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How does drought affect residential water demand and price elasticity?

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Urban water scarcity is an important social and economic concern, particularly as the intensity, duration, and frequency of droughts are increasing in many regions. We consider whether drought induces changes to water demand and the price elasticity of demand for water that may last beyond a drought's official end date. If drought shocks prompt long-term changes in water demand behavior, and these changes occur at broad geographic scale, they could have important implications for modeling adaptive responses to water scarcity. We assemble a novel dataset on residential water demand and pricing in the western United States to test empirically for effects of drought on water demand and price elasticity. We perform our analysis with aggregate quantity, price, and drought data, accounting for endogenous prices under increasing-block water tariffs and using both average and marginal water fees in estimating water demand functions. Results are consistent with the hypothesis that households may become less price-sensitive after exposure to drought. However, we find no systematic evidence of long-run, drought-related reductions in water demand, itself.

JEL: Q21, Q25

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1 Introduction

Urban water scarcity is frequently identified as an important social and economic concern globally (He et al., 2021; Dolan et al., 2021) and in the United States, in particular (Brown et al., 2019). Economists tend to highlight the role of water management institutions that allocate resources inefficiently within and across sectors as contributors to this problem, noting, for example, that re-allocation via markets or other means might go a long way toward mitigating urban water constraints (Zilberman et al., 1993; Olmstead, 2010; Debaere et al., 2014). Given current institutions and legal water allocation regimes, however, cities in arid regions often struggle to meet peak seasonal water demand. Recent examples include Cape Town, São Paulo, Las Vegas, and Melbourne (Hughes et al., 2025).

The intensity, duration, and frequency of droughts are increasing in many regions (Xu et al., 2019; Caretta et al., 2022; Trenberth et al., 2013), complicating the challenge of urban water demand management. What changes might we expect in urban water demand behavior from exposure to drought? Conventional wisdom among U.S. water utilities suggests that periodic drought induces changes in water demand that last well beyond a drought's official end date, an effect sometimes referred to as the "drought shadow" (Alliance for Water Efficiency, 2014). Another phenomenon anecdotally attributed to drought is "demand hardening" or the tendency of water demand to become less responsive to demand management policies over time as households and firms make investments in water conservation, some of which leave them with less capacity to respond in the future (Howe and Goemans, 2007; Kenney, 2014). If drought shocks prompt long-term changes in water demand behavior, and these changes occur at broad geographic scale, they could have important implications for modeling adaptive responses to water scarcity, making this a worthy subject for research.

The peer-reviewed empirical literature on both of these effects is thin and mixed, however. Considering the pure demand effect first, urban households and firms affected by drought may respond to mandatory or voluntary water supply restrictions or price increases by installing water-efficient technologies (fixtures, appliances, landscaping, industrial process machinery), which, even with a rebound effect, could suppress long-run demand (Brelsford and Abbott, 2017; Musolesi and Nosvelli, 2011). While the effects would be smaller and easier to reverse, simple behavioral changes (e.g., shorter showers) might also persist after a drought. Research in Barcelona, Spain suggests that post-drought water consumption decreased by 4-5 percent after a major drought in 2007-2008 (Bernardo et al., 2015). During a severe drought in the U.S. State of California in 2011-2017, the state called for a 25 percent reduction in water use relative to 2013. In response, households self-reported engaging in many conservation behaviors and reducing water demand (Stone and Johnson, 2022). However, empirical evaluation suggests that compliance with the statewide conservation mandate at the water utility level may have reached only about 50 percent (Soliman, 2022), and public announcements about the crisis do not appear to have induced statistically significant water savings (Browne et al., 2021). In terms of long-run impacts, some analyses suggest that water usage in California appears to have returned to its pre-drought levels fairly quickly after restrictions were lifted (Soliman, 2022), while others find that water conservation by residential users persisted for several years (Bolorinos et al., 2022).

Brelsford and Abbott (2017) find that a drought alert in Las Vegas, Nevada may have decreased demand contemporaneously, but the alert coincided with many different conservation policies, so the effect may not be attributable to drought, alone, and it is not clear how long the effect persisted. In a field experiment conducted in the Atlanta, Georgia area, a drought-related social comparison nudge reduced household water demand, but this effect declined significantly within a few months (Ferraro and Price, 2013). Similarly, behavioral interventions to encourage residential water conservation during a drought in California appear to have had effects that lasted for less than 6 months (Jessoe et al., 2021). Thus, empirical evidence for a "drought shadow" is mixed, whether we consider droughts, alone, or the various policies implemented to achieve water savings during these hydrologic extremes.[1]

Turning to drought's impacts on price elasticity, Klaiber et al. (2014) and Mansur and Olmstead (2012) both find that urban households are less price-elastic during dry conditions, but these estimated effects are seasonal (occurring regularly in the summer months), rather than responses to seasonally-anomalous drought conditions. In contrast, one study suggests that residential water users in Colorado may actually be *more* sensitive to prices during drought periods (Kenney et al., 2008). In a meta-analysis of water demand studies, the price elasticity of demand appears to be smaller in areas prone to water scarcity, though this result exploits cross-sectional variation in climate, rather than experience with drought in locations observed repeatedly over time (Garrone et al., 2019). Two recent studies provide strong empirical evidence of demand hardening at the utility scale. Stone et al. (2020) find that urban households are less responsive to water prices after a major drought in Colorado, even though prices increased quite steeply in the post-drought period. And in a study of Phoenix, Arizona, conversion to drought-tolerant landscaping has reduced price responsiveness among households in the metro area (Brent, 2016). Whether such effects occur more generally at broad spatial scale is an open question.

