Journal of Water Economics 53 (2026): 1–32

Income redistribution, water scarcity and water rates in the 225 largest US cities

Mary Tiana Randriamaro
Washington State Department of Natural Resources

Joseph Cook
School of Economic Sciences, Washington State University

As in the electricity sector, water utilities commonly use increasing-block tariffs despite economists' theoretical advice to set the volumetric price at the long-run marginal cost of supply. The most common justifications are to shift costs away from lower-income users (who are presumed to use less water) and to provide conservation incentives in the face of scarcity. Following a recent paper in the electricity sector, we calculate water and sewer rate redistributiveness for 225 US cities and explore whether this measure is related to local water scarcity and income inequality. We combine data on rates, customer assistance programs, county-level Census demographics, utility characteristics, and presidential vote shares with a nation-wide dataset on water consumption. We also introduce a long-term measure of water scarcity (Padowski and Jawitz, 2012) to the debate on whether customers in water-scarce regions really do face higher prices. As in the electricity sector, we find that water rates are more redistributive in areas with higher local income inequality, though this result is sensitive to how we define our redistribution measure. We also find no evidence that customer assistance programs are a substitute for increasing-block tariffs. We find little evidence that rates are more redistributive in areas with higher water scarcity. We discuss whether, as in electricity, redistributive water tariffs may be ineffective at providing much assistance to lower-income customers.

JEL: L95, Q25, Q53

Keywords: water tariff, income redistribution, increasing-block tariffs, water scarcity

---

Corresponding author: Mary Tiana Randriamaro (mary.randriamaro@wsu.edu).

Acknowledgements: We thank Nicholas Kraabel for excellent research assistance in compiling the information on the water utilities used in the study. Alexander Danilenko of the World Bank also generously shared rates data on a subset of these utilities from the Bank's International Benchmarking Network (IBNET) database. We thank Julie Padowski for sharing her data on water scarcity, and the Water Research Foundation for sharing the Residential End Use survey data. We are also grateful for the helpful comments from Michael Brady, Ana Espinola-Arredondo, and Ron Griffin on earlier drafts, though all opinions and errors are ours alone.

Disclosure statement: We do not have any known competing financial interests or personal relationships that could have influenced the work. The data and code are available as online supplementary files.

Manuscript received: 5 Dec 2024; final version accepted: 1 Nov 2025; available online: 7 Nov 2025.

Available at https://www.journalofwatereconomics.com.

1 Introduction

Like the electricity sector, the water industry is characterized by very high fixed costs and low marginal costs. As such, standard economic advice would be to use a two-part tariff, with the fixed (non-volumetric) fee set to cover fixed charges and the volumetric fee set to the long-run marginal cost of procuring and producing water. Economic efficiency is, however, only one of several competing objectives that utilities and regulators must balance in setting tariffs, including fairness, equity, conservation, revenue sufficiency, and stability (Boland, 1993; Boland and Whittington, 1998; Pinto and Marques, 2015; Porcher, 2014; Pinto and Marques, 2016; Grafton et al., 2020).

A recent paper in the electricity sector (Levinson and Silva (2022), hereafter LS) showed theoretically how a utility might use differentiated volumetric prices to maximize welfare when it is practically or politically infeasible to differentiate the fixed charge based on income [1]. Given this theoretical prediction, the rising use of increasing-block rate structures, and the fact that utilities often have explicit goals of "affordability" and "fairness", LS also explored the empirical question of whether electric utilities indeed deviate more from efficient tariffs in areas with higher income inequality. They use nationally-representative data on electricity consumption and a broad survey of electricity tariffs to calculate each utility's "electric Gini", a measure of how much the utility's rates shift or redistribute the revenue burden from low electricity users to high users. A utility with only a fixed charge (no volumetric rates) would ask each user to contribute equally and would have an "electric Gini" of zero, while a utility with a steeply-rising increasing block tariff would have a higher corresponding Gini measure. They find that regulators do appear to use tariffs for income redistribution: areas with higher income inequality are more likely to have higher electric Gini measures. The relationship persists even with controls for politics, low-income heating assistance programs, investor-owned utilities and others. They find, however, that these redistributive rates are ineffective at actually redistributing income because the correlation between electricity use and income is in fact quite low.[2]

The objective of our paper is to investigate whether these relationships also apply to water and sewer tariffs for large cities in the United States. Although a number of empirical papers (described in the next section) have examined the choice of tariff *structure* (e.g. uniform rate vs. increasing block tariffs), few have focused on the properties of the tariff. For example, two utilities might both have increasing-block tariffs (IBTs) with two price tiers, but the block sizes and marginal block prices could vary substantially. This might send quite different signals to customers and result in a different pattern of who bears more of the burden of paying for services. As in electricity, water utilities and their

[1] Like electricity providers, water utilities do not observe the income of their customers. They can, however, observe the value of the served property, and Brent et al. (2025) and others have suggested charging differentiated fixed charges based on property value. Although not done in the United States, many utilities in New Zealand charge a uniform annual general charge via council fees (property taxes), typically where water use is unmetered (New Zealand Infrastructure Commission, 2024). These charges can be a set fixed fee, or based on the value of the property (Garnett and Sirikhanchai, 2018).

[2] As discussed below, we lack data on the income of customers and therefore generally avoid using the term "progressive" throughout the paper. We reserve that term for the conventional economic meaning that higher income customers would pay a larger share of the costs of a city's water and sewer services (either as a percentage of income or as higher bill amounts) than low-income customers. We instead follow LS in using the term "redistributive" defined around high vs. low consumption, rather than high vs. low income.

regulators may have different priorities regarding affordability and differ in how they attempt to use rates to redistribute income. Unfortunately, data is scarcer in the water sector than the electricity sector. There is as yet no nationally-representative database of water and sewer rates, in part because the water sector is more fragmented, with many small utilities. We collected water and sewer rates, as well as data on customer affordability programs, for the largest cities in the US (those with populations over 100,000) as of late 2019. To isolate the properties of each utility's tariffs, LS uses a nationally-representative survey of electricity consumption to calculate the Gini for each utility, "as if" the full set of households nationwide paid the electricity tariffs of, for example, Los Angeles. They do this to avoid possible endogeneity between rates and consumption, as we discuss in more detail when defining our redistribution measure. There is unfortunately also no nationally-representative survey of water consumption. We use the best available data - the Water Research Foundation's Residential End Use survey – to calculate a similar measure that we call the water rates redistribution index (WRRI) of combined water and sewer rates for US cities with populations over 100,000. This unit-free redistribution index is constructed from the total water and sewer bills including all variable and fixed charges. As with the "electric Gini", it ranges from 0 to 1, with higher values indicating more redistributive rates.

We confirm two main results from LS's work in the electricity sector: water and sewer rates tend to be more redistributive in cities with higher income inequality, and customer assistance programs do not appear to be substitutes for more redistributive tariffs. The relationship between redistribution and income inequality loses statistical significance, however, when we use geographically-partitioned water consumption data. We also explore two additional measures of redistribution in appendices: the share of revenues derived from the top 10% of water users and the fitted change in average volumetric price used in Switzer (2019). Like LS, we also find that neither local politics (proxied by county-level Presidential vote shares) but unlike LS we find in some models that publicly-owned water utilities have more redistributive rates than investor-owned utilities. Like LS, we find that utilities that serve larger numbers of customers have more redistributive rates, perhaps due to cost differences from economies of scale.

Although the two sectors share many characteristics, one key difference between electricity and water provision is that water is very expensive to transport over long distances. Local availability - water scarcity - is therefore more important in water and in theory should be reflected in tariffs used to signal that scarcity. IBTs can send these signals to consumers who use more than a minimum "lifeline" volume, and indeed IBTs are often referred to as "conservation rates" in the water sector. There is, however, little empirical evidence of such a relationship between water scarcity and water prices. Using data from public water utilities in the 35 largest metropolitan areas in the United States, Luby et al. (2018) find that the average monthly bill for a household using 12 ccf (thousand cubic feet) is actually *lower* in cities facing *greater* water scarcity. They use the Natural Resources Defense Council (NRDC)'s Water Supply Sustainability Index (WSSI) as their measure of relative water scarcity because it integrates "several factors, including water demand and groundwater use as a share of available precipitation, susceptibility to drought, projected increases in freshwater withdrawals, and projected increases in summer water deficit" Luby et al. (2018). In a reply, Switzer and Teodoro (2019) use the same rates data but examine the relationship between the highest marginal price and a different measure of water scarcity, the 10-year monthly average of the commonly-used Palmer Drought Severity Index (PDSI). They find no evidence of a relationship between water prices and scarcity. They also point out that the NRDC's WSSI is a *projection* of water demand to 2050, and argue that the PDSI does a better job of representing current regional moisture levels that should in theory be more reflective of current prices.[3] In a related paper discussed in more detail below, Switzer (2019) finds that areas with higher PDSI (more moisture over the previous ten years) are less likely to use increasing block rates and charge less redistributive water rates.

We contribute to this line of research by a) simultaneously modeling the redistribution and scarcity-signaling motivations of utilities and b) using a measure of water scarcity that reflects the massive amount of existing infrastructure to convey water long distances to cities. This measure, constructed by Padowski and Jawitz (2012) for the same 225 US cities with populations over 100,000, measures water availability as the sum of cumulative river flows, water storage, and imported water. Dividing this amount by the city's population gives a per capita measure of water availability. We find no relationship between our water rates redistribution index and this measure of water availability. However, we do find that a dummy for the three cities that Padowski and Jawitz (2012) consider as "high" risk is associated with more redistributive rates. For comparison, we also report results using the NRDC and PDSI water scarcity measures.

The remainder of this paper is structured as follows. After a review of the literature, we describe our dataset in Section 3 and methods in section 4. Our empirical results are in section 5, followed by a conclusion with a discussion of limitations and implications from the findings.

