information), (e) were missing data on system characteristics (*e.g.*, missing water source type), (f) were excluded from the US EPA's CWS Service Area Boundary dataset or (g) did not have an estimated population based on the Data for Good[30] raster layer needed for dasymetric mapping for the service area boundary analyses. The final national dataset included 36 611 CWS (with 521 176 total records), which is approximately 74% of total active CWS. These 36 611 CWS serve a total estimated population of 203.1 million, which is approximately 65% of the total estimated population served by all CWS (Fig. 1).

Sociodemographic data

Past work indicates findings related to sociodemographic disparities in pollutant exposures can vary based on the spatial units of analysis (modifiable areal unit problem).[31–33] We

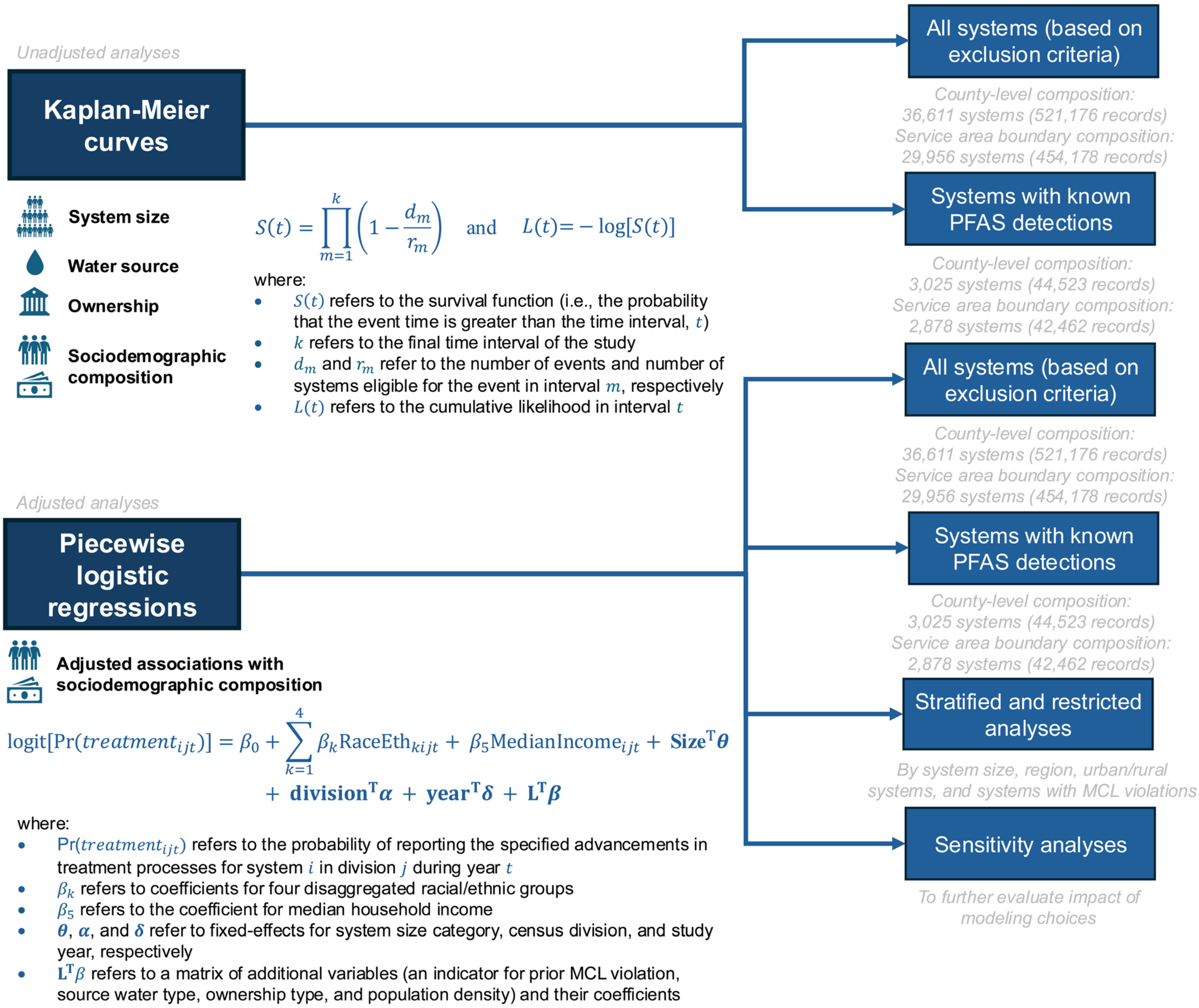

Fig. 1 Schematic of the statistical approaches used in this study on 36 611 US CWS nationwide. The Kaplan–Meier analyses quantify unadjusted associations between CWS characteristics and probability of adopting reverse osmosis, ion exchange, or activated carbon processes from 2004–2022. The piecewise logistic regressions estimate adjusted associations between sociodemographic composition and the probabilities of adopting the same treatment processes, controlled for system size, census division, study year, prior MCL violation, source water type, ownership type, and population density. The four disaggregated racial/ethnic groups referenced above (β_k) refer to groups of individuals who identified as: (1) Hispanic/Latino; (2) non-Hispanic/Latino Black; (3) non-Hispanic White; (4) non-Hispanic Asian, Native Hawaiian, and other Pacific Islander residents; and (5) non-Hispanic American Indian and Alaskan Native.

therefore estimated the sociodemographic characteristics of communities served by US CWS at both the county and service area boundary spatial resolutions throughout this study. County resolution data directly correspond to the US Census[34] and are the most widely available spatial unit available in SDWIS.[1,29] However, CWS commonly serve populations at smaller spatial scales that may not follow county boundaries. CWS service area boundaries used in this study are from a new data product first made available by the US EPA in 2024.[35] While CWS service area boundaries more accurately represent populations served and are not aligned with census geographical subdivisions, many are still modeled/uncertain at this time.[35]