In this paper, we assemble a novel dataset on residential water demand and pricing in the western United States to test empirically for effects of drought on water demand (the "drought shadow") and price elasticity ("demand hardening"). We perform our analysis using aggregate quantity, price, and drought data at the water utility level. Our approach accounts for endogenous prices under increasing-block water tariffs and uses both average and marginal water fees in estimating water demand functions. Results are consistent with the demand hardening hypothesis that households may become less price-sensitive after exposure to drought. However, we do not find evidence consistent with long-run, drought-related reductions in water demand, itself.

2 Data

There is no central repository for data on water consumption and pricing in the United States. Researchers estimating water demand functions in the U.S., thus, face a data

[1] In an important application focusing on energy demand that provides a contrast to results in the literature for water demand, Costa and Gerard (2021) study the effects of a drought in Brazil that reduced hydroelectricity generation and resulted in a mix of household quotas and incentives to reduce electricity use. They find that about 23 percent of the reduction in residential electricity use attributable to this policy intervention, which lasted only 9 months, has persisted for 12 years.

collection challenge. One approach is to work with individual water utilities to obtain household-level data on water consumption along with utility-level price schedules. There are many examples of this approach in the literature (e.g., Ferraro and Price (2013); Klaiber et al. (2014); Wichman (2014); Clarke et al. (2017); Asci et al. (2017)). Other water demand research uses household-level consumption data and utility price schedules from the Residential End Uses of Water Survey, which collected several months of water demand data from a small number of utilities in the United States and Canada in the mid-1990s (Olmstead et al., 2007; Olmstead, 2009; Mansur and Olmstead, 2012).

We take a different approach, collecting aggregate price and quantity data to estimate utility-level demand functions for residential water, for two reasons. First, in order to answer our primary research questions about the impacts of drought on water demand and price elasticity, we require significant variation in drought exposure over time and geographic space, which is difficult to achieve working with data from a single utility, or even a small number of utilities. Second, our interest is in broad-scale changes in water demand behavior, and results from a modest number of individual utilities might have low external validity. Given the tradeoffs between external validity and plausibly causal interpretation of demand parameter estimates, our approach complements the literature that examines the impact of drought on water use within individual utilities using quasi-experimental or experimental methods (Ferraro and Price, 2013).[2] Note that our approach requires that we collect and standardize data from many different sources, and in some states, the raw data may be more reflective of water supply to the residential sector than of water demand from this sector. While the two are likely to be strongly correlated, water supply data could include system leakage (beyond any household meter), seepage, and unbilled water. To the extent that these supply-side factors respond to drought conditions (e.g., through utility investment in reducing water losses), the effects we estimate could combine drought responses by both households and their water utilities.

2.1 Water demand and pricing data

In this section, we describe the water price and use data obtained from each state. Additional subsections describe how we construct a standardized estimate of water use (average per capita monthly consumption by utility-year) and a common set of price tiers for the analysis.

2.1.1 California water fees and quantities

For the State of California, we collect water *fees* from the Electronic Annual Reports (eAR) of public drinking water systems managed by the Division of Drinking Water (DDW) within the State Water Resources Control Board (SWRCB).[3] eAR is an annual survey of public water systems that collects water system information intended to assess regulatory compliance. The reports are publicly available since 2013, though response rates and the consistency in reporting water prices improve from 2017 onward. Prior to 2017, the reports exclude information on usage cutoffs for each price tier, as well as fixed charges.

[2] Wichman (2024) compiles a similarly-large, utility-level dataset for two states in the eastern U.S. to examine the efficiency and equity implications of water pricing strategies.

[3] See https://www.waterboards.ca.gov/.

Since 2017, utilities have been asked to report total water bills (including fixed charges and volumetric rates) for standard quantities of 6, 12 and 24 hundred cubic feet (CCF).[4] Thus, we retain reports from 2017-2020. On average, 80 water utilities report their water rates in each year of this sample.

We import water *consumption* data for California utilities from the Water Conservation and Production Reports prepared by the SWRCB. [5] The reports contain population served, monthly potable water production, and water usage percentages by sector (residential, commercial, industrial, institutional) for urban water suppliers from 2014 onward. From the reports, we are able to calculate monthly total and per-capita residential water usage for each reporting public drinking water system and match these data with the water fee data obtained from California's eARs, 2017-2020.

2.1.2 Texas water fees and quantities

For the State of Texas, we obtain water fees and water consumption data from the Texas Municipal League (TML) Water & Wastewater Survey.[6] Only municipal utilities are included. The survey includes population served, total number of connections, average per-capita water usage, and total residential fees at monthly quantities of 5000 and 10000 gallons, including fixed charges, and the data are publicly available since 2015. On average, 580 cities report their water fees and consumption levels in each year.

2.1.3 Arizona water fees and quantities

We obtained water fees for each water utility in the State of Arizona from the University of North Carolina at Chapel Hill Environmental Finance Center (EFC). EFC partners with the Arizona Municipal Water Users Association, League of Arizona Cities and Towns, Northern Arizona Municipal Water Users Association, and Water Resources Research Center at the University of Arizona to collect these data. Since 2014, the EFC has surveyed nearly all of the rate-charging water and wastewater utilities in Arizona. Total water fees are reported for consumption quantities of 3000, 4000, 5000, 7000, 10000 and 15000 gallons, including fixed charges. On average, 400 utilities are surveyed each year.

The data on water *consumption* levels for Arizona are obtained from the Arizona Department of Water Resources. The department reports the annual amount of drinking water demanded and supplied in acre-feet for each use (e.g., residential) for each of the six active management areas (AMAs) in the state. Unfortunately, this aggregation of the available consumption data prevents us from exploiting the variation in water fees and quantities within an AMA. Thus, we calculate per-capita average monthly water consumption for each year in each AMA by dividing total monthly usage by population. This means that in Arizona, we use the same average per capita monthly consumption for all water utilities in the same AMA. On average, there are 75 utilities in our Arizona dataset each year.