2 Literature Review

Although a standard economic prescription would be for a two-part tariff with a single volumetric price (as noted above), in practice the increasing-block tariff structure is the most common in the US. A 2018-2019 water and wastewater rate survey in the 50 largest cities in the United States by Black & Veatch Management Consulting, LLC reported an increase in the use of IBTs by about 30% between 2001 and 2018 matched with a decline in the popularity of decreasing blocks tariffs. This is in part because tariff design is a political process[4] (in some cases subject to regulation) that must balance other objectives of fairness, revenue sufficiency and stability, and (increasingly) "affordability". There is naturally a very large economic literature estimating how customers respond to tariffs (Dalhuisen et al. (2003); Mansur and Olmstead (2012); Sebri (2014); Wichman et al. (2016), and many others). Many economists have also weighed in with advice for tariff designers in how to best balance these objectives (Boland, 1993; Boland and Whittington, 1998; Griffin, 2001; Pinto and Marques, 2016; Grafton et al., 2020).

[3]In the earliest study we are aware of that examined determinants of water rate structures, Hewitt (2000) used data from a 1994 Ernst and Young survey of water rates in "more than 100 of the largest US cities" and found that utilities in sunnier, drier places were more likely to use an increasing block tariff.

[4]Hanemann (2023) provides a wonderful illustration of this in recounting his role in redesigning water rates in Los Angeles in the early 1990s.

As Allaire and Dinar (2022) note, however, there has been much less attention to either formally modeling or empirically estimating why water utilities choose the rates that they do. Those that explore this question focus on the choice of rate structure (e.g single volumetric vs. IBT) or examine the drivers of an average bill for an assumed average level of water consumption. Allaire and Dinar (2022) usefully group drivers into internal and external factors. Internal drivers include technical, managerial and financial capacity, as well as "motivating" factors such as reliance on purchasing the raw water supply, expected investments, utility governance models (e.g. municipal vs. private ownership), and social interactions with other utility staff through conferences, professional associations, and other venues. External drivers include the regulatory environment and climate (local temperature and precipitation).

Several papers find that, as expected, costs drive rates and rate structures. Thorsten et al. (2009) find that North Carolina utilities with higher cost factors charge higher average prices. Using a survey from four southern US states, Boyer et al. (2012) find that rising treatment costs, regulatory costs, and the need for investment all increase the likelihood of adopting increasing block or uniform tariffs rather than flat (non-volumetric) rates. Using a ten-year panel of California utilities, Allaire and Dinar (2022) find that utilities who must purchase their raw water supplies are more likely to have transitioned into an increasing-block tariff or a budget-based rate (BBR) structure (which the authors group together as "pro-conservation water rates"). Using a near-census of utilities in Arizona, Georgia, New Hampshire and Wisconsin, El-Khattabi et al. (2023) also find that utilities who purchase their raw water supply charge higher average bills. In Canada, Gurung and Martínez-Espiñeira (2019) observe that utilities who source their water from surface water bodies compared to groundwater (and therefore presumably have lower costs) are more likely to adopt a single volumetric or IBT rather than a non-volumetric tariff.

Several papers also find evidence for the role of social interaction and peer effects: utilities are more likely to adopt an IBT or BBR if a larger fraction of utilities in their hydrological unit adopt them (Allaire and Dinar, 2022), and having a neighboring utility with higher bills is significantly correlated with a utility itself charging higher bills for an average consumption amount (Thorsten et al., 2009; El-Khattabi et al., 2023; Boyer et al., 2012; Chica-Olmo et al., 2013).

The empirical evidence regarding the role of ownership in water prices is more mixed. Several studies in the US find that municipally-owned systems charge lower average bills than investor-owned utilities (El-Khattabi et al., 2023; Barbosa and Brusca, 2015; Wait and Petrie, 2017). Allaire and Dinar (2022) find that California "special districts" are more likely to adopt IBTs or BBRs, arguing that such special governance arrangements are more subject to public opinion than private utilities or municipally-owned systems and that public opinion may favor IBTs. In Italy, however, Romano et al. (2015)'s find that private ownership is unrelated to tariffs. Studies also generally confirm the presence of economies of scale in water provision: utilities with more service connections tend to charge lower prices (El-Khattabi et al., 2023; Gurung and Martínez-Espiñeira, 2019).

One central focus of this paper is asking whether rate designers, believing that high water users are wealthier, use more redistributive water rate structures in locations with higher levels of income inequality as an attempt to redistribute income through bills. Thorsten et al. (2009) find that communities with higher median incomes charge higher average combined water and sewer bills, but that those with a higher share of customers below the federal poverty line also charge higher water bills. El-Khattabi et al. (2023) find that average bills (calculated for one consumption level of 4,000 gallons) are significantly lower when the estimated service population has a higher level of income inequality.

We are aware of two studies that have examined the internal properties of water tariff structures rather than average bills or choice of rate structure. Both used a measure of rate redistribution defined roughly as the average escalation in prices at various volumes. Suárez-Varela et al. (2015) examined this "price escalation" in the volumetric component of tariffs of 967 Spanish water utilities, modeling the fixed charge amount and number of blocks in the IBT as separate, simultaneous equations in a conditional mixed process model. They found that locations with more average rainfall and more full reservoirs over the prior three years charged less redistributive tariffs. They also find no evidence that private management affects the degree of price escalation, though it is associated with a larger number of tariff blocks. Switzer (2019) measures the escalation in average prices (including fixed charges) of tariffs in 852 US cities. We describe his approach in more detail below and use it as an alternate measure of rate redistributiveness in sensitivity analyses. As noted above, he finds that drier places, as measured by PDSI, do indeed use rates that incline more steeply. More redistributive rates are also associated with utilities that need to purchase their water supply and serve larger populations. He also finds that utilities serving areas with a higher percentage of the population below the poverty line, and those with lower median incomes, use *less* redistributive rates. In addition to using the Padowski and Jawitz scarcity measure discussed in the introduction, our approach differs from these two studies in that we integrate information on the distribution of household water use. This allows us to calculate a different measure of rate redistribution: each rate structure's potential to redistribute the burden of financing from low users to high users. In addition, neither study directly measured the relationship between rate redistribution or "escalation" and income inequality.

Finally, two other recent papers have discussed the distributional and equity implications of water pricing systems that use some form of individualized pricing. Smith (2022) uses billing data from Denver, Colorado before and after a change that based summer rates on a household's average water consumption during the prior winter. Geolocated billing data allowed him to match customers to average household demographics of the census block they were located in. He finds that the introduction of average winter consumption rates improved progressivity: lower income households, minority households, renters, and households with more people paid lower volumetric prices. Brent et al. (2025) examine temporary drought surcharges on individualized or "budget-based" rates in two utilities in California, again using billing data. They find that existing budget-based rates are generally regressive, with lower-income customers paying a high share of their income on water than high income customers, and that drought surcharges do little to improve progressivity. They also construct Lorenz curves similar to those here and in LS.

3 Data

3.1 Water and sewer tariffs

There is currently no comprehensive database of water, wastewater and stormwater rates in the United States, so we collected 2019 US residential water and sewer rates from public websites[5] of all 225 cities with populations larger than 100,000, in part to match the cities examined by Padowski and Jawitz (2012).[6] This approach over-represents medium and large utilities. According to the EPA Safe Drinking Water Information System (SDWIS) database, utilities serving more than 10,000 people account for only 3% of utilities because of the large number of small water systems in the US. In aggregate, however, the utilities in our sample serve approximately 27% of the US population. We recorded the volumetric tariff structure (increasing block, decreasing block, uniform), volumetric charges, and fixed (non-volumetric) service charges. Utilities use a variety of quantity measures; we converted rates to thousands of gallons (kgal) for consistency. Seventeen utilities have minimum charges, which we code as a fixed charge. Ten utilities (4% of cities) use some form of rate-based budgets for water and/or sewer rates, requiring additional assumptions about consumption to calculate rates.[7] For the utilities providing only water services, we found the corresponding sewer provider to collect sewer rates.

Table 1 provides summary statistics for the tariffs of the utilities in our sample. Only one utility uses non-volumetric "flat" rates where customers pay the same fixed amount each month. Thirty percent use "uniform" rates with a single volumetric price that does not change with quantity. Fourteen percent use decreasing block rates, where the marginal volumetric price declines with increasing water consumption. The remainder (55%) use increasing-block tariffs, with 2 to 8 blocks (Table 1).Uniform rates are most prevalent for sewer charges. Four percent of the utilities reported rate structures that varied by season.

3.1.1 Customer assistance programs (CAPs)

We also examined each utility's website to determine if it had any kind of customer assistance program (CAP). As with rates, we used cached versions of the websites from 2019 to exclude CAPs introduced during the COVID-19 pandemic. Note that although there was and is a federal Low-Income Heating Assistance Program (LIHEAP) in energy, there was no corresponding federal water assistance program in 2019; all programs were locally administered. About half of the utilities in our data had some form of CAP in 2019.[8] The most common type of program was a bill discount program.

[5]We used the "Wayback Machine" to view cached versions of utility websites as of December 2019: https://archive.org/web/.

[6]We also thank Alexander Danilenko of the World Bank for sharing rates data on a subset of these utilities from the Bank's International Benchmarking Network (IBNET) database.

[7]Our assumptions about the structure of water budgets and tariffs are based on information from the utilities' websites or the data source. For instance, a common type of rate uses the average winter consumption (AWC) of the customer as a benchmark in increasing block tariff tiers, as seen in El Paso, TX, Denver, CO, and Lafayette, LA. The first tier upper bound is calculated as a fraction of the AWC. Other types of rates are based on the lot size of the homes (San Antonio, TX) while others are based on a specified water allocation (Palmdale, CA).

[8]Information on CAPs is also publicly-available at https://waterassistanceprograms.org.