County-level sociodemographic data were obtained directly from the 5-year American Community Survey (ACS) by the US Census Bureau.[34] Self-identified race/ethnicity of US residents from the ACS were grouped as follows: (1) Hispanic/Latino; (2) non-Hispanic/Latino Black (Black); (3) non-Hispanic White (White); (4) non-Hispanic Asian, Native Hawaiian, and other Pacific Islander residents; and (5) non-Hispanic American Indian and Alaskan Native (American Indian/Alaskan Native). Individuals who did not identify as non-Hispanic White were summed to estimate the percentage of people of color served by each CWS. Urbanicity was assessed using population density and the 2003 Rural-Urban Continuum Codes (RUCC) from the US Department of Agriculture.[36] We used an RUCC of <3 and ≥3 to distinguish CWS serving counties in metropolitan areas from CWS serving counties in non-metropolitan areas.[36] For CWS serving multiple counties, we used the total county-level populations to calculate population-weighted averages for each sociodemographic variable. Indicators of area-level socioeconomic status included the percentage of residents under the federal poverty line, median value of owner-occupied housing units, median income, the percentage of income spent on rent, the percentage of residents without a high school degree, the percentage of residents aged 16–64 who were unemployed, and the percentage of homeowners.

For analyses conducted at the CWS service area boundary scale, we used the US EPA's Community Water System Service Area Boundary dataset (version 1.2) and census tract sociodemographic data from the ACS.[35] These data comprise both known (state-provided) and estimated (place-matched or statistically modeled) service area boundaries.[35] We estimated sociodemographic composition within these boundaries using dasymetric mapping.[37] Additional details on this approach are provided in the SI Section 1.

Statistical analysis

Fig. 1 summarizes the datasets, statistical models, and sensitivity analyses conducted in this work. Throughout this work, we used time-to-event (survival) analysis. These approaches are commonly used to examine longitudinal data in applied quantitative fields (such as epidemiology or econometrics) because they reduce the potential for reverse causation (*e.g.*, if infrastructure changes led to changes in community sociodemographic composition).[38] In this case, "survival" refers to the probability that a CWS continues to operate without the adopting new water treatment (reverse osmosis, ion exchange, GAC, and/or PAC) up to a certain year. The study window considered here was defined by treatment data availability for 2004–2022.

We adopted a staggered entry study design that allows the year of entry into the study based on the first year of available records to be relative, rather than based on the calendar year.[39] Our statistical analysis included two main components: (a) unadjusted/crude estimates of the probabilities of adopting reverse osmosis, ion exchange, or activated carbon processes based on CWS characteristics including system sizes, source water type, ownership type, and sociodemographic composition; and (b) adjusted estimates that quantify sociodemographic disparities in adoption of reverse osmosis, ion exchange, or activated carbon processes (Fig. 1). We further assessed the sensitivity of the adjusted estimates to different statistical modeling assumptions, the analytic sample, and the geographic scale of the underlying sociodemographic data.

We compared results of our time-to-event analysis to a case study of CWS with known PFAS detections ($n = 3025$) that served a total estimated population of 85.9 million US residents, including CWS in every state and 98% of all US counties. Frequently, the detectable levels in these datasets for PFOS and PFOA exceeded the 2024 MCLs for these compounds of 4 ng L^{-1} (Fig. 1). CWS with elevated PFAS detections were thus identified using three monitoring datasets: (1) the Third Unregulated Contaminant Monitoring Rule (2013–2015; minimum reporting levels of 10–90 ng L^{-1} for 6 PFAS);[40] (2) a compilation of PFAS statewide sampling data from 28 states (2017–2024; uniform detection limits of 5 ng L^{-1} for 6 PFAS);[41] and (3) the April 2025 release of the ongoing Fifth Unregulated Monitoring Rule (2023-ongoing; minimum reporting levels of 2–20 ng L^{-1} for 29 PFAS).[42] Section 2 of the SI contains an additional description of these monitoring datasets.

Unadjusted time-to-event analysis (Kaplan–Meier estimator)

We used the Kaplan–Meier estimator to compare discrete, nonparametric estimates of survival curves. In this case, "survival" refers to groups of CWS that have not yet reported adoption of the treatment processes considered in this study during each year of the follow-up period. We compared Kaplan–Meier estimates among: (a) CWS size categories defined by the US EPA,[43] (b) source water for each CWS (groundwater or surface water), and (c) publicly and privately owned systems. We also compared Kaplan–Meier estimates between quartiles of each sociodemographic factor obtained from the census data. To account for spatial clustering in the sociodemographic data, 95% confidence intervals (CIs) for survival estimates were computed using non-parametric county-level cluster bootstrapping with 10 000 resampled datasets.[44] The lower 2.5th and upper 97.5th percentile values of the bootstrapped coefficient estimates were used as the lower and upper confidence limits, respectively.[45]

For interpretation, we compared the incurred incidence of treatment adoption at different time intervals (hereafter referred to as "cumulative likelihoods" and commonly known as cumulative hazards). These were calculated using the negative log survival function.[46] To further facilitate interpretation, we compared these cumulative likelihoods with cumulative incidences (the conditional probability of reported adoption of reverse osmosis, ion exchange, or activated carbon processes) for all Kaplan–Meier analyses and confirmed that these estimates were similar (Fig. S4–S7).

Adjusted time-to-event regression models (piecewise logistic models)

We used piecewise logistic models to examine whether racial/ethnic and socioeconomic composition was associated with reported adoption of reverse osmosis, ion exchange, or activated carbon processes over the study window. Piecewise logistic models are well-known parametric approaches for analyzing discrete time-to-event data.[47] Our model specification allows the odds of treatment adoption to vary discretely between each year of follow-up. This approach is well-suited to these data because they are discretized into a relatively small number of years (<20), compared to more continuous time-to-event settings.