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[4] The state provides detailed reporting instructions for individual utilities at https://www.waterboards.ca.gov/.

[5] See https://www.waterboards.ca.gov/.

[6] See https://www.tml.org/229/Water-Wastewater-Survey-Results/.

2.1.4 Washington water fees and quantities

Water fees (including fixed charges) and consumption levels for Washington State are obtained from the Tax and User Fee Survey of the Association of Washington Cities (AWC).[7] The survey is performed every two years, and it has a utility rates section which includes average monthly consumption of drinking water for single-family residential users in cubic feet, population served, number of connections, and total water fees at consumption levels of 500, 1000, and 2000 cubic feet. This survey began in 2018. On average, 63 municipal utilities are surveyed every two years.

2.1.5 Construction of average per capita monthly consumption for the dataset

Using each state's data, we calculate average per capita monthly consumption, our main dependent variable, which varies by utility-year. However, because the form of the raw data differs across states, this calculation also differs across states.

For California utilities (2017-2020), the raw data report total water production, percentage of residential use, and population of the utility service area. Water production is reported in varying units (hundred cubic feet (CCF), acre-feet, gallons, and millions of gallons).[8] The number of connections or households served is not available in the data, so we calculate average per capita monthly consumption for each utility-year as follows: Total water production × percentage of residential use × unit conversion rate to CCF / population / 12.

For Texas water utilities (2015-2021), the raw data include average monthly usage per residence in gallons, number of connections, and population of the utility service area. In this case, we calculate average per capita monthly consumption for each utility-year as follows: Average monthly usage per residence × number of connections × unit conversion rate to CCF / population.

For Washington State (2018, 2020, 2022), the raw data include average monthly usage per residence in CCF, number of connections, and population of the service area. The Washington data are reported for municipal water utilities, so the utility names correspond to cities. We calculate average per capita monthly consumption by utility-year as follows: Average usage per month × number of connections / population.

For Arizona (2014, 2015, 2017, 2019), the raw data include total residential usage in acre-feet and population of the utility service area, separated by small and large providers. The number of connections is not available in the Arizona data. We sum large provider and small provider demand to obtain total water usage in each year, and we sum large provider population and small provider population to obtain total population. We then calculate average per capita monthly consumption as follows: Total usage in a year in acre-feet × conversion rate to CCF / population/12.

Given the nature of the residential water quantity data available from the states in our sample, our final dataset is an unbalanced utility-year panel. Figure A1 in the Appendix graphs average per capita monthly consumption by utility-year for our sample, and Table 2 provides summary statistics. In Table 2, we can see that average per capita monthly

[7] See https://wacities.org/data-resources/municipal-rates-and-fees/.

[8] The unit conversion rates we use are as follows: 1 CCF = 100 cubic feet; 1 acre-foot = 43560 cubic feet; 1 gallon = 0.133681 cubic feet; 1 million gallons = 133681 cubic feet.

consumption ranges from about 2 CCF among Washington utilities, to about 5.75 CCF among California utilities. Figure A1 shows the long right tail in per capita consumption that is typical of water demand data. While our dependent variable is under 6 CCF, on average, within each state, some utility-years have much higher average per capita monthly consumption, especially in California and Texas.

2.1.6 Construction of standardized water fee tiers for the dataset

Table 1: Original and adjusted water fee tiers and quantity cutoffs by state

State	Unit	# tiers	Q1	Q2	Q3	Q4	Q5	Q6	
AZ	GAL	6	3000	4000	5000	7000	10000	15000	*original*
	CCF	6	4.01	5.34	6.68	9.35	13.36	20.05	*adjusted*
CA	CCF	3	6	12	24				*original*
	CCF	6	6	6	6	12	12	24	*adjusted*
TX	GAL	2	5000	10000					*original*
	CCF	2	6.68	13.36					
	CCF	6	6.68	6.68	6.68	13.36	13.36	13.36	*adjusted*
WA	CCF	3	5	10	20				*original*
	CCF	6	5	5	5	10	10	20	*adjusted*

Note: Table reports original number of water fee tiers with associated quantity cutoffs by state, as well as the "adjusted" number of tiers and quantity cutoffs, created to compile a dataset for estimating aggregate water demand functions. For the adjusted parameters needed to merge the data, we convert each water utility's quantity cutoffs to a set of six tiers, the highest number of tiers in the dataset (reported for utilities in Arizona), and we convert all the consumption quantities to CCF.

The utilities in our data have many different water fee structures. Some are uniform, in which the same marginal volumetric water price is paid regardless of consumption, and others are tiered, in which the marginal price increases with consumption. Utilities with tiered prices have different quantity cutoffs for each tier, and different price levels. In addition, water consumption levels and the consumption cutoffs of tiered price structures are provided in several different units across states: CCF, cubic feet, acre-feet and gallons. We convert all water consumption levels and cutoffs to CCF in order to merge and collectively analyze the different state datasets. To overcome the problem of different numbers of cutoffs, we expand each utility's volumetric rate structure to include six tiers, the number reported for utilities in Arizona, and the highest number of tiers in the data. For example, California has 3 tiers, and its first tier threshold is below the third tier threshold reported for Arizona utilities, thus we assign the first-tier price to the first three consumption levels in California. The second consumption threshold in California is less than 4th and 5th cutoffs in the Arizona data, thus we assign the second-tier price in each California utility to the 4th and 5th consumption levels reported in California. The third tier threshold reported in California is more than 6th cutoff reported for Arizona utilities, thus we assign California utilities' third-tier price to their 6th consumption level. We expand the price structures of all states in the dataset in the same way. Utilities with uniform volumetric prices are assigned the same water fee (inclusive of fixed charges) for all six tiers. Table 1 presents the changes made to integrate the water pricing and consumption data across multiple states. Throughout the paper, we use P1-P6 to refer to the volumetric water fees corresponding to consumption levels Q1-Q6.