Table 1: Characteristics of residential water rates for large US cities

	Rates (Average $/kgal)	Thresholds (Average kgal)	Utilities (n)
Water Tariff Structure			
Increasing Blocks (IBT)			125
Decreasing Blocks (DBT)			31
Increasing/Decreasing Blocks			1
Uniform	4.01		68
Budget-based rate			6
Seasonal rates*			9
Water Fixed Charge	$13.13		225
IBT			
First block	2.41	4.55	125
	(1.91)	(3.03)	
Second	4.24	21.20	125
	(2.33)	(55.19)	
Third	5.93	115.05	106
	(4.51)	(378.54)	
Fourth	8.42	452.71	69
	(7.49)	(2033.95)	
Fifth	11.44	74.37	25
	(13.52)	(124.62)	
Sixth +	8.74	20.32	12
	(7.07)	(17.62)	
Sewer Tariff Structure			
Increasing Blocks			43
Decreasing Blocks			14
Uniform	5.71		126
Flat Rate	$45.97		42
Budget-based rate			4
Sewer Fixed Charge**	$13.54		172

Notes: In parentheses are the standard deviations. There are 9 utilities with IBT that have 6 blocks, 3 have 7 blocks, and 3 have 8 blocks. *The utilities with seasonal rates include Los Angeles, CA; Salt Lake City, UT; Riverside CA; Phoenix, AZ; Lafayette, LA; Seattle, WA; Boise, ID; Omaha, NE; and New Haven, CT. Except for New Haven, CT, which has a uniform rate, the other 8 utilities have IBTs as their summer (seasonal) rate. **The fixed monthly charge also includes the utilities with only a flat rate for their sewer.

We also estimated the value of each CAP based on a benchmark consumption of 4 kgal per household (15 cubic meters). Because utilities typically advertise the maximum possible benefit, our calculations assume the person was most in need, had the lowest income, or had the maximum amount of debt that could be forgiven.[9] For the 50 utilities

[9] For programs reduced bills by a set a percentage, we used the estimated bill for 4 kgal including fixed

with CAPs, where such a calculation is possible, we estimate that the benefits have an average value of $320 per year.

3.2 Water consumption

As in LS, we calculate our measure of rate redistribution using a set of broadly representative consumption data rather than the local consumption data for each utility. Conceptually, this is to avoid the possible endogeneity between each utility's consumption profile and its rate structure, since customers will of course react to the water tariffs in place for their utility. As LS (pg 353) says: "we want to focus solely on the utilities' choice of tariff design, not the ratepayers' choices of consumption, which is why we construct hypothetical bills based on representative ratepayers." In this sense our measure of progressivity might be thought of as "hypothetical" rate redistribution. For example, suppose a city reforms their tariff design to be more redistributive, raising the marginal price for large users substantially and lowering the price for small users. Customers would likely adjust their water use, with high users consuming less water and low water users increasing their water use. If we calculated the rate redistributiveness using the new rates but the old pattern of water consumption, we would find higher rate redistributiveness than using the new rates and the adjusted pattern of consumption. The spirit of the Levinson and Silva argument is that we are interested in the intent of the city's tariff reform of making rates more redistributive rather than the result of whether this caused redistribution.

We use residential water consumption from the Water Research Foundation's Residential End Uses of Water, Version 2 (REU2016). It consists of representative random samples of single-family customers of 23 utilities in North America that encompass significant climatic, geographic, and demographic diversity (DeOreo et al., 2016). We use annual (billed) water use records for 11,469 households.[10] While the data may not be nationally representative of residential water customers, it is the broadest available household-level water consumption dataset in the US. An earlier version of the dataset was used in a study of water demand (Mansur and Olmstead, 2012).

Figure 1 plots the distribution of monthly water consumption in the REU data. The monthly consumption ranges between 0 and 199 kgal with an average monthly consumption of 7.9 kgal.[11] The right-skew of the distribution shows the importance of large water users.

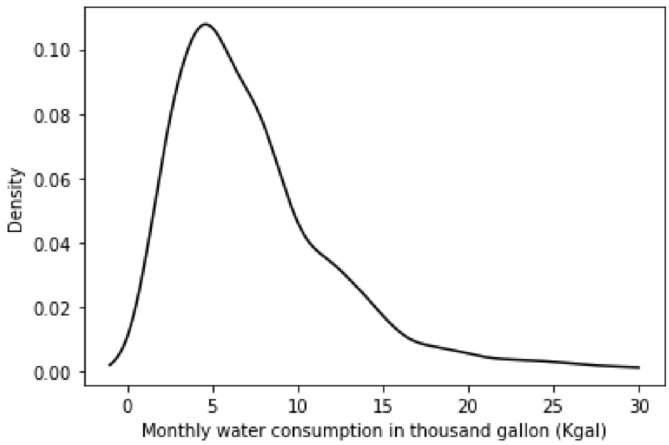
Our main analysis calculates distributional statistics for each utility's rate structure

charges. For utilities with "lifeline" rates, we used the estimated bill and deducted the cost for using the "lifeline" quantity of water. To calculate the value of low-interest repayment plans, we assumed an average 16.3%, the average consumer debt interest rate in 2019. For flexible terms programs, we totaled the amount of water debt consumers could incur over the program time period and compounded the annual interest rate over that time period, and used that as the benefit the program provided. There are few other estimation types but they are all with the intent to derive the maximum amount of benefit the program provides.

[10]The REU2016 project also collected daily use for 3,657 households from meter logging exercises, though this data is not used here.

[11]The USGS uses national datasets, state agency data, and local contacts to estimate water withdrawals and usage and reports that domestic deliveries by public water suppliers totaled 39,000 Mgal/d in 2015 and represented water provided to 283 million people at single-family and multifamily dwellings. This implies an average of 137.81 gal/d per household, or 4.1 kgal per month, which is much lower than the REU estimates. For indoor home uses, the USGS reports that each person uses about 80-100 gallons of water per day. Our average monthly consumption more than doubles the USGS estimate.

Figure 1: Monthly water use in the REU



using the full set of REU consumption data nationwide. Because water use patterns may vary seasonally and geographically however, we explore a sensitivity analysis (described in more detail in the Results section) that partitions utilities into those in the rainy "East" and the arid "West", using the 100th meridian as a rough dividing line.[12] In other words, for a utility in the West, we calculate its distributional statistics using consumption data only from other utilities in the West.

3.3 Demographics

In order to match the utilities with demographic characteristics, ideally we could identify the service areas for each utility from secondary data. Levinson and Silva (2022) use the zip codes corresponding to each county and the population of each zip code to construct a weighted average of the county characteristics, weighted by the combined populations of the zip codes served by each utility. Unfortunately, the zip codes served by water utilities are unavailable, nor are a common database of geo-coded service boundaries. Instead, we identify the county and/or cities served by each utility and use them to substitute for the service area.[13] The majority of the utilities serve one county. When a utility services multiple counties, we approximate its service area from its website and roughly estimate the fraction of each county served to weight county-level demographic characteristics. There were 11 counties that were served by more than one utility, in which case the utilities will share common demographics in our data. We use the 2019 American Community Survey (ACS) 5-year estimates at the county level to estimate average household incomes and income Gini coefficients. We combine them with county-level Democratic party vote shares, averaged across the 2000-to-2020 presidential elections from the County Presidential Election Returns from the MIT Election Lab. We also collected the number

[12]The American geologist and explorer John Wesley Powell in 1878 suggested the 100th Meridian as the boundary between the humid eastern United States and the arid Western plains. It cuts through Texas, Oklahoma, Kansas, Nebraska, and the Dakotas.

[13]To get the service areas, we used information from the utilities' websites, the Environmental Working Group (EWG), the EPA, and the 2019 Water and Wastewater Survey by the American Water Works Association (AWWA).

of people served by each utility from its website to measure the overall size of the utility. Similarly, we observed whether the utility was privately- or publicly-owned from SDWIS.

3.4 Water scarcity

In addressing our research question of how scarcity affects rates, the key question is which measure best represents what rate-setters perceive or use when designing rates. Given that rate changes are complicated, subject to regulatory approval, and often take effect for multiple years, short-term (monthly or seasonal) measures of drought may not drive perceptions.[14] As discussed earlier, Switzer and Teodoro (2019) and Switzer (2019) use the Palmer Drought Severity Index (PDSI), a zero-centered index that ranges from extremely dry (-4) to extremely wet (+4). Widely used in hydrology, it gauges drought conditions on monthly to seasonal timescales, so PDSI is most useful as a lagged indicator. Switzer and Teodoro (2019) use the monthly PDSI value averaged over the period 2008 to 2017. In replicating their approach, we average monthly values from 2010 to 2019. One could argue that utilities *should* be focusing on longer-run projections of water supply availability. Luby et al. (2018) use the Natural Resources Defense Council (NRDC)'s Water Supply Sustainability Index (WSSI), a long-term measure of water supply intended to estimate shortfalls by the year 2050. The WSSI takes four values: 1(low risk) to 4(severe risk).

We argue that the measure of water availability and vulnerability developed by Padowski and Jawitz (2012) provides a more policy-relevant estimate of water scarcity because it is the only one that accounts for an "area's ability to construct infrastructure to extract, import, and store water", which affects the volume of water available in any given time. Padowski and Jawitz (2012) estimated the water availability and vulnerability of all major urban areas in the contiguous United States with populations greater than 100,000 using two methods: the "runoff" approach, where water availability is equal to the volume of locally renewable water available to an urban area and the "hydraulic" approach, where the available water is the sum of all natural and captured mean annual flow and storage volumes. They find that using the runoff method consistently produces lower volumes of available water compared to the hydraulic-based method, since the former does not take into account cumulative river flows, water storage, and water imports. In other words, hydrologically-based measures like the PDSI are likely to overestimate water scarcity because of the role of stored and imported water in many cities. The total hydraulically-based available water of our utilities ranges from 641 liters per capita for San Antonio, TX to a comfortable 1.8 million liters per capita per day (lpcd) for Duluth, MN. They identify the average minimum volume of available water in an urban area to avoid scarcity issues as $Q^* = 1500$ lpcd, where urban areas falling 1 standard deviation below Q^* (or $Q < 770$ lpcd) are considered at "high" risk for water scarcity due to their low mean annual availability. Only three cities are at "high" risk of water scarcity: San Antonio (TX), Miami-Dade County (FL), and Lincoln (NE). Urban areas one standard deviation above Q^* ($Q > 2200$ lpcd) are categorized as having no scarcity issues. Those having water

[14] Utilities do, of course, use temporary drought surcharges (Brent et al., 2025). These could be seen as substitutes for permanent conservation-oriented rate structures; tariff designers may want to send a higher scarcity signal only on a temporary basis, and encourage higher water use (and higher utility revenue) when supplies are adequate. These temporary surcharges are not our focus here.

between 770 and 2, 200 lpcd are characterized as "moderate" risk (Padowski and Jawitz, 2012). Eleven utilities are at moderate risk.