Several adjustments to the model, including fixed effects, were considered to reduce potential confounding bias arising from relationships with sociodemographic factors and treatment adoption. Source water contamination levels in the national analysis are not fully known but we were able to assess whether a system reported an MCL violation prior to 2004 (excluding the total and revised total coliform rules) and whether drinking water was sourced from surface water or groundwater.[29] Both were included as fixed effects in the models. In addition, contamination levels and sociodemographic composition are known to vary over time and region,[1,7,48,49] so we included fixed effects for year, census division (East North Central, East South Central, Middle Atlantic, Mountain, New England, Pacific, South Atlantic, West North Central, West South Central, and Puerto Rico),[50] and owner type (publicly or privately owned). We also included indicators for system size (very large, large, medium, small, very small) and adjusted for population density and median household income.[34]

We did not incorporate all area-level socioeconomic status measures from the ACS into one model due to multicollinearity (Fig. S8). Primary models included the percent of people of color. A second set of models disaggregated this category into four racial/ethnic groups (Hispanic/Latino; non-Hispanic Black; non-Hispanic Asian, Native Hawaiian, and other Pacific Islander residents; and non-Hispanic American Indian and Alaskan Native). Another model introduced a quadratic term for median household income to investigate potential non-linearity on the log odds scale.

We conducted several secondary analyses on specific subgroups of CWS. We stratified by system size categories (very large/large, medium, and small/very small systems) and source water type (groundwater and surface water) to evaluate heterogeneity in the associations compared to the unstratified model. We stratified by RUCC $\geq$3 and $<$ 3 to evaluate differences in the associations among urban and rural CWS. To investigate region-specific heterogeneity, we stratified according four census regions, which are inclusive of the census divisions described previously.[50] We also included a model that restricted the analysis to CWS that reported a non-coliform MCL violation prior to 2004.

Systems that implemented substantial non-treatment measures, such as source water protection, may be less likely to adopt reverse osmosis, ion exchange, or activated carbon processes. To examine the effect of this possibility, we restricted the analytic sample to systems that did not respond "yes" to having implemented source water protection in line with individual state policies based on data in SDWIS (28 055 CWS or 77%).[29] In all models, 95% confidence intervals were calculated using either county-level cluster bootstrapping (county-level sociodemographic composition) or system-level cluster bootstrapping (service area boundary sociodemographic composition).

We disaggregated the single pre-2004 MCL violation indicator included in the primary analyses into separate MCL violation indicators for the five most common violations (total and revised total coliform rules, total trihalomethanes, total haloacetic acids, arsenic, and nitrate).[29] We also conducted a sensitivity analysis that replaced the fixed effects for census division with nine fixed effects for climatic regions using data from the National Oceanic and Atmospheric Administration[51] (in addition to a fixed effect for Puerto Rico). Additional sensitivity analyses that we conducted are described in the SI Section 3. To compare model fit across these regression analyses, we compared estimates of the time-dependent area under the receiver operating curves (AUROC)[52] (described in more detail in the SI). All data processing steps and statistical analyses were performed in R version 4.2.2.[53]

Results

Within our study window between 2004–2022, 5.1% of US CWS (serving ~40 million individuals) adopted reverse osmosis, ion exchange, or activated carbon. The most frequently adopted treatment technology for the study sample was ion exchange (46% of total events), followed by GAC (21% of total events), PAC (19%), and reverse osmosis (14%). Table S1 and S2 provide descriptive statistics for the study sample.

Technology adoption by large CWS much faster than smaller ones

Results of the survival analysis showed CWS with large (>10 000–100 000) and very large (>100 000) service populations had significantly higher cumulative likelihoods of adopting reverse osmosis, ion exchange, or activated carbon processes compared to smaller ones from the second reporting year until the end of the study window (Fig. 2A). By the end of the study window, the cumulative likelihood of adopting these treatment technologies among very large CWS was 7-fold greater (0.34 [95% confidence interval (CI): 0.26, 0.43]) than small CWS (0.045 [95% CI: 0.041, 0.048]) (Table S3). Results of these analyses can be interpreted as the probabilities of reported adoption of reverse osmosis, ion exchange, or activated carbon processes over the study window (Fig. S4–S7).

Between 2004–2022, our unadjusted analyses indicated that publicly owned CWS and those sourcing surface water sources more frequently adopted reverse osmosis, ion exchange, or activated carbon processes compared to privately owned systems and CWS using groundwater sources (Table S3 and Fig. S9, S10). Typically, smaller populations are served by privately owned CWS that source drinking water from groundwater rather than surface water[29,54] (Table S1 and S2). However, these overlapping characteristics cannot fully account for differences in the unadjusted cumulative likelihoods. Models that stratified groundwater and surface water systems separately showed similar differences in cumulative likelihoods of treatment adoption by CWS size as the unadjusted national dataset (Fig. S11), with the fastest rates and highest cumulative adoption among large and very large CWS.

A limitation of the nationwide analysis is that complete data on differences in source water contamination were not available. However, among the subset of CWS with elevated PFAS, results were similar to the wider analysis of all CWS (Fig. S12–S14). Confidence intervals for statistically significant results among the CWS with elevated PFAS were wider than results of the national scale analysis, likely reflecting the smaller sample size. Among CWS with elevated PFAS concentrations, a greater rate of adoption was observed for the larger-sized CWS, as observed for the full analytic sample of CWS (Fig. S12). Early adoption of technology useful for PFAS removal among the largest CWS occurred at 7–8 times the rate of small and very small CWS over an 18 year time period (Fig. S12).