The literature is mixed as to whether consumers respond to marginal or average prices under increasing-block tariffs (Taylor et al., 2004; Olmstead et al., 2007; Olmstead, 2009; Wichman, 2014; Clarke et al., 2017; Browne et al., 2021). Recall that the data we obtain from the four states combine fixed charges and volumetric charges into a set of total water fee estimates at different levels of consumption. Thus, the water fees in our demand functions all reflect some aspects of an average price, because we cannot separate out the fixed from the volumetric components of these charges. However, we accommodate the literature on marginal vs. average prices in demand estimation by developing two different water fee variables in our demand equations. In models using the marginal water fees, we simply assign the marginal fee at the average observed level of consumption for each utility-year (the fee for the tier at which average consumption takes place). Marginal water fees over time for each state are graphed in Appendix Figure A2, showing that most such fees are less than $200 per CCF, with some higher exceptions in California and Texas.

To create an average fee variable for each utility-year, we multiply the consumption threshold for each tier by the fee for that tier (for all infra-marginal tiers of consumption), add this to the actual average consumption in the marginal tier multiplied by the marginal fee, and divide this total expenditure estimate by total consumption. We employ marginal water fees in our main models and test robustness to the use of average water fees in the Appendix. Note that given our data constraints, these marginal and average fee variables likely vary less than true marginal and average prices, due to our inability to separate out fixed charges from the marginal fees reported by utilities in each state. Figure 1 shows the distributions of these two price variables, which overlap significantly.

Moreover, under increasing-block prices, marginal and average water fees are functions of water consumption. As consumption rises, the volumetric fee also rises, so regressing quantity on water fees will confound the upward-sloping supply function with downward-sloping demand. Due to this endogeneity concern, we use instrumental variables (IV) models in our main specifications. Following Olmstead et al. (2007) and Olmstead (2009), we use the full set of tiered water fees in each utility-year as marginal and average water fee instruments in the IV models.

Figure 2 shows the utility boundaries included in the collected dataset and where they are located in the United States. Table 2 reports summary statistics for the raw data separately for Arizona, California, Texas and Washington. Our dependent variable, average per capita monthly consumption, varies from a mean of about 200 cubic feet among utilities in Washington to almost 575 cubic feet in California. Average population served is largest in California and Texas utilities (at 110,557 and 104,920 respectively) and much smaller in Arizona (25,114) and Washington (15,115). The residential fees summarized in Table 2 reflect total water fees at the reported volume tiers as they vary in the state datasets. Nonetheless, if we look at the typical total monthly fees paid for 6.68 CCF in Arizona, 6 CCF in California, 6.68 CCF in Texas, and 5 CCF in Washington, we see that these amounts are quite similar (between $34 and $37) for Arizona, Texas and Washington, and substantially higher (about $55) in California.

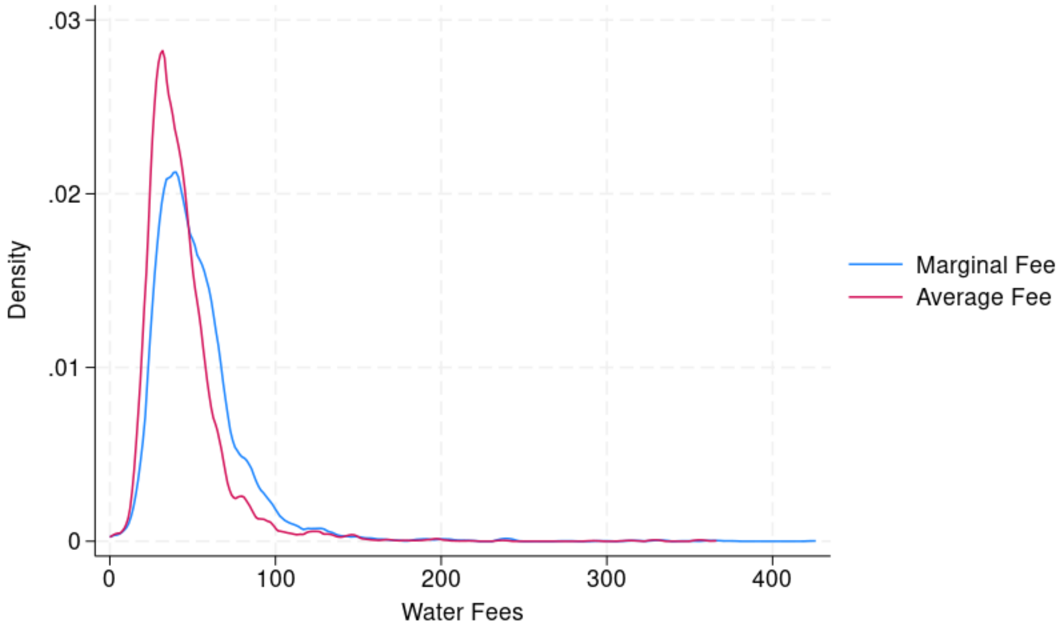


Figure 1: Distribution of average and marginal fees

Notes: The figure presents the distributions of average water fees and marginal water fees ($/CCF) in our sample.