This hydraulic measure may be more salient to rate setters. Padowski and Jawitz (2012) analyzed text of news articles from the Google News archive for each urban area during the years 1980 to 2011 for keywords related to water vulnerability. They found that the mean number of articles increased with increasing water scarcity using both the run-off and hydraulic approaches. The trend was more pronounced, however, for the hydraulic approach: incorporating the infrastructure for storage and long-term conveyance "may better reflect the reality of urban water scarcity as reported in the popular press" (Padowski and Jawitz, 2012).

4 Methods

4.1 Water Rate Redistribution Index

To assess how each utility's tariff redistributes costs among ratepayers, we follow LS in estimating what the hypothetical distribution of water/sewer bills would be for each utility if it had customers that were representative of all US households, in our case using the REU2016 monthly consumption data. LS call this measure the "electric Gini", though we use the term "Water Rate Redistribution Index" (WRRI) rather than "water Gini" both because we think it more accurately describes the measure and in order to distinguish it from a recent paper examining the Gini coefficient of water *consumption* (Cook et al., 2021). As with any Gini coefficient, the WRRI ranges from 0 to 1. More redistributive rate structures have higher values: they shift more costs from low water users to higher water users. The hypothetical sets of water/sewer bills vary across utilities based only on differences in the utilities' rate structures. The total bill is the sum of the fixed and volumetric water and sewer charges. Applying the REU consumption data to our set of 225 tariffs, the average combined water and sewer bill is $102.

We use two alternative measures of rate redistribution in sensitivity analyses. One is the share of utility revenue generated from the highest decile of water consumers (Cook et al., 2021). The second is Switzer (2019)'s measure of rate redistributiveness (which Switzer terms "progressivity"): the average rate at which the price per kgal changes in increments of 1,000 gallons up to 13,000 gallons. We determine the price per kgal for each of the first 13 blocks and regress the price on the number of thousand gallons consumed (Switzer, 2019).[15] His measure is the slope of the regression line. A positive slope implies more redistributive rates (higher water users paying more per unit of water) while a negative slope implies a regressive rate. A slope of 0 indicates that consumption has no effect on the price per unit of water (Switzer, 2019).

Table 2 illustrates these measures with data from five utilities with very different

[15] We began by calculating the monthly bills of each utility at consumption blocks 1, 2, 3, ... 13 thousand gallons excluding any fixed charges as per Switzer (2019). We then calculate the difference in bills between the consumption levels to get the price per thousand gallon ie. the bill for 2 kgal minus the bill for 1 kgal, the bill for 3 kgal minus the bill for 2 kgal, etc up to the difference between the bills for 13 kgal minus 12 kgal. We then run a regression with the price per thousand gallon as the dependent variable and the consumption blocks, X = (1, 2, 3, ...13), as the explanatory variables.

water tariff structures.[16] The tariff used in the hypothetical city of Flatsville has only a fixed, non-volumetric charge. Since all customers pay the same amount, the WRRI is zero, the share of revenue generated by the top 10% water users is exactly 10%, and the Switzer measure is also zero. Albuquerque Bernalillo County Water Utility Authority has a uniform volumetric rate, which again implies Switzer's measure is zero. But the WRRI and the top 10% share are positive, driven by the skewed distribution of water use in the REU data. Even with uniform volumetric rates, higher water users contribute more revenue. Buffalo Water Authority uses a decreasing/declining block tariff, which implies lower WRRI and 10% scores. Sioux Falls's IBT has modest jumps in the first two blocks but then jumps significantly in the third and fourth blocks. Finally, California American Water Monterey has a steeply-inclining IBT and the highest WRRI, shares of revenue from the top 10% water users, and Switzer (2019)'s progressivity index.

Table 2: Five example utilities with different water tariff structures

Description	**Fixed Charge**	**\$/kgal Charge**	**WRRI Annual**	**Top 10% share**	**Switzer measure**
Flatsville (Fixed monthly charge only)	25.00		0.00	0.10	0.00
Albuquerque Bernalillo (Uniform)	15.91	2.70	0.23	0.21	−0.00
Buffalo Water Authority (DBT)	16.63	3.05 then 2.75	0.16	0.18	−0.00
Sioux Falls (IBT) (Flat then steep)	3.29	5.01 then 5.36 then 10 then 15	0.35	0.27	0.039
CA Amwater Monterey (Steep IBT)	21.48	8.94 then 13.41 then 31.3 then 58.12 then 71.54	0.35	0.33	4.36

Notes: Using the monthly usage in the REU2016 annual water use data to the 225 water and sewer rates leads to an average monthly household bill of \$102 and an average WRRI of 0.27, with a standard deviation of 0.09 and an average share of revenue from the top 10% customers of 0.23 with a standard deviation of 0.05. The Switzer measure ranges from -1 to 1.57 with an average of 0.14.

[16] The tariffs reported in the table are illustrations of the differences in water tariff only, not including sewer tariff, because only a small percentage of the utilities have IBTs for sewer. However, the different redistribution measures use both water and sewer rates.

Figure 2: Water Lorenz Curves for Example Utilities

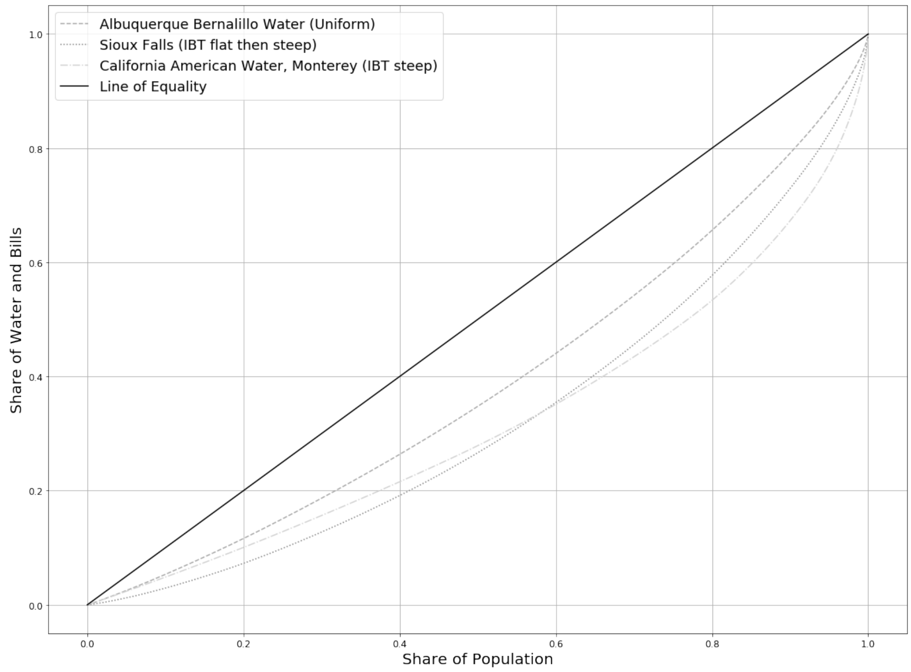


Figure 2 shows the water bill Lorenz curves for the five utilities in Table 2. Following LS, our Lorenz curves represent the share of bills per share of population. The Lorenz curves here involve expenditures, not income, and so they have a different interpretation from the standard income-inequality Lorenz curves. Normally, lower-hanging curves corresponding to higher Gini coefficients represent more income inequality. Here, however, lower-hanging curves with higher WRRI are more redistributive: a larger share of total utility revenues come from households that use more water. Because the hypothetical city of Flatsville has only a fixed monthly charge, it would lie along the 45-degree line of equality where the WRRI is zero. A low redistribution index implies a Lorenz curve that is closer to the 45-degree line. This is followed by Buffalo Water Authority (with its DBT), Albuquerque, Sioux Falls and California American Water Monterey.

4.2 WRRI regression model

Our key hypothesis is that utilities serving customers in areas with unequal income, high poverty, and low median income adopt more redistributive rates. The intuition is that income inequality drives a desire to protect the poor from high prices and use water prices for income redistribution. Our secondary hypothesis is that redistributive rates also send strong conservation signals, so we would expect more redistributive rates – rates that are more punitive for high water users - in locations with higher water scarcity.

We estimate a simple OLS model with the WRRI as the dependent variable. The model presumes that the redistribution index of utility i can be explained by a vector of factors X_i and an error term.

$$WRRI_i = \alpha + \beta X_i + \epsilon$$

In sensitivity analyses, we replace the WRRI on the left-hand side with a) the revenue share from the top 10% of customers and b) Switzer's rate redistribution measure.

We include several variables expected to influence utilities' choice of rate design, including: (a) demographic characteristics of the utility's consumers, including income inequality (measured using the income Gini), poverty level, and median income; (b) politics measured by the share of Democrat votes from previous presidential elections between 2000 and 2020, (c) the utilities' characteristics including the presence of a customer assistance program, public ownership, size (number of residential customers), a dummy for whether the utility is located west of the 100th meridian, and a dummy for whether the utility sources water from groundwater rather than surface water (drawn from SDWIS). Finally, we include a measure capturing water scarcity. In our main specification this is the hydraulically-based measure from Padowski and Jawitz, but we explore the two alternate measures discussed earlier in sensitivity analyses. In the Appendix, Figure A1 shows pairwise correlations of these variables and Figure B1 presents bivariate scatter plots.

5 Results

5.1 WRRI OLS results

Of the 225 utilities where we collected rate data, 160 are located east of the 100th meridian and 65 in the more arid west. Figure 3 maps the utilities, color-coded by their value for the water rates redistribution index (WRRI). Darker colors indicate more redistributive water and sewer rates; the figure shows no obvious regional patterns.