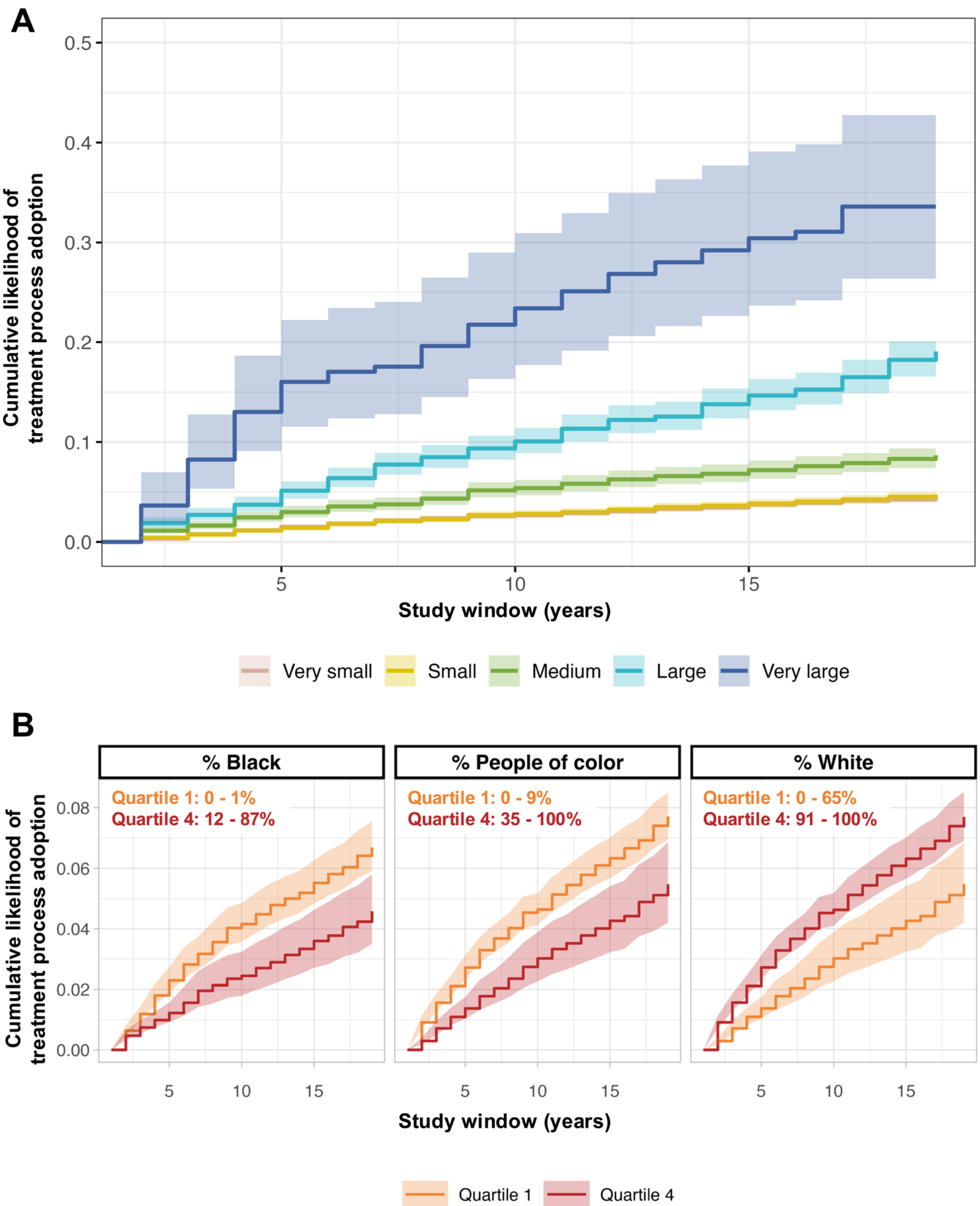

Fig. 2 Cumulative likelihoods of adopting reverse osmosis, activated carbon, or ion exchange among $n = 36\,611$ US community water systems (CWS) with different sizes and sociodemographic composition between 2004–2022. Panel (A) shows CWS size categories based on numbers of customers served as: very small 25–500; small: 501–3300; medium: 3301–10,000; large: 10 001–100 000; and very large: >100 000. Panel (B) shows quartiles of racial/ethnic composition based on the counties served by the CWS, where "People of color" refers to all groups except those self-identifying as non-Hispanic White based on data from the American Community Survey (ACS) by the US Census Bureau.[34]

Lower treatment adoption among CWS serving highest proportions of people of color

Our unadjusted analyses at the county-scale spatial unit revealed CWS serving the highest proportions (fourth quartiles) of people of color, Black, and American Indian/Alaskan Native residents were significantly less likely to report adoption of reverse osmosis, ion exchange, or activated carbon compared to those serving the lowest proportions (first quartiles) (Fig. 2B and S15 and Table S4). By the end of the study window, the probability of reported adoption of these technologies was approximately 6.7% [95% CI: 5.9%, 7.6%] among the lowest (first) quartile of the proportion of Black residents compared to 4.6% [95% CI: 3.5%, 5.8%] among the highest (fourth) quartile (Table S4).

Adjusted models showed consistent inverse relationships between the county-scale proportion of Black residents served by each CWS and frequency of adoption of reverse osmosis, ion exchange, or activated carbon processes between 2004–2022

(Table 1). A 10-percentage-point increase in Black residents at the county-scale was associated with a 19.3% decrease [95% CI: −26.2%, −12.1%] in the odds of reporting adoption of reverse osmosis, ion exchange, or activated carbon processes. For the subset of CWS with elevated PFAS concentrations (adjusted models incorporating county-level sociodemographic composition), a 23.9% [95% CI: −34.9%, −13.0%] lower odds of reporting adoption of reverse osmosis, ion exchange, or activated carbon processes (Table 1 and Fig. 4) was associated with each 10-percentage-point increase in the proportion of Black residents served.

We stratified national models at the county scale and examined the predicted probabilities of adopting reverse osmosis, ion exchange, or activated carbon processes in major US regions (Fig. S16). Fig. 3 shows the East South-Central division that includes Alabama, Kentucky, Mississippi, and Tennessee as an example. Results show significantly different rates of adoption of treatment processes as a function of system size, regardless of the sociodemographic composition of customers served by CWS. Among large and very large CWS, as the proportion of Black residents at the county-scale increased, the predicted probabilities of adopting reverse osmosis, ion exchange, or activated carbon processes decreased from 10% to 1.0% (Fig. 3). In contrast, among medium, small, and very small systems, predicted probabilities of adopting reverse osmosis, ion exchange, or activated carbon were <1.0% for CWS regardless of the proportions of Black residents. Similar trends were observed for other divisions (Fig. S16).