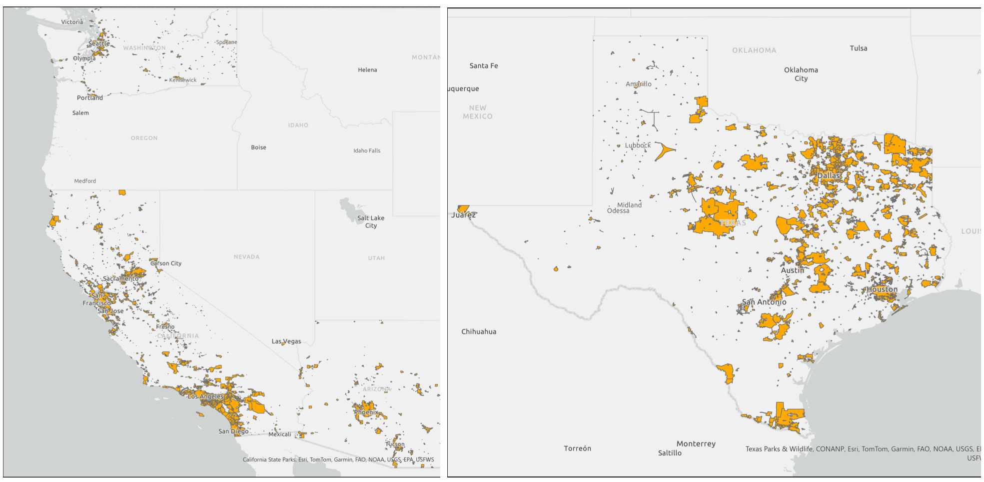


Figure 2: Maps of water utility boundaries in dataset collected from individual states

Notes: The map depicts water utility service areas included in the dataset as yellow-shaded areas in Arizona, California, and Washington State on the left, and in the State of Texas on the right.

Table 2: Summary statistics by state

A: Arizona

	Mean	Std. dev.	Min	Max
Drought index (scPDSI)	−3.53	0.96	−5.44	0.00
Consumption (CCF)	4.74	0.59	3.53	6.12
Residential Fees				
4.01 CCF	28.05	14.44	4.36	92.35
5.34 CCF	30.75	15.17	4.36	107.10
6.68 CCF	33.65	16.14	5.00	121.85
9.35 CCF	39.68	18.55	5.00	151.35
13.36 CCF	49.49	23.30	5.00	195.60
20.05 CCF	70.09	35.02	5.00	269.35
Population served	25 113.89	127 015.9	37	1 579 000

B: California

	Mean	Std. dev.	Min	Max
Drought index (scPDSI)	−1.75	1.08	−4.22	0.76
Consumption (CCF)	5.75	21.60	0.18	351.31
Residential Fees				
6 CCF	55.45	26.18	1.11	156.09
12 CCF	77.06	40.09	2.22	242.65
24 CCF	130.70	114.62	1.06	893.91
Population served	110 556.8	154 129	459	1 017 795

C: Texas

	Mean	Std. dev.	Min	Max
Drought index (scPDSI)	−0.17	1.57	−5.44	3.47
Consumption (CCF)	3.44	2.87	0.13	50.35
Residential Fees				
6.68 CCF	36.99	15.13	2.98	138.75
13.36 CCF	59.18	25.32	4.3	363.00
Population served	104 920.10	433 133.50	47	2 325 502

D: Washington

	Mean	Std. dev.	Min	Max
Drought index (scPDSI)	−2.04	0.74	−4.54	−0.56
Consumption (CCF)	1.99	10.27	0.10	67.25
Residential Fees				
5 CCF	34.24	15.27	2.12	80
10 CCF	42.42	19.18	2.12	98.70
20 CCF	59.63	31.14	2.12	138.03
Population served	15 115.42	26 851.98	103	92 964

Notes: Summary statistics for PDSI, average per capita monthly consumption, residential water fees, and population served, by state.

2.2 Data characterizing drought conditions

The primary variable used to characterize drought conditions in our models is the Self-calibrating Palmer Drought Severity Index (scPDSI) from the University of East Anglia's Climatic Research Unit.[9] The scPDSI is calculated from time-series of precipitation and temperature, together with fixed parameters related to the soil/surface characteristics at each location (Wells et al. (2004); Van der Schrier et al. (2013)). Values of the index are available monthly worldwide for the period 1901-2022 on a 0.5-degree grid, which we aggregate to the utility, the spatial scale of the water demand models. The scPDSI is a standardized index that generally spans -10 to +10, with [-0.5,0.5] reflecting near normal conditions, values less than -0.5 reflecting drier than normal conditions, and values greater than 0.5 reflecting wetter than normal conditions. The index classifies drought conditions as follows: -1.00 to -1.99 is mild drought, -2.00 to -2.99 is moderate drought, -3.00 to -3.99 is severe drought, and -4.00 and less is extreme drought.

To aggregate the scPDSI data to a yearly level and merge them with our water demand data, we define two new variables: (1) the count of months in each utility-year that have an average scPDSI value less than or equal to -3.00 (in the severe or worse drought range); and (2) an area-under-the-curve (AOC) measure that captures the duration and severity of drought by utility-year. For this second measure, we graph the scPDSI for each utility-year and calculate the area under the resulting curve where the scPDSI is less than -3 (the utility's service area is experiencing severe or worse drought). Figure 3 presents an example of our AOC approach, plotting the monthly scPDSI values for Alpine Domestic Water Improvement District, one of our sample water utilities in eastern Arizona near the New Mexico border, for the year 2014. The shaded area in the figure is the value of the AOC drought variable for that utility-year.

In Appendix Figure A1, which graphs average per capita monthly consumption by utility-year for our sample, we indicate utility-years for which the AOC drought measure is greater than zero (those with any months in which the scPDSI has a value less than -3) with open circles, and utility-years for which AOC=0 with closed circles. There is no obvious visual correlation between drought and consumption in this figure.

2.3 Additional data sources

We use water utility boundary maps to characterize drought conditions for each utility. For this purpose, we obtain the California water utility boundary map from the California State Geoportal, and the Texas water utility boundary map from the Public Utility Commission of Texas. For the remaining two states, we download drinking water service area boundaries from the Environmental Policy Innovation Center/SimpleLab's comprehensive national dataset of drinking water service area boundaries. [10] We first join cities to water utility systems if the data on rates and consumption are collected at the city level (as they are in Texas and Washington) by matching to the extent possible on location. Then, we join our utility system boundaries to the various drought indices using ArcGIS Pro and GeoPandas.