Figure 3: Water utilities and redistribution index (WRRI)

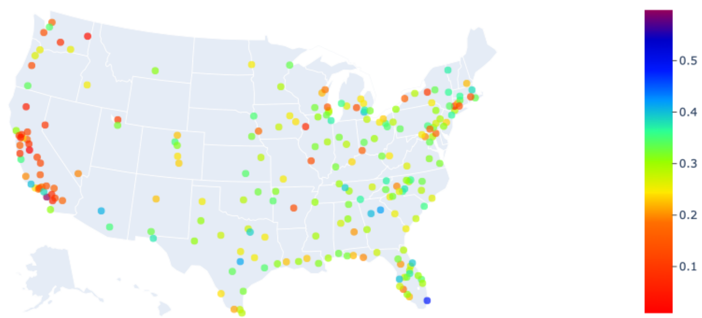


Figure 4 plots the distribution of the monthly WRRI values as well as the distribution of the shares of revenue from the top 10% of water users. The average WRRI is 0.27 with a maximum of 0.60 while the average share of revenue from the top 10% users is 0.23 or 23%. Utilities in the East do have slightly more redistributive rates: the average WRRI in the East is 0.29 (σ = 0.067) versus 0.22 (σ = 0.11) in the West (two-tailed t-stat=5.75).[17]

[17]When we calculate the WRRI by partitioning consumption data East v. West (discussed more below), this reverses: the average WRRI in the East is 0.25 (σ = 0.057) versus 0.29 (σ = 0.096) in the West (two-tailed t-stat=3.85).

Figure 4: Characteristics of the monthly WRRI and revenue shares from the top 10% of water users

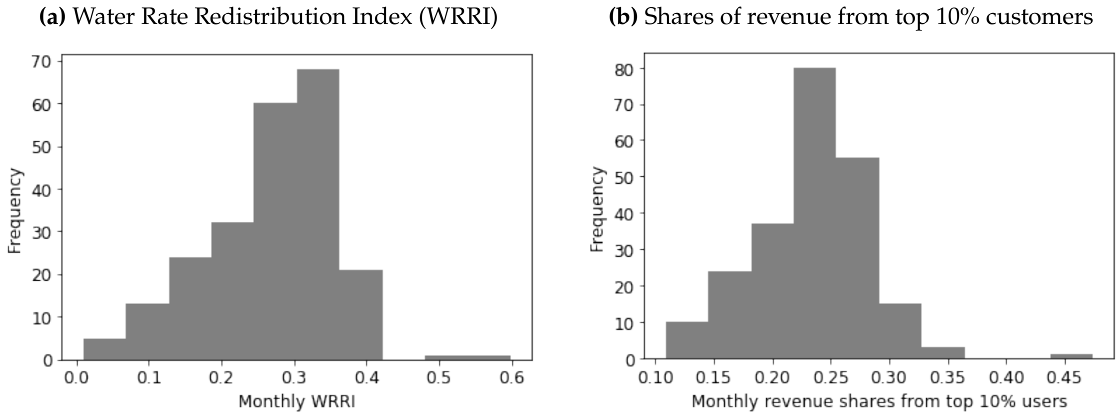


Table 3 presents the regression results with the WRRI as the dependent variable. Model 1 begins by regressing the redistribution index on the household income Gini, with no other covariates. The coefficient on the income Gini is positive and statistically significant: utilities that serve ratepayers with more unequal incomes have more redistributive water prices. If income is indeed correlated with water use, they would also be more progressive rates, a point we return to in the Conclusions section. How should one interpret the magnitude of the coefficient of 0.686 in Model 1, given that both it and the outcome variable are unitless? The income inequality Gini in our data ranges from 0.40 to 0.57. If we predict the WRRI using Model 1 and the lowest and highest values of income inequality, the average predicted WRRI changes from 0.22 under the lowest local income inequality to 0.34 under the highest level of local income inequality. This implies moving the WRRI from its third decile to its ninth decile (see also Figure 4a for a sense of the distribution).

Using another measure of income inequality, the share below the federal poverty line (Model 2), we again find a positive coefficient suggesting that areas with more poverty use more redistributive rates, though it is not statistically different from zero. Areas with higher median income, however, use less redistributive rates (Model 3).

Model 4 explores the relationship between rate redistribution and water scarcity, omitting measures of income inequality. Using Padowski and Jawitz (2012)'s continuous, hydraulic-based estimate of water availability, we find no relationship between water scarcity and rate redistribution. In results not shown, using a dummy variable for the utilities in areas in high risk of water scarcity results in a positive and highly significant coefficient of 0.12 (standard error of 0.04) indicating that rates tend to be more redistributive in areas at high risk. Recall, however, that only three of the 225 cities are considered high risk.

In Model 5, we include both the income Gini and the Padowski-Jawitz measure of water scarcity. The relationship between rate redistribution and income inequality persists and the relationship with water scarcity remains insignificant.

Finally, Model 6 adds other covariates that may explain rate redistributiveness. The coefficient on the income Gini remains positive and statistically-significant but its magnitude drops by half. We find no relationship with politics as proxied by presidential vote shares. By including a dummy variable for the presence of customer assistance programs (CAPs), we can test whether CAPs are substitutes for redistributive rates. We find no statistically-significant relationship. CAPs do not appear to be substitutes, even though such programs provide a way to help low income users (and other groups of customers such as veterans and seniors), pay for water. [18] Utilities that are publicly-owned also have more redistributive rates than those that are investor-owned. We include three factors that may reflect overall cost differences between utilities: we find that rates are more redistributive in utilities that serve more customers or that charge higher average prices, though we find no relationship with whether the utility sources water from more costly groundwater (compared to surface water). Finally, we find that after controlling for local water scarcity, utilities in the West charge less redistributive rates, a point we turn to next. Compared to LS, however, our R-squared remains low throughout. Most of the variation in the rate structures is clearly explained by variables that are not captured in our models.

Table 3: OLS regression (dep. variable = WRRI)

	(1)	(2)	(3)	(4)	(5)	(6)
Income Gini	0.686***				0.689***	0.388**
	(0.242)				(0.246)	(0.180)
Below poverty		0.00145				
		(0.00105)				
Median income			-0.00814**			
			(0.00335)			
P-J scarcity ('000 LCD)				0.00000762	0.0000112	0.00000541
				(0.0000199)	(0.0000229)	(0.0000137)
Democrat vote share						-0.0483
						(0.0510)
CAPS						-0.00377
						(0.00978)
Publicly-owned						0.0361*
						(0.0211)
Avg price per kgal						0.00315*
						(0.00161)
Population served						2.18e-08*
						(1.11e-08)
Source from groundwater						-0.00170
						(0.0125)
West						-0.0646***
						(0.0195)
Constant	-0.0532	0.246***	0.317***	0.267***	-0.0555	0.0489
	(0.120)	(0.0170)	(0.0200)	(0.0145)	(0.122)	(0.0869)
Observations	225	225	225	225	225	225
R-squared	0.048	0.005	0.015	0.000	0.048	0.226

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the state level. WRRI calculated using REU consumption data pooled at the national level.

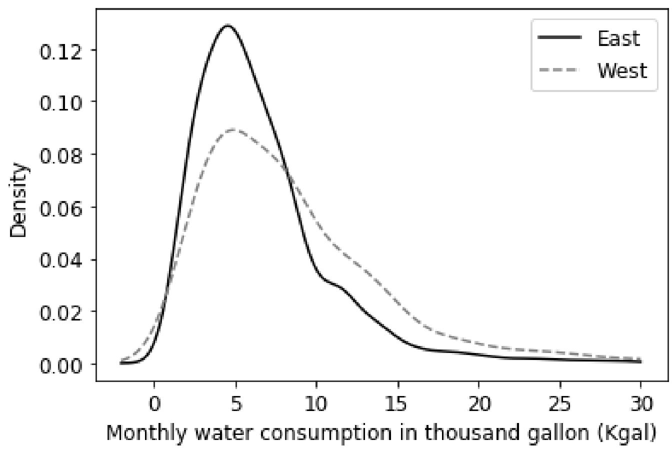
[18] Bivariate plots between the WRRI and income Gini, water scarcity, democrat vote share, and average water price per unit are shown in Appendix Figure B1 but find no apparent relationship between rates and CAPs.

5.2 Sensitivity analyses

We explore four sensitivity analyses: a) re-estimating and analyzing our WRRI measure by partitioning water use in the western vs. eastern US, b) exploring alternative measures of rate redistribution as outcomes, c) re-estimating our model but dropping the sewer component of rates, and d) exploring alternate measures of water scarcity.

Because of differences in rainfall patterns during the outdoor growing season, we might be making a mistake by ignoring structural differences in the distribution of water use in the eastern and western US, for example by applying the water use of households in Cleveland to the water rates of Las Vegas. Figure 5 shows the distribution of average monthly water consumption from the REU survey, by location east or west of the 100th meridian.[19] Average water use in the Western utilities who participated in the REU project is higher, with a larger right tail. To account for these differences, we re-estimate our WRRI measures by applying to each utility's rate structure *only* the consumption profile of other utilities in its region (East vs. West). The REU data contains information on 6,266 Western and 5,203 Eastern households in 65 Western and 160 Eastern water utilities.

Figure 5: Monthly Consumption Distribution by Location



The coefficient on income inequality remains positive (Table 4) but its magnitude is one third of the level in the model that calculates the WRRI based on pooled national data (Table 3) and is no longer statistically different from zero. We continue to find no relationship between water scarcity and rate redistribution (Models 4 and 5). The model with a larger set of covariates (Model 6) shows somewhat similar patterns: we still find no relationship with politics, the presence of a CAP program, and the three proxies for costs (average price, population served and sourcing from groundwater) show a similar pattern to Table 3. However, the relationship between redistribution and public ownership disappears. The coefficient on a utility being located in the West, however, switches signs

[19] The REU2016 does separate total annual consumption into "seasonal" and "nonseasonal" annual consumption. Participating utilities were to report annual non-seasonal consumption as the water use during the winter period. The annual seasonal use is therefore the difference between the annual and the non-seasonal use. However, the number of months in each season is not clearly defined in the data and our confidence in the seasonal data is low. We therefore ignore seasonality and use the annual data to calculate an equal monthly average consumption.

and is statistically significant.