In adjusted models, we did not consistently observe significant associations between adoption of advancements in water treatment processes and proportions of the additional racial/ethnic groups in each county served by CWS (Table 1 and S5–S9). One exception was for medium CWS where the proportion of American Indian/Alaskan Native residents at the county-scale was inversely associated with reported adoption of reverse osmosis, ion exchange, or activated carbon processes (−35.9% [95% CI: −88.0%, −1.4%]).

Results were consistent for CWS at greater risk of contamination

Results for the proportion of Black residents in adjusted models were generally consistent throughout additional analyses, highlighting, in particular, that these results were not sensitive to the spatial unit and were generalizable to subgroups of systems at greater vulnerability of drinking water contamination. Nationwide, we found similar results within CWS service area boundaries and county-scale analyses for associations between the proportions of Black residents and reported adoption of reverse osmosis, ion exchange, or activated carbon processes (Table 1 and Fig. 4). Confidence intervals for both spatial units consistently overlapped but results at the service area boundary scale typically had narrower confidence intervals and were attenuated compared to results obtained from the models incorporating county-level sociodemographic composition (Fig. 4 and Tables S5 and S6). Among systems in rural locations (RUCC < 3), piecewise logistic models showed the

Table 1 Change in odds of adoption of reverse osmosis, ion exchange, or activated carbon processes for US community water systems[a]

	County sociodemographic composition[b]		Service area boundary sociodemographic composition[c]	
	All CWS[d]	Elevated PFAS[e]	All CWS[d]	Elevated PFAS[e]
% Hispanic/Latino (10% change)	4.6 [−1.4, 10.5]	4.0 [−6.6, 14.3]	4.5 [1.0, 8.0]	3.0 [−4.3, 10.6]
% Black (10% change)	−19.3 [−26.2, −12.1]	−23.9 [−34.9, −13.0]	−14.2 [−18.9, −9.7]	−9.9 [−19.2, −0.8]
% Asian, Native Hawaiian and other Pacific Islander (10% change)	2.8 [-17.0, 22.0]	−10.8 [−45.9, 35.7]	−1.8 [−15.9, 10.9]	13.1 [−10.4, 35.2]
% American Indian/Alaskan N ative (10% change)	−2.5 [−18.5, 8.4]	−19.2 [−69.7, 15.4]	8.9 [−5.9, 19.1]	−65.0 [−93.3, −21.2]
Median income (10 000 USD change)	0.2 [−5.2, 5.6]	−1.6 [−11.0, 7.6]	−2.3 [−4.7, 0.0]	−4.1 [−9.0, 0.7]
N (total CWS)	521 176 (36 611)	44532 (3025)	454 178 (29 956)	42 462 (2878)

[a] Results show adjusted percent changes in odds of adoption of reverse osmosis, ion exchange, or activated carbon processes [95% confidence intervals from county-level or system-level cluster bootstrapping] between 2004–2022 associated with customer sociodemographic composition for US community water systems (CWS) at the county or service area boundary level from piecewise logistic regression models. Models were adjusted for % Hispanic/Latino, % Black, % Asian, Native Hawaiian and other Pacific Islander, % American Indian/Alaskan Native, and median household income (from the American Community Survey),[34] CWS size, source water type, owner type, an indicator for prior MCL violation, population density, fixed effects for census division, and fixed effects for the year on study. Associations for all racial/ethnic variables are shown for a 10-percentage-point increase and the association for median income is shown for a $10,000 USD increase. [b] Models include county-level sociodemographic composition. County served information was determined using the safe drinking water information system.[29] [c] Models include sociodemographic composition at the service area boundary level. Service area boundaries were obtained from the US Environmental Protection Agency's CWS service area boundary dataset (version 1.2).[35] [d] Models include all CWS after applying the exclusion criteria (see Methods). [e] Models include only CWS with elevated PFAS detections above the minimum reporting levels or uniform detection limits across the Third Unregulated Contaminant Monitoring Rule monitoring (2013–2015),[40] a compilation of statewide PFAS sampling data from 28 states (2017–2024),[41] and the ongoing Fifth Unregulated Contaminant Monitoring Rule (2023-ongoing).[42]