[9] See https://crudata.uea.ac.uk/cru/data/drought/.

[10] See https://www.policyinnovation.org/technology/water-utility-service-area-boundaries.

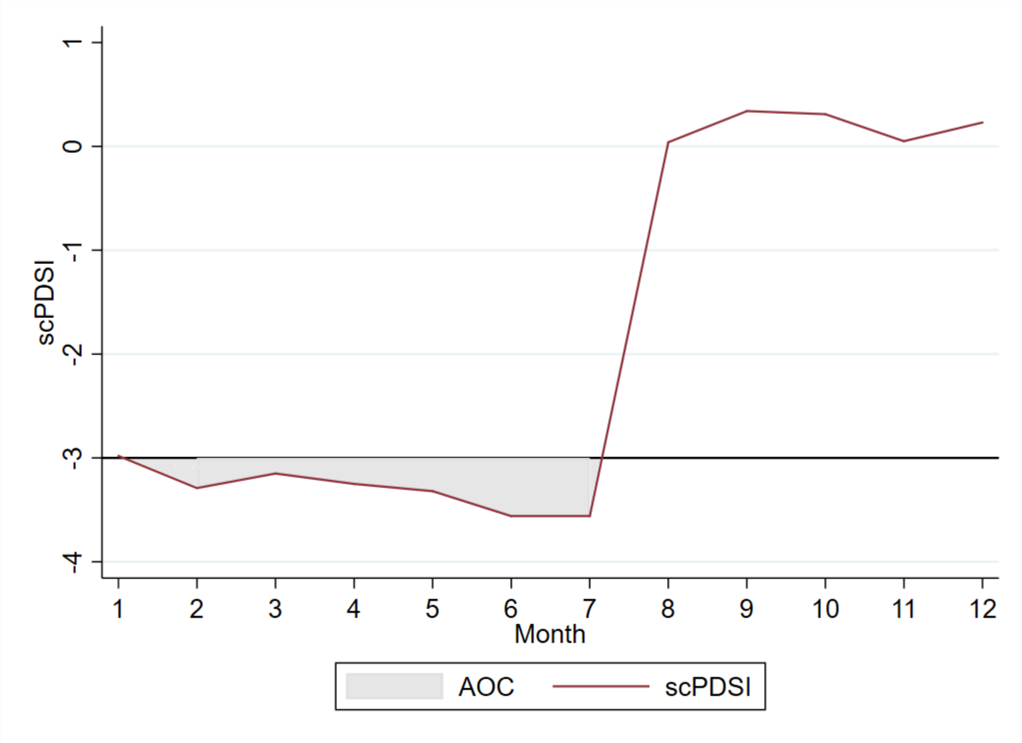


Figure 3: Example of area-under-the-scPDSI-curve calculation for one utility-year

Notes: The figure demonstrates how we calculate the AOC drought measure. The sample curve plotted is for the Alpine Domestic Water Improvement District in Arizona in 2014. The x axis indicates the calendar months in a year, and the y axis shows the value of the scPDSI drought severity index in each month. We calculate the gray area between the scPDSI value and the horizontal line at -3 as the AOC, because -3 is the scPDSI threshold for severe drought.

2.4 Data cleaning

After merging the data to construct an unbalanced utility-year panel, we sort the data by public water system ID (PWSID, a unique identifier for each U.S. water utility), year, and water consumption, and we drop observations missing consumption, with consumption equal to zero, or with consumption less than 50 or greater than 4000 cubic feet, given that the average U.S. monthly per capita consumption is about 300-400 cubic feet, according to the U.S. Environmental Protection Agency.[11] (Note that the summary statistics in Table 2 are for the raw data, which do include these high-consumption observations.)

3 Empirical Methods

We estimate aggregate water demand functions using a standard log-log form to understand whether and how water demand and price elasticity respond to drought. Equation (1) describes the basic model.

$$lnQ_{ut} = \alpha + \beta_1 lnP_{ut} + \beta_2 D_{ut} + \beta_3 lnP_{ut} \times D_{ut} + \delta_u + \lambda_t + \epsilon_{ut} \quad (1)$$

[11]See https://www.epa.gov/watersense/statistics-and-facts/.

In Equation (1), lnQ_{ut} is the natural log of average per capita monthly water consumption in utility u in year t, lnP_{ut} is the natural log of the water fee by utility-year, D_{ut} is a drought severity measure by utility-year (using the two different approaches described in Section 2.3), δ_u is a utility fixed effect, and λ_t is a year fixed effect. We include δ_u to control for non-time-varying utility service area characteristics that may affect water demand and be correlated with drought responses, and we include λ_t to account for water demand shocks over time common to all utilities, such as those related to national macroeconomic conditions. In some of the models discussed in Section 4, we add state x year fixed effects to Equation (1), controlling for underlying state heterogeneity in water demand, conservation policies and other factors. ϵ_{ut} is a normally-distributed, idiosyncratic error term. The coefficients of interest are the price elasticity of demand (β_1), the marginal effect of drought conditions on water demand (β_2), and the marginal effect of the interaction between drought and price (β_3), which captures the effect of drought on price elasticity.