Table 4: OLS regression (dep. variable = WRRI), calculated with consumption data partitioned East vs. West

	(1)	(2)	(3)	(4)	(5)	(6)
Income Gini	0.203				0.203	0.140
	(0.158)				(0.158)	(0.153)
Below poverty		-0.000991				
		(0.00128)				
Median income			0.00648			
			(0.00439)			
P-J scarcity ('000 LCD)				-0.00000267	-0.00000161	0.000000129
				(0.0000160)	(0.0000171)	(0.0000163)
Democrat vote share						0.00931
						(0.0395)
CAPS						-0.00606
						(0.00987)
Publicly-owned						-0.0127
						(0.0117)
Avg price per kgal						0.00340**
						(0.00129)
Population served						1.59e-08**
						(6.76e-09)
Source from groundwater						0.00222
						(0.00778)
West						0.0401***
						(0.0112)
Constant	0.169**	0.279***	0.225***	0.265***	0.170**	0.146**
	(0.0733)	(0.0214)	(0.0256)	(0.00496)	(0.0735)	(0.0688)
Observations	225	225	225	225	225	225
R-squared	0.006	0.004	0.014	0.000	0.006	0.178

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the state level.

Appendix Table C1 and C2 reports the OLS results using two alternate measures of rate redistribution as the dependent variable: the share of revenues raised from the top decile of water users and Switzer (2019)'s measure. Note that the calculation of the first measure (revenue from top 10%) again requires information on the distribution of water consumption; we return to pooled, national data. But Switzer's price escalation measure does not use consumption data. Results are generally similar when using the shares of revenue from the top water users: higher income inequality is associated with rates that collect a higher share of revenue from the top decile of water users. Moving from the lowest observed level of local income inequality to the highest, the predicted share of revenue from the top decile of water users increases from 21.1% to 26.9%. This relationship persists when inequality and scarcity are modeled simultaneously. Water scarcity is not a statistically-significant predictor of rate redistribution. As in the main results using the pooled national data, water rates in the West tend to be less redistributive.

The results using Switzer (2019)'s measure also show that rates are more redistributive in areas with higher income inequality, and we also find no relationship with the percent of the population below poverty (Table C2). We find a statistically significant and negative correlation with water availability: rates are less redistributive in areas with more available water per capita. We find no effect of politics, the presence of a CAP, public ownership, average prices, or sourcing from groundwater. Using Switzer's measure, we find utilities in the West use more redistributive rates.

In theory, the cost of providing wastewater services should have little connection to local water scarcity, so we repeat our main analysis (again using pooled consumption data) but omitting the cost of sewer services from our calculation of the WRRI. The relationship between the WRRI and income inequality is positive and significant, though it loses significance in the model with a full set of covariates (Appendix Table D1). We find no relationship with water scarcity.

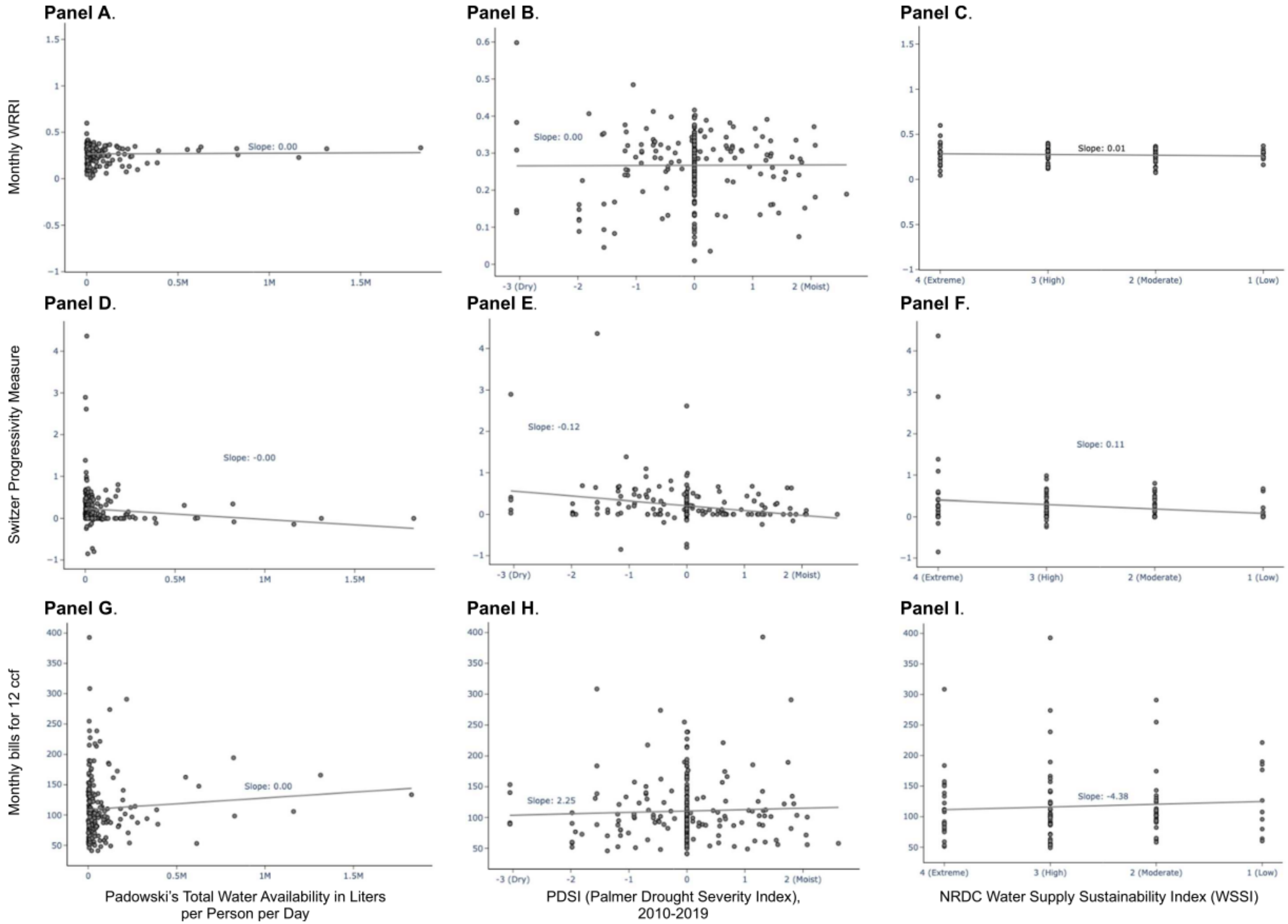
Finally, we explore the relationship between tariffs and the other two measures of water scarcity used in prior research. Each of the nine panels of Figure 6 shows the simple bivariate scatterplot of a measure of water rates on the y-axis against a measure of water scarcity on the x-axis. The first two rows show rate redistribution as measured by our WRRI measure and Switzer's average price escalation measure. The third row shows a different metric of rates (not rate redistribution) that was used in both Luby et al. (2018) and Switzer and Teodoro (2019): the combined water and sewer bill for a household that uses 9 kgal.[20] Water scarcity decreases from left to right for each of the three measures. We plot the simple correlation coefficient in each. As suggested by the models above, only the correlations between scarcity and Switzer's measure of rate redistribution are statistically different from zero: correlations with all three measures are negative.

6 Conclusion

We analyzed the properties of combined water and sewer rates in the largest 225 cities in the US to investigate two questions. First, do tariff designers and regulators appear to use water tariffs for redistributive goals as they do in the electricity sector? The answer is a qualified yes. Cities with higher levels of income equality tend to have more redistributive water rates as well as electricity rates (Levinson and Silva, 2022), and we find similar results using an alternate measure of rate redistribution (the share of revenue from the top 10% of water users). Our preferred results are, however, more tenuous than those in LS. This is in part because of our much smaller collection of tariffs and lower statistical power, but also because our results are sensitive to whether we calculate the WRRI using pooled nationally-representative data on water consumption or using data that partitions utilities in the West vs. East (we return to this issue below). In the latter, the relationship weakens substantially and loses statistical significance. The relationship does persist, however, using an alternate measure of rate escalation that does not use consumption data at all.

[20] More precisely, we calculated this based on 12 ccf, or 12 hundred cubic feet, since this was the consumption amount used in Luby et al. (2018) and Switzer and Teodoro (2019). Twelve ccf is 8,976 gallons, or approximately 34 cubic meters.

Figure 6: Relationship between water scarcity and water tariff based on three different measures of scarcity and water rate redistribution



Perhaps surprisingly, we also find no correlation between the redistributiveness of rates and whether the utility has CAPs. This could possibly be measurement error if utilities had assistance programs but did not advertise them on their websites. The design of CAPs also varied by utility both in terms of the type and level of support and who qualified. Given our limited sample size, we do not have power to investigate this variation although it is possible that some utilities with generous CAP programs may indeed have less redistributive rate structures. It is also possible that rate setters do not view CAPs as robust substitutes. Participation rates are generally believed to be low because of administrative burdens (we are unaware of any CAPs in the US that automatically enroll participants).

Redistributive rates, such as an increasing block tariff with steeply rising block costs, also serve an important second purpose in the water sector: they encourage conservation in the face of local scarcity. One might predict that communities facing more severe long-term water supply risks would use redistributive tariffs to signal this scarcity. We find no relationship between the WRRI and Padowski and Jawitz's continuous measure of water supply risk that captures the amount of stored and transported water available to a community, though we do find that rates are more redistributive in the cities with the highest level of water supply risk. We argue that this measure is preferable to two others used in the literature exploring this question, though we find no relationship using those alternate measures of local water scarcity, nor between the bill for 12 ccf and any of the three measures of scarcity. We do find a statistically significant relationship between scarcity and a measure of rate escalation used in Switzer and Teodoro. After controlling for this scarcity motivation, the relationship between income inequality and rate redistribution generally remains.

This exercise has several obvious limitations. It is ultimately a single cross-sectional regression and focuses only on large cities. As more data on water and sewer rates becomes available, it will be important to test whether these relationships hold among smaller cities and towns. With a longer time series of rates, researchers might use panel data, like Allaire and Dinar (2022), to examine how changes in these drivers affect rate adoptions or revisions. As noted earlier, our regression has low explanatory power. There are a host of other internal and external drivers of rate structures that we could not include because of data limitations, including cost structures, investment plans, infrastructure age, and others.