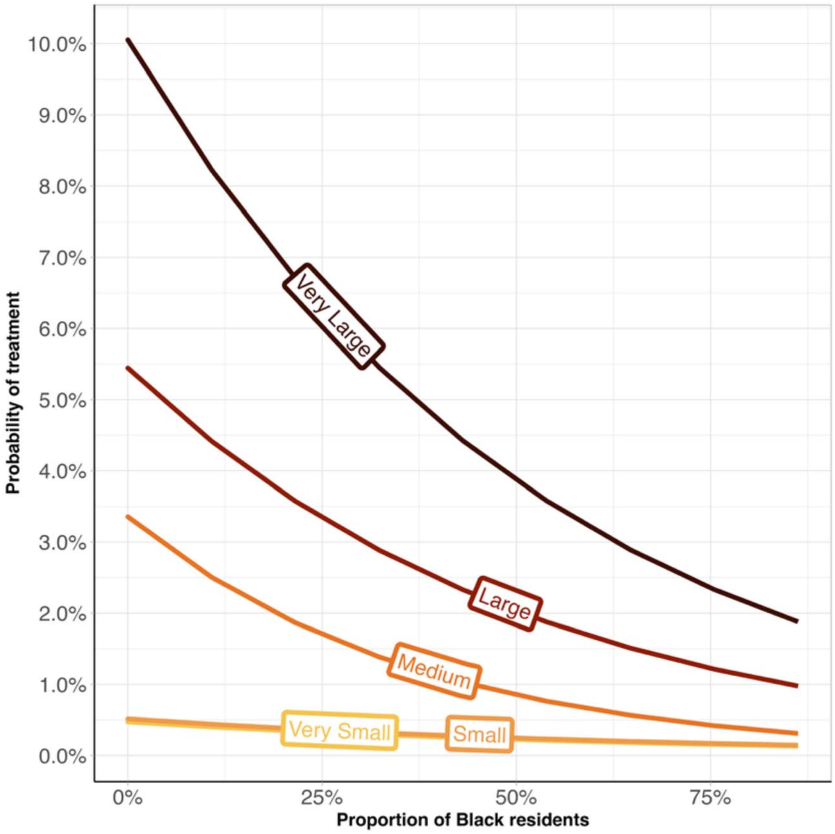

Fig. 3 Example predicted probabilities of adopting advancements in water treatment processes among US East South Central division community water systems (CWS) with varying sizes and proportion of Black residents served. Size categories as defined by US EPA are based on the number of customers served by CWS and include: very small: 25–500, small: 501–3,300, medium: 3301–10 000, large: 10 001–100 000, and very large: >100 000.[43] Predicted probabilities are shown from the division-specific, empirical minimum and maximum % non-Hispanic Black residents for publicly owned CWS in the East South Central division (Alabama, Kentucky, Mississippi, Tennessee) without a pre-period MCL violation (excluding total coliform) and with division-specific mean values for household income, population density, and other racial/ethnic groups within the first year of reporting.

odds of reporting adoption of reverse osmosis, ion exchange, or activated carbon processes were significantly lower with higher percentages of Black residents for rural CWS (Fig. 4, Tables S5 and S6). Decreases in the odds were also observed for urban and groundwater systems but were less precise and not significant (*e.g.*, −12.1% [95% CI: −23.6%, 0.5%] and −4.4% [95% CI: −15.5%, 7.3%], respectively) (Fig. 4 and Tables S5–S7).

Importantly, among CWS with prior MCL violations (excluding total coliform), 10-percentage-point increases in the proportion of Black residents served by a CWS were similarly associated with 22.1% [95% CI: −36.6%, −8.8%] lower odds of reporting adoption of reverse osmosis, ion exchange, or activated carbon processes (Table S5–S6). In line with a prior study examining nationwide trends in drinking water quality violations, the most common violations among the study sample were for the total and revised coliform rules, followed by rules for nitrate, total trihalomethanes, haloacetic acids, and arsenic.[7] Similar results were observed when restricting the study sample to CWS that did not report additional source water protection measures and when we disaggregated the MCL indicator in the primary model into five separate indicators (Table S8). Taken together, these analyses indicate that our results were not driven by the available data that can help account for variation in water quality between systems.

Stratified models showed that associations varied across census regions. At both spatial scales, significant inverse associations were observed between the proportions of Black and American Indian/Alaskan Native residents served by CWS and reverse osmosis, ion exchange, or activated carbon processes in the South region, but not within other regions (Table S9). These results indicate that sociodemographic disparities observed here at the national scale may be concentrated among CWS in the southern US. Associations for the additional racial/ethnic groups were more variable at the nationwide scale and sensitivity to the spatial scales was observed in models stratified by CWS size, source water type, and region. For example, at the service area boundary scale, the proportion of American Indian/Alaskan Native residents was inversely associated with reported adoption of reverse osmosis, ion exchange, or activated carbon processes for certain subgroups of CWS (including large/very large, medium, and systems with elevated PFAS detections), but a significant association was observed at the county scale only for medium CWS. Section 4 of the SI contains additional