As noted earlier, in some models P_{ut} represents an average water fee, and in others it is a marginal fee. For water utilities with tiered prices, average and marginal water fees are endogenous. Thus, we use IV to estimate the main demand models, using the full set of tiered water fees for each utility-year as instruments. The first stage in the IV models is Equation (2), and the second stage is Equation (3).

$$lnP_{ut} = \omega + \gamma_1 lnP1_{ut} + \gamma_2 lnP2_{ut} + ... + \gamma_6 lnP6_{ut} + \nu_{ut} \tag{2}$$

$$lnQ_{ut} = \alpha + \beta_1 \widehat{lnP_{ut}} + \beta_2 D_{ut} + \beta_3 ln\widehat{P_{ut} \times D}_{ut} + \delta_u + \lambda_t + \epsilon_{ut} \tag{3}$$

Note that our research design does not allow us to differentiate between the impacts of drought, itself, on water demand and price elasticity, and the impacts of time-varying conservation and other drought mitigation policies. The utility fixed effect controls for any underlying non-time-varying heterogeneity among utilities that may tend to differentially implement such policies, and year effects control for changes in the tendency of all utilities or states in the region to adopt drought policies over time. But to the extent that drought policies change by utility-year, our estimates of β_1, β_2, and β_3 will incorporate policy responses, as well as direct drought responses.

To test our hypotheses regarding the drought shadow and demand hardening, we add some lagged variables. Using both the OLS and IV approaches described above, our basic demand equation with lags is Equation (4), which includes a set of four lagged drought variables, as well as a set of four interactions between current water fees and lagged drought.

$$lnQ_{ut} = \alpha + \beta_1 lnP_{ut} + \sum_{l=0}^{4} \omega_l D_{u(t-l)} + \sum_{l=0}^{4} \gamma_l lnP_{ut} \times D_{u(t-l)} + \delta_u + \lambda_t + \epsilon_{ut} \tag{4}$$

In Equation (4), estimates of ω_l will quantify the marginal effect of current and past drought on current water demand, and estimates of γ_l will quantify the effect of current and past drought on the price elasticity of demand. We choose four years of lags for these sets of variables because this is the maximum number possible, given the limited number of years in our data.[12]

4 Results

Table 3 reports results from estimating Equation (1) in columns 1 and 2, and from our IV approach (Equation (3)) in columns 3-6, using the marginal water fee at the observed average level of water consumption as the price variable. In Table 3 we use the number of months in a year in which the scPDSI value is less than or equal to -3 (severe or worse drought) to characterize drought conditions by utility-year. Table 4 reports results from the same set of models using the marginal fee, but instead employing our area-under-the-curve approach to characterizing drought duration and severity by utility-year. In both tables, the OLS models generate positive and significant price coefficients, reflecting the expected endogeneity bias. Using the IV models in columns 3-6, in contrast, demand curves are downward-sloping. For this reason, we interpret the IV coefficients, but not the OLS coefficients.

In columns 3 and 4, we include both a drought variable and log price, and we vary the time controls in the specification, using utility and year FEs individually in column 3, and a full set of state x year effects along with utility FEs in column 4. Across the choice of controls, price elasticity in the IV models ranges from -0.11 to -0.31, and drought in the current year reduces water consumption. In columns 5 and 6 of Tables 3 and 4, we add an interaction between the marginal water fee and the drought variable, testing for demand hardening, along with the contemporaneous drought effect. In both tables, drought appears to make consumers less responsive to the marginal water fee, reducing elasticity by about 25%. The price elasticity estimates when we use the AOC measure to characterize drought in Table 4 are somewhat smaller in magnitude than when we use the count of drought months by utility-year to do so in Table 3, but otherwise, the results are similar across the two tables.

At the bottom of Tables 3 and 4, we report the results of tests for weak instruments and the robustness of our estimates to weak instruments for all of the IV models (columns 3-6 in each table). The first-stage F-statistic is small in all of the IV models and never greater than the Stock-Yogo rule-of-thumb critical value of 10, so we fail to reject the null hypothesis that the instruments are weak. Regardless, post-estimation tests from the 2SLS models suggest that the coefficient estimates for the endogenous regressors (price elasticity and the impact of drought on price elasticity) are robust to weak instruments. The Conditional Likelihood Ratio test statistic (Moreira, 2003) and the Anderson-Rubin test

[12] We recognize that richer data would support better alternatives to this simple distributed lag model. Prior papers examining the impacts of past drought on current water demand (or electricity demand in the case of Costa and Gerard (2021)) typically exploit variation from a discrete drought shock and use experimental or quasi-experimental approaches to estimate impacts. Our setting is obviously quite different, in that our data include hundreds of water utilities, and we characterize drought on an annual basis for each location using continuous measures derived from the scPDSI. The closest paper to ours in the literature may be Bernardo et al. (2015), in which the authors estimate a pooled linear regression with a single lag using a panel-specific AR-1 autocorrelation structure. While our use of robust standard errors should correct for any autocorrelation in water consumption, we do not model an autocorrelated error structure directly, as we do not know of a way to do so using instrumental variables.

statistic (Anderson and Rubin, 1949) both reject the null hypotheses that these parameter estimates are equal to zero in columns 3-6 of Tables 3 and 4. We also use the CLR test results to obtain weak-instrument-robust 95% confidence intervals for the endogenous regressors, reported in the Table 3 and 4 notes, and while somewhat wider than those for our reported estimates, they are qualitatively similar. Thus, despite weak instruments, we proceed with our interpretation of the model results as described above.

Table 3: Water demand models using drought months

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV	(6) IV
Drought Months	0.00	0.00	0.00	0.00	−0.45	−0.45
	(0.01)	(0.01)	(0.01)	(0.00)	(0.04)	(0.04)
Drought Months × lnP					0.11	0.11
					(0.01)	(0.01)
lnP	0.48	0.49	−0.12	−0.11	−0.31	−0.30
	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)
Utility FE	X	X	X	X	X	X
Year FE	X		X		X	
State x year FE		X		X		X
U (utilities)	1730	1730	1730	1730	1730	1730
T (years)	8	8	8	8	8	8
N (observations)	4872	4872	4872	4872	4872	4872
R^2(overall)	0.02	0.01	0.01	0.11	0.01	0.04
First-Stage F Stat.			3.91	3.87	3.82	3.77
Conditional LR Test Stat.			7.84	6.80	9.01	8.55
...p-value			(0.00)	(0.00)	(0.00)	(0.00)
Anderson-Rubin Test Stat.			78.88	87.97	92.72	102.70
...p-value			(0.00)	(0.00)	(0.00)	(0.00)

Note: Table reports coefficient estimates and standard errors (in parentheses) from regressing the log of average monthly per capita water consumption on the annual number of severe or worse drought months (scPDSI≤ -3), the log marginal water fee, and a (drought months × marginal fee) interaction. Observations are utility-years. The weak-instrument-robust 95% confidence intervals using the CLR test for lnP are [-0.23, -0.04], [-0.23, -0.03], [-0.42, -0.21], and [-0.43, -0.21] for columns 3, 4, 5, and 6, and for Drought Months × lnP they are [0.03, 0.22] and [0.03, 0.22] for columns 5 and 6.