These limitations also point back to the question of whether water utilities in the Western US and their consumers are different, and whether one should prefer a specification that pools the REU consumption data nationally or partitions it geographically. On one hand, partitioning risks introducing endogeneity between rates and consumption, while pooling risks applying unrealistic consumption profiles to utilities. This problem is compounded by our lack of confidence in the REU seasonal profiles of consumption. Our regression results generally point to a positive relationship between redistributiveness and local income inequality, though we have less confidence in the magnitude of the relationship because there seems to be no correct answer to the question of whether to pool the REU data. The fact that a dummy variable controlling for Western utilities switches signs after partitioning the consumption data is also puzzling and could be due to a correlation between omitted regional consumption patterns and income inequality that is not accounted for when the WRRI outcome variable does not adjust for differences between Eastern and Western utilities.

Although we argue that the Padowski and Jawitz measure of water scarcity is a preferable measure of scarcity, the inclusion of imported and stored water raises questions about the timing and financing of water-related investments. Utilities in the West are more likely to obtain their water from distant sources that require large-scale storage and conveyance investments, and these investments have often been heavily subsidized by federal and state governments (e.g. California's State Water project, the Central Arizona Project). This could allow a utility to have relatively high water security but maintain modest rates. On the other hand, locally-financed projects would decrease the water scarcity measure and simultaneously increase costs. These could then be passed through to increased consumer bills and, if recovered through fixed charges, would reduce the redistributiveness of rates. (Although economists routinely recommend recovering capital costs through the fixed, non-volumetric component of bills, we know of no evidence that water tariff designers routinely follow this advice.) These locally-financed investments may have occurred in the distant past, however, and current rates reflect only the maintenance costs of projects rather than their capital costs. Furthermore, many large cities in the western US have protected, senior water rights under the prior appropriations doctrine but fail to include in customer tariffs the underlying scarcity value of these water rights (the opportunity cost in alternative uses).

Levinson and Silva (2022) answer a second question: if rate designers seem to use electricity rates for redistribution, is it effective? Their answer is no. Although the correlation between income and electricity use is positive (redistributive rates are in fact progressive), it is actually quite weak. Because of this, and because overall electricity bills are a relatively small share of household income for most households, moving a community from the least-redistributive rate structure to the most-redistributive rate structure has a vanishingly small impact on the community's income inequality. In other words, the utility ends up subsidizing some rich households who happen to use a small amount of electricity and penalizing some poor households who use a lot of electricity but are mistakenly assumed to be rich.

Levinson and Silva (2022) answer this question using data from a nationally-representative survey conducted by the US Energy Information Administration that contains information both on electricity usage and income. Although a meta-analysis of water demand studies finds a positive but small income elasticity (Havranek et al., 2018), we are unaware of a high-quality, nationally-representative dataset that contains both income and metered (rather than self-reported) water use to answer the simpler question of how strongly income and water use are related in the US. It thus remains an open question whether redistributive water rates may be more effective than redistributive electricity rates.[21] Two

[21] The debate over whether IBTs are "pro-poor" has also raged for three decades among analysts studying low- and middle-income countries. In this context, one might expect the progressivity to be even worse because the poorest households typically lack a connection to the piped network. Compared to connected customers, they pay higher prices for poorer quality water to water vendors and at other alternative sources. Poor households are also more likely to share a connection with other households, pushing their total water consumption into the highest blocks of the tariff (Whittington, 1992). The other complication is that the average price is commonly much lower than cost-recovery: every unit of water sold is subsidized, no matter which tariff block. Households who use more water therefore receive larger subsidies (Fuente, 2019). There is

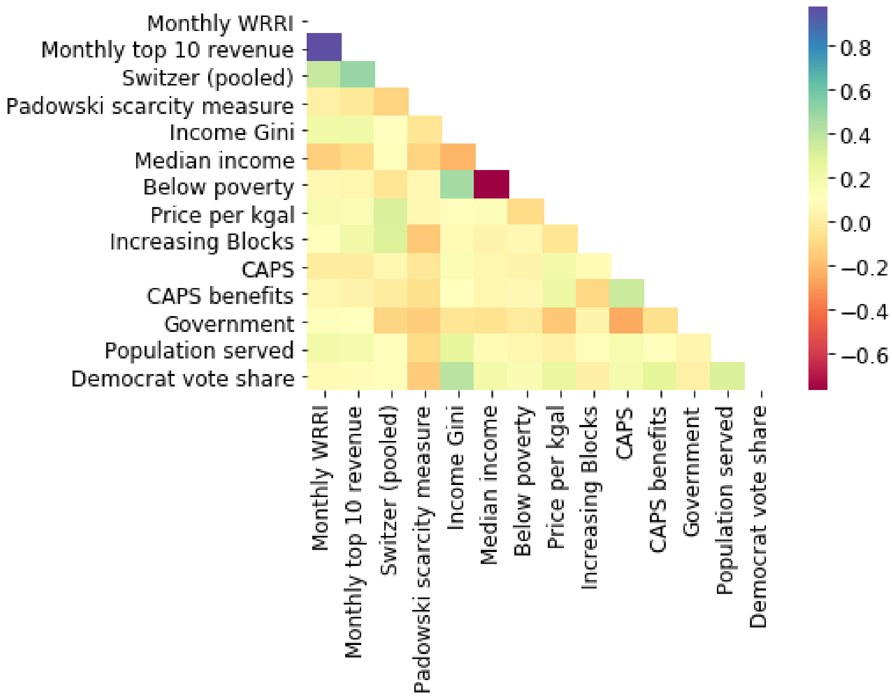
reasons for the low correlation documented in Levinson and Silva (2022) would seem to apply equally to indoor water use: higher income households spend less time at home and are more likely to have efficient appliances. If low-income households are larger, this would be another reason for a low correlation. On the other hand, outdoor water use will be strongly correlated with lot size in many arid locations, which is in turn correlated with wealth.[22] High-quality datasets on water consumption paired with socioeconomic data, similar to the 2009 RECS survey on energy conducted by the US Energy Information Administration, would be a critical tool in advancing our understanding of how to balance the goals of protecting affordability and financing resilient water and sewer infrastructure services.

now a degree of consensus that IBTs are ineffective at helping the poor in low- and middle-income countries (Andres et al., 2019, 2021; Wheeler et al., 2023).

[22]Smith (2022) finds strong evidence of the correlation between water use and census-block level average income in Denver, Colorado.

Appendix A: Pairwise correlations

Figure A1: Water tariff redistribution pairwise correlation

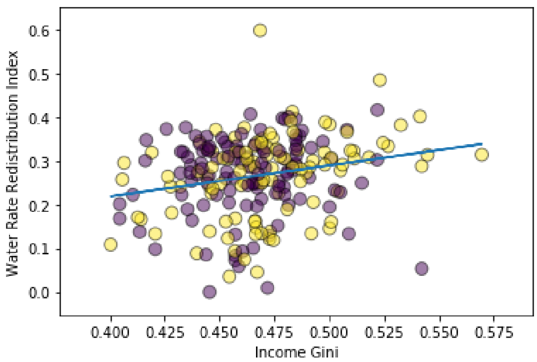


Appendix B: CAPS scatter plots

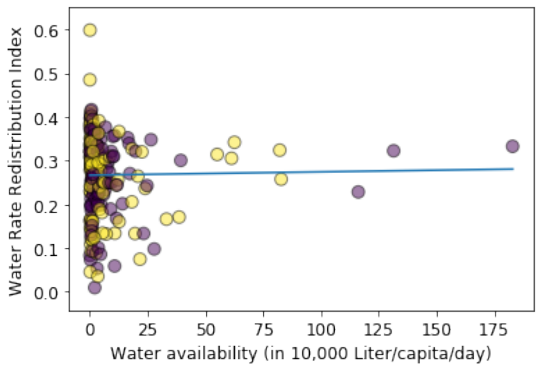
The yellow circles identify the utilities that have CAPs.

Figure B1: Rates redistribution and affordability programs (yellow if a utility has CAPs)

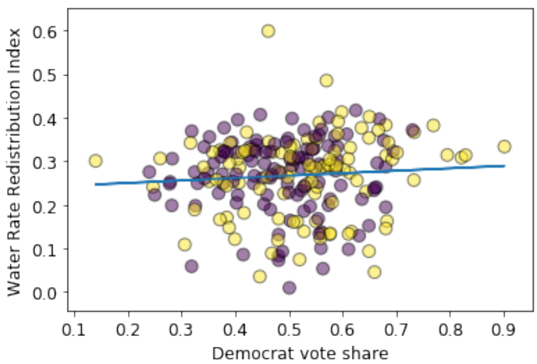
(a) WRRI, income inequality, and CAPs



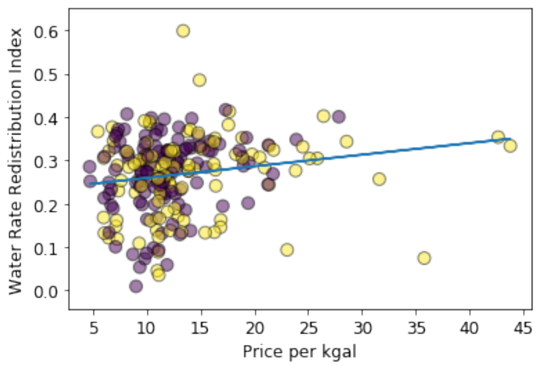
(b) WRRI, water scarcity, and CAPs



(c) WRRI, democrat vote share, and CAPs



(d) WRRI, water price, and CAPs



Appendix C: Alternate measures of rate progressivity

Appendix C.1: Share of revenue derived from the top ten percent of water users

Table C1: Progressivity = share of revenue derived from the top ten percent of water users

	(1)	(2)	(3)	(4)	(5)	(6)
Income Gini	0.348***				0.347***	0.210**
	(0.125)				(0.125)	(0.0928)
Below poverty		0.000617				
		(0.000582)				
Median income			-0.00296*			
			(0.00164)			
P-J scarcity ('000 LCD)				-0.00000522	-0.00000340	-0.00000527
				(0.0000106)	(0.0000119)	(0.00000825)
Democrat vote share						-0.0230
						(0.0277)
CAPS						-0.00308
						(0.00558)
Publicly-owned						0.0168
						(0.0109)
Avg price per kgal						0.00158
						(0.000994)
Population served						1.12e-08*
						(5.87e-09)
Source from groundwater						0.00359
						(0.00675)
West						-0.0265***
						(0.00877)
Constant	0.0716	0.225***	0.253***	0.235***	0.0723	0.117**
	(0.0603)	(0.00826)	(0.0117)	(0.00651)	(0.0606)	(0.0444)
Observations	225	225	225	225	225	225
R-squared	0.043	0.003	0.007	0.000	0.043	0.169