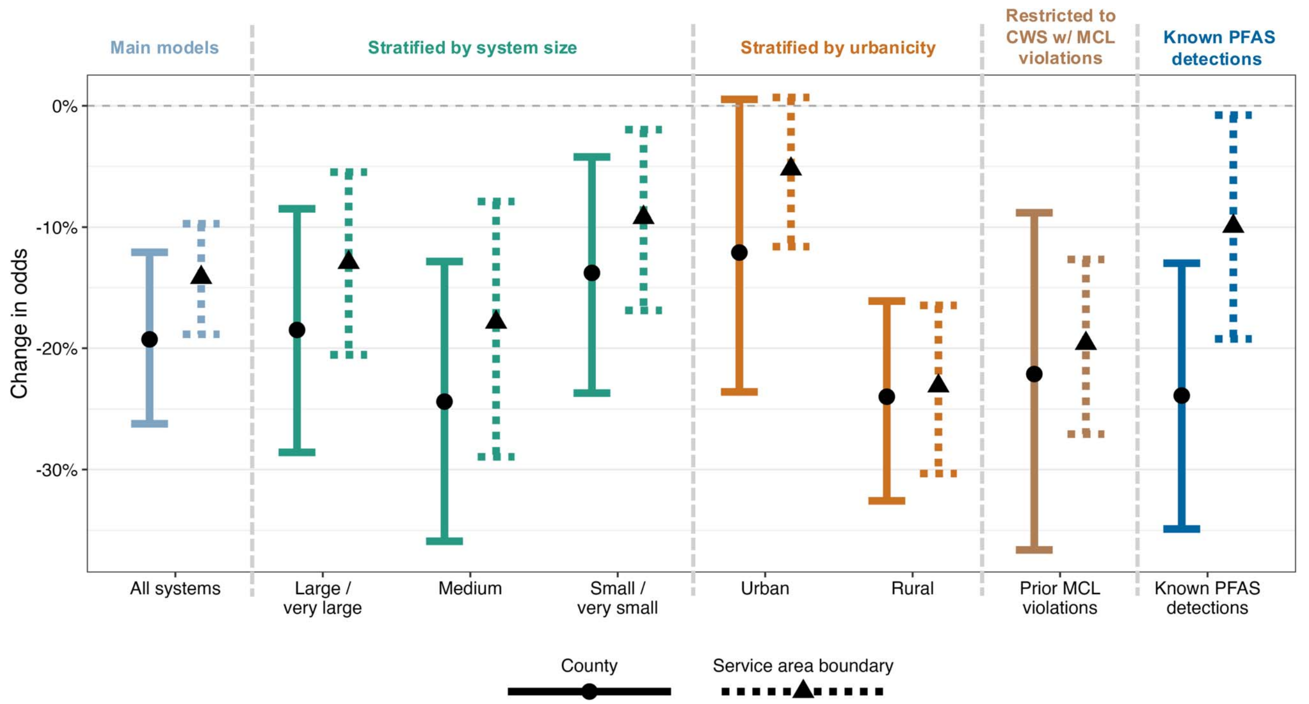

Fig. 4 Adjusted change in odds of adopting advancements in water treatment processes between 2004–2022 with each 10% change in proportions of non-Hispanic Black residents at the county-scale and community water system (CWS) service area boundary scale. Point estimates with 95% confidence intervals determined from either county- or system-level cluster bootstrapping are shown. County scale results are shown as solid lines, while CWS service area boundary results are shown as dashed lines. Results are from piecewise logistic regressions that adjusted for several sociodemographic factors at the county or service area boundary level (% Hispanic/Latino, % Black, % Asian, Native Hawaiian and other Pacific Islander, % American Indian/Alaskan Native, and median household income), CWS size, source water type, owner type, prior maximum contaminant level (MCL) violation, population density, census division, and year.

description on these results and Fig. S17 and Table S5–S9 show more comparisons.

Limited statistically significant relationships with other area-level socioeconomic factors

Unadjusted analyses showed significant correlations with other area-level socioeconomic factors at the county scale. CWS serving counties with the lowest (first quartiles) median value of owner-occupied housing units and median income were significantly less likely than those in the highest quartiles to report adoption of reverse osmosis, ion exchange, or activated carbon processes (Table S4 and Fig. S18). CWS serving counties with the highest proportions (fourth quartiles) of residents under the federal poverty line and residents with less than a high school degree were significantly less likely than the first quartiles to report adoption of reverse osmosis, ion exchange, or activated carbon processes (Table S4 and Fig. S18). In each instance, differences in treatment process adoption rates between the first and fourth quartiles increased over the study window (Fig. S18).

Reported adoption of reverse osmosis, ion exchange, or activated carbon processes showed heterogeneous and non-linear relationships with median household income at the county-scale and varied as a function of CWS size. For example, among small and very small CWS, each $10 000 USD increase in median household income was associated with a 6.1% increase [95% CI: −0.1%, 12.1%] in the odds of reporting adoption of reverse osmosis, ion exchange, or activated carbon processes (Table S5) but these relationships exhibited non-linearity (Table S10 and S11). Additional description of these results and comparisons of model fit can be found in the SI Section 4.

Discussion

Large and very large CWS included in our study sample serve approximately 163 million US individuals accounting for ∼80% of the study population (Table S1 and S2). This is similar to prior nationwide estimates.[55] By contrast, small or very small CWS account for more than 80% of the CWS included in our study, but only ∼18 million individuals. Smaller CWS with fewer customers face greater challenges in implementing infrastructure updates and maintaining ongoing operating expenses compared to larger ones.[11] For example, smaller CWS are known to exhibit longer time lags between MCL violations and appropriation of funds from federal and/or state agencies to address contamination compared to larger systems.[14] Following a major infrastructure update, smaller CWS are more likely to require additional staff to maintain treatment technology than larger ones. Typically, costs of infrastructure updates are passed on to customers within a service area, although specific analyses of the ability of utilities to raise funds to cover expenses are uncommon.[14,21,56,57] However, for smaller CWS, infrastructural updates may inflate water costs in a prohibitive way. The US EPA estimates that 12.1–19.2 million households lack affordable access to water and that unaffordability concerns are concentrated among smaller CWS and CWS serving Tribal populations.[57]

Factors affecting differences in technology implementation for removing diverse contaminants by CWS include understaffing and technical knowledge gaps that can affect a system's capacity to conduct regular drinking water monitoring.[14] Larger CWS more frequently achieve the necessary economies of scale, staffing, and have the necessary space and resources for capital investments.[11,14] Existing data suggest capital, operations, and maintenance costs of GAC and ion exchange vary based on location and pre-existing water quality, but generally decrease per gallon per day capacity, making them less expensive (per unit volume) for larger operations.[58] According to both system- and household-level metrics, high quality drinking water is currently disproportionately costly for communities with small populations and for low-income households.[21,59] Initial evidence suggests that the PFAS National Primary Drinking Water Regulations will increase existing disparities due to costs of treatment implementation.[21] Our results suggest that structural policy changes, such as those using social welfare functions[60] to support costly investments in water treatment infrastructure for CWS serving smaller and historically marginalized communities, could therefore help to address disparities in water quality.

Sociodemographic disparities in drinking water quality have been previously observed for metals and metalloids (including arsenic,[61] barium, uranium, chromium[3]), PFAS,[4,5] nitrate,[1] and in several studies on violations of the National Primary Drinking Water Regulations.[7,62,63] Factors driving disparities in drinking water quality across the US are still poorly understood,[10] but are thought to reflect differences in the technical, managerial, and financial capacities of CWS.[11,14,56] Enforcement for federal or state policies that were enacted during this time period, such as the updated arsenic MCL (2006)[64] or state-level PFAS MCL, may have driven some of the results observed here, although this may imply these results are at least partially applicable to a broader group of contaminants.