*Notes:**p<0.1; **p<0.05; ***p<0.01. Standard errors (in parentheses) clustered at the state level. Uses consumption data from REU pooled at the national level

Appendix C.2: Switzer's progressivity measure

Table C2: Progressivity = Switzer's average price escalation measure

	(1)	(2)	(3)	(4)	(5)	(6)
Income Gini	1.649**				1.584**	1.647**
	(0.719)				(0.701)	(0.670)
Below poverty		-0.00344				
		(0.00675)				
Median income			0.0402			
			(0.0247)			
P-J scarcity ('000 LCD)				-0.000259***	-0.000251***	-0.000293**
				(0.0000930)	(0.0000915)	(0.000112)
Democrat vote share						-0.230
						(0.289)
CAPS						-0.0528
						(0.0475)
Publicly-owned						-0.0969
						(0.0786)
Avg price per kgal						0.0260
						(0.0195)
Population served						5.24e-08*
						(2.89e-08)
Source from groundwater						0.0728
						(0.0597)
West						0.170***
						(0.0493)
Constant	-0.557*	0.264**	-0.0334	0.234***	-0.507	-0.723*
	(0.331)	(0.124)	(0.135)	(0.0400)	(0.325)	(0.369)
Observations	225	225	225	225	225	225
R-squared	0.010	0.001	0.014	0.013	0.022	0.162

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors (in parentheses) clustered at the state level

Appendix D: Sensitivity analysis - omitting sewer rates from the calculation of WRRI

Table D1: OLS regression results on WRRI, omitting the cost of sewer services from the WRRI

	(1)	(2)	(3)	(4)	(5)	(6)
Income Gini	0.462**				0.460**	0.123
	(0.193)				(0.192)	(0.186)
Below poverty		0.0000466				
		(0.00119)				
Median income			-0.00235			
			(0.00339)			
P-J scarcity ('000 LCD)				-0.0000100	-0.00000761	-0.0000106
				(0.0000196)	(0.0000228)	(0.0000253)
Democrat vote share						0.0369
						(0.0504)
CAPS						-0.0133
						(0.0112)
Publicly-owned						-0.00731
						(0.0166)
Avg price per kgal						0.00322**
						(0.00154)
Population served						1.90e-08*
						(1.06e-08)
Source from groundwater						0.0184
						(0.0204)
West						-0.0315**
						(0.0141)
Constant	0.0830	0.298***	0.313***	0.300***	0.0845	0.193**
	(0.0898)	(0.0187)	(0.0226)	(0.00867)	(0.0890)	(0.0878)
Observations	225	225	225	225	225	225
R-squared	0.025	0.000	0.001	0.001	0.025	0.132

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors (in parentheses) clustered at the state level. Use consumption data from the REU, pooled at the national level.

References

Allaire, M. and Dinar, A. (2022). What drives water utility selection of pricing methods? evidence from California. *Water Resources Management*, 36(1):153–169.

Andres, L. A., Saltiel, G., Misra, S., Joseph, G., Cordoba, C. L., Thibert, M. D., and Fenwick, C. (2021). Troubled tariffs: Revisiting water pricing for affordable and sustainable water services. Technical report, World Bank.

Andres, L. A., Thibert, M. D., Cordoba, C. L., Danilenko, A. V., Joseph, G., and Borja-Vega, C. (2019). Doing more with less: Smarter subsidies for water supply and sanitation. Technical report, World Bank.

Barbosa, A. and Brusca, I. (2015). Governance structures and their impact on tariff levels of Brazilian water and sanitation corporations. *Utilities Policy*, 34:94–105.

Boland, J. J. (1993). Pricing Urban Water: Principles and Compromises. *Journal of Contemporary Water Research and Education*, 92(1):7–10.

Boland, J. J. and Whittington, D. (1998). The Political Economy of Increasing Block Tariffs in Developing Countries. EEPSEA Special and Technical Paper, International Development Research Centre, Ottawa, Canada.

Boyer, C. N., Adams, D. C., Borisova, T., and Clark, C. D. (2012). Factors driving water utility rate structure choice: Evidence from four southern US states. *Water Resources Management*, 26(10):2747–2760.

Brent, D. A., Wietelman, D., and Wichman, C. (2025). Conservation and distributional consequences of pricing scarce water during droughts. Technical report, Resources for the Future.

Chica-Olmo, J., González-Gómez, F., and Guardiola, J. (2013). Do neighbouring municipalities matter in water pricing? *Urban Water Journal*, 10(1):1–9.

Cook, J., Brühl, J., and Visser, M. (2021). Distributional statistics of municipal water use during Cape Town's drought: Implications for affordability, conservation, and tariffs. *Water Resources Research*, 57(6):e2020WR028219.

Dalhuisen, J. M., Florax, R. J., de Groot, H. L., and Nijkamp, P. (2003). Price and income elasticities of residential water demand: A meta-analysis. *Land Economics*, 79(2):292–308.

DeOreo, W., Mayer, P., Dziegielewski, B., and Kiefer, J. (2016). Residential End Uses of Water, Version 2: Executive Report. Technical report, Water Research Foundation.

El-Khattabi, A. R., Gmoser-Daskalakis, K., and Pierce, G. (2023). Keep your head above water: Explaining disparities in local drinking water bills. *PLOS Water*, 2(12):e0000190.

Fuente, D. (2019). The design and evaluation of water tariffs: A systematic review. *Utilities Policy*, 61:100975.

Garnett, A. and Sirikhanchai, S. (2018). Residential water tariffs in New Zealand. Technical report, BRANZ.

Grafton, R. Q., Chu, L., and Wyrwoll, P. (2020). The paradox of water pricing: Dichotomies, dilemmas, and decisions. *Oxford Review of Economic Policy*, 36(1):86–107.

Griffin, R. C. (2001). Effective water pricing. *Journal of the American Water Resources Association*, 37(5):1335–1347.

Gurung, A. and Martínez-Espiñeira, R. (2019). Determinants of the water rate structure choice by Canadian municipalities. *Utilities Policy*, 58:89–101.

Hanemann, M. (2023). Policy note: An alternative approach to designing tariffs for household water use: The case of Los Angeles. *Water Economics & Policy*, 9(4):2271004.

Havranek, T., Irsova, Z., and Vlach, T. (2018). Measuring the income elasticity of water demand: The importance of publication and endogeneity biases. *Land Economics*, 94(2):259–283.

Hewitt, J. A. (2000). An investigation into the reasons why water utilities choose particular residential rate structures. In Dinar, A., editor, *The Political Economy of Water Pricing Reforms*, pages 259–278. Oxford University Press.

Levinson, A. and Silva, E. (2022). The electric gini: Income redistribution through energy prices. *American Economic Journal: Economic Policy*, 14(2):341–65.

Luby, I. H., Polasky, S., and Swackhamer, D. L. (2018). US urban water prices: Cheaper when drier. *Water Resources Research*, 54(9):6126–6132.

Mansur, E. T. and Olmstead, S. M. (2012). The value of scarce water: Measuring the inefficiency of municipal regulations. *Journal of Urban Economics*, 71(3):332–346.

New Zealand Infrastructure Commission (2024). Valuing water: Sustainable water services and the role of volumetric charging. Technical report, New Zealand Infrastucture Commission, Te Waihanga.

Padowski, J. C. and Jawitz, J. W. (2012). Water availability and vulnerability of 225 large cities in the United States. *Water Resources Research*, 48(12):W12529.

Pinto, F. S. and Marques, R. C. (2015). Tariff structures for water and sanitation urban households: A primer. *Water Policy*, 17(6):1108–1126.

Pinto, F. S. and Marques, R. C. (2016). Tariff Suitability Framework for Water Supply Services. *Water Resources Management*, 30(6):2037–2053.

Porcher, S. (2014). Efficiency and equity in two-part tariffs: The case of residential water rates. *Applied Economics*, 46(5):539–555.

Romano, G., Masserini, L., and Guerrini, A. (2015). Does water utilities' ownership matter in water pricing policy? An analysis of endogenous and environmental determinants of water tariffs in Italy. *Water Policy*, 17(5):918–931.

Sebri, M. (2014). A meta-analysis of residential water demand studies. *Environment, Development and Sustainability*, 16(3):499–520.

Smith, S. M. (2022). The effects of individualized water rates on use and equity. *Journal of Environmental Economics and Management*, 114:102673.

Suárez-Varela, M., Martínez-Espiñeira, R., and González-Gómez, F. (2015). An analysis of the price escalation of non-linear water tariffs for domestic uses in Spain. *Utilities Policy*, 34:82–93.

Switzer, D. (2019). Introducing a new measure of residential water rate progressivity. *AWWA Water Science*, 1(2):e1132.

Switzer, D. and Teodoro, M. P. (2019). Comment on "U.S. Urban Water Prices: Cheaper When Drier" by Ian H. Luby, Stephen Polasky, and Deborah L. Swackhamer. *Water Resources Research*, 55(7):6316–6321.

Thorsten, R. E., Eskaf, S., and Hughes, J. (2009). Cost plus: Estimating real determinants of water and sewer bills. *Public Works Management and Policy*, 13(3):224–238.

Wait, I. W. and Petrie, W. A. (2017). Comparison of water pricing for publicly and privately owned water utilities in the United States. *Water International*, 42(8):967–980.

Wheeler, S. A., Nauges, C., and Grafton, R. Q. (2023). Water pricing, costs and markets. Technical report, Global Commission on the Economics of Water, Paris.

Whittington, D. (1992). Possible adverse effects of increasing block water tariffs in developing countries. *Economic Development and Cultural Change*, 41(1):75–87.

Wichman, C. J., Taylor, L. O., and von Haefen, R. H. (2016). Conservation policies: Who responds to price and who responds to prescription? *Journal of Environmental Economics and Management*, 79:114–134.