Our findings on differences between CWS sizes are supported by an analysis of 2024 treatment records for all active CWS, which also documented the co-removal of total trihalomethanes and haloacetic acids among a case study of CWS that installed treatment to remove PFAS over 2018–2022.[65] The social patterning of drinking water quality problems may also reflect historical settlement patterns of different sociodemographic groups, systemic discrimination, spatial patterning of contamination sources, and differential regulatory action (*e.g.*, leading to reduced regular monitoring and action, even if there are known drinking water quality problems).[10,11,14] Small systems tend to face compounded challenges in these regards and additional challenges in identifying contamination due to monitoring constraints.[11,14]

Treatment processes examined in this study (reverse osmosis, ion exchange, GAC, and PAC) may incur prohibitive implementation and maintenance costs for some CWS.[17] In total, the US EPA estimated the total annualized costs of the 2024 National Primary Drinking Water Regulations for PFAS would be $1.5 billion US dollars (USD). Of this total cost, 97% was attributed to treatment and 3% was for sampling, implementation, and administrative costs.[16,66] Other estimates are higher, in the range from $2.7–3.5 billion USD annually.[22] Historically, insufficient public funds have been allocated for maintaining and improving drinking water quality. As a result, water costs have increased for consumers, placing a disproportionate burden on impoverished communities.[67]

Conclusions

This study provides the first direct quantitative evidence of national differences in adoption of several advancements in drinking water treatment processes among US CWS with varying sizes and sociodemographic composition of residents. Disparities between CWS sizes and along sociodemographic lines were observed among a large group of CWS nationally and a case study of CWS with elevated PFAS detections. Early adoption of technology useful for removal of emerging contaminants among the largest CWS occurred at 7–8 times the rate of small and very small CWS over an 18-year time period. Our results suggest that there may be disparities that shape treatment technology adoption and result in differences in drinking water quality for communities that vary in sociodemographic composition and population size.

Past work has suggested that the occurrence of PFAS and other contaminants, including various endocrine disrupting compounds, are underestimated in US drinking water supplies.[68,69] Evidence also suggests that a diverse group of unregulated contaminants may pose greater hazards than currently regulated compounds, but persistent data gaps limit inference.[70,71] Addressing contamination, including early adoption of reverse osmosis, ion exchange, or activated carbon technology, may occur for a variety of reasons and can have the co-benefit of preventing consumer exposures to emerging pollutants that have not yet entered the regulatory landscape. Inferences from this study are valuable for evaluations of future drinking water rules at the state or nationwide scales. For example, with additional years of treatment data and more complete drinking water quality monitoring, future work could examine the implementation of the National Primary Drinking Water Regulations for PFAS.[27]

Strengths of this study included leveraging a large administrative CWS dataset, enabling nationwide, stratified, and subgroup analyses. Time-to-event methods facilitated the analysis of drinking water treatment process records over 18 years. Time-to-event and longitudinal approaches are uncommon in the drinking water quality disparities literature. Compared to cross-sectional studies, these study designs provide clearer temporal ordering and the ability to control for time-invariant factors. Very few studies, if any, have specifically quantified differences in the rate of treatment process adoption across CWS or improvements in water infrastructure more generally.[10,27,72] By comparing models with two different spatial units of analysis for sociodemographic data (county-level and service area boundary sociodemographic composition), we were able to assess the robustness of our statistical results across spatial scales.

Study limitations included that the administrative data were analyzed based on reported adoption of reverse osmosis, ion exchange, or activated carbon processes, but data on efficiency and targeted contaminants were not available. Conclusions related to system-level decision-making dynamics cannot be made, as other contaminant management strategies (*e.g.*, shutting off certain groundwater wells, switching water sources, or water system consolidation) may be enacted to improve drinking water quality and systems may need to balance funding constraints, compliance for other rules, and water affordability.[14,57,73,74] Increased water costs due to treatment may also push consumers to rely on unregulated drinking water sources.[75] Water quality conditions not directly analyzed here may influence which treatment process is adopted and available flow volumes can influence whether non-treatment options are possible.[16] For some contaminants, site remediation and emission reductions may be pursued to reduce contamination of source waters.[58] Our study is not meant to imply that all community water systems currently need to have advanced treatment in place to address PFAS contamination. We therefore specifically included various statistical controls that pertain to differences in drinking water quality or water system characteristics across CWS. We also used a case study of CWS with elevated PFAS detections and other subgroup analyses to examine systems most at risk for drinking water quality issues, although current data gaps limit a complete understanding of US drinking water quality across space and time.[71] More complete, unified datasets on continuous concentrations of various contaminants linked with metadata on service populations and treatment infrastructure are thus necessary for future work.[71,76] In addition, since this study did not specifically evaluate drinking water contamination, direct connections to human health outcomes cannot be inferred. However, a study design that considered the remediation of drinking water contamination as a natural experiment examined the impacts of changes in exposures on health outcomes, such as low birthweight and preterm birth, within an impacted community in Minnesota. This study also investigated the reversal of adverse health outcomes in the impacted community as a result of reductions in exposures.[77]

Our results underscore the necessity of considering both CWS characteristics and the sociodemographic composition of the communities served by CWS in future studies. Future work could examine the implementation of drinking water regulations, as well as other physical (*e.g.*, additional treatment processes) and non-physical factors (*e.g.*, staffing, training, and funding) that may influence drinking water quality disparities related to PFAS and other contaminants.

Author contributions

J. M. L.: conceptualization, data curation, methodology, formal analysis, writing – original draft preparation, visualization. M. Q. D.: data curation, writing – review & editing. G. A.: writing – reviewing & editing. E. M. S.: conceptualization, writing – original draft preparation, writing – reviewing & editing, supervision, funding acquisition.

Conflicts of interest

The authors declare no competing interests.

Data availability

Code for this manuscript are publicly available *via* the following link: https://github.com/SunderlandLab/treatment_adoption_disparities. Replication datasets and a data dictionary are available on the Harvard Dataverse: https://doi.org/10.7910/DVN/PSDXDM. Raw data obtained *via* a Freedom of Information Act request to the EPA are also available on the Harvard Dataverse: https://doi.org/10.7910/DVN/XKWJV1.

Supplementary information (SI): literature search terms, details on data processing, details on PFAS monitoring datasets, details on sensitivity analyses, and all tables and figures. See DOI: https://doi.org/10.1039/d5em00930h.

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