We test the robustness of these primary results along a few different dimensions in Appendix A. Tables A1 and A2 in Appendix A report results from estimating the same models reported in Tables 3 and 4, but using the average water fee instead of the marginal fee, given that the literature is mixed regarding which of the two is most salient under tiered pricing. The marginal fee and average fee results are very similar.[13] Note that the first-stage F statistics are somewhat larger, indicating that the instruments may be better

[13] A meta-analysis by Marzano et al. (2018) suggests that elasticities estimated with marginal price may be somewhat smaller than those estimated with average price. While our slightly smaller elasticity estimates for the marginal fee models are consistent with this finding, the confidence intervals for these sets of estimates overlap significantly, so we hesitate to draw any conclusions from marginal vs. average fee comparisons. Recall, also that our marginal and average water fee variables are likely to differ from each other less than true marginal and average prices, because both of these variables include fixed charges given our data constraints.

Table 4: Water demand models using AOC drought measure

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV	(6) IV
AOC	0.01	0.00	0.00	0.00	−0.31	−0.32
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)
AOC × lnP					0.08	0.08
					(0.01)	(0.01)
lnP	0.48	0.49	−0.12	−0.11	−0.20	−0.19
	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)
Utility FE	X	X	X	X	X	X
Year FE	X		X		X	
State x year FE		X		X		X
U (utilities)	1730	1730	1730	1730	1730	1730
T (years)	8	8	8	8	8	8
N (observations)	4872	4872	4872	4872	4872	4872
R^2(overall)	0.02	0.01	0.01	0.11	0.01	0.04
First Stage F Stat.			3.92	3.88	3.90	3.86
Conditional LR Test Stat.			7.87	6.81	24.30	23.88
...p-value			(0.00)	(0.00)	(0.00)	(0.00)
Anderson-Rubin Test Stat.			78.96	88.02	214.66	229.81
...p-value			(0.00)	(0.00)	(0.00)	(0.00)

Note: Table reports coefficient estimates and standard errors (in parentheses) from regressing the log of average monthly per capita water consumption on the AOC drought measure, the log marginal water fee, and an (AOC × price) interaction. Observations are utility-years. The weak-instrument-robust 95% confidence intervals using the CLR test for lnP are [-0.23, -0.04], [-0.23, -0.03], [-0.31, -0.11], and [-0.31, -0.11] for columns 3, 4, 5, and 6, and for Drought Months × lnP they are [0.02, 0.23] and [0.03, 0.23] for columns 5 and 6.

predictors of the average water fee than of the marginal fee. Post-estimation tests suggest the estimates are robust to weak instruments, as they do in Tables 3 and 4.

In Tables A3 through A6, we drop all observations from each state in the sample, one at a time, beginning with Arizona in Table A3. Recall that in Arizona, our consumption data are estimated at the Active Management Area level, rather than the utility level, introducing some measurement error in Q. The magnitudes of the price elasticity estimates, the response of consumption to drought in the current year, and the effect of drought on price elasticity are all smaller than those reported for the full sample in Tables 3 and 4. The results are otherwise robust to dropping the Arizona observations, with the exception that for the IV models that do not include a price-drought interaction (columns 3 and 4), the Conditional Likelihood Ratio and Anderson-Rubin tests suggest that the coefficient estimates for the endogenous regressors are not robust to weak instruments.

As is clear in Figure A1 in the Appendix, the majority of the utility-years experiencing drought in our sample are in Arizona, which may explain the reduction in the magnitude of the estimated demand parameters when we drop that state. When we perform the same exercise for the other states, dropping California in Table A4, Texas in Table A5, and Washington in Table A6, the coefficient estimates differ little from those in Table 4. As was true when we dropped Arizona systems, when we drop observations from Texas and do not include the price-drought interaction (Table A5, cols. 3-4), the Conditional Likelihood Ratio test indicates that the coefficient estimates for the endogenous regressors are not robust to weak instruments.

Taken together, our baseline results and robustness checks suggest that drought reduces contemporaneous demand and price elasticity in the residential sector in the western United States. The fact that in a few cases the estimated coefficients from models without the price-drought interaction are not robust to weak instruments is an important caveat. Moreover, this also highlights the potential importance of controlling for drought and its influence on households' reaction to water prices in residential demand estimation, at least in our study region.

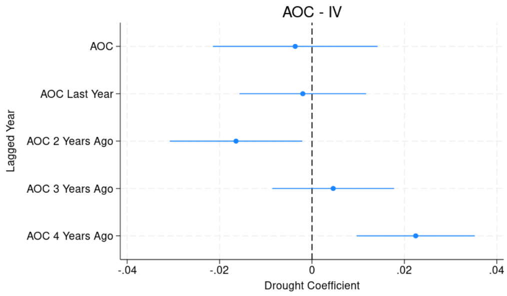
In Figure 4, we report results from estimating Equation (4) in a series of tests for the persistence of the effects of drought on demand over time, with results in panels (a) and (b) using average water fees, and in panels (c) and (d) using marginal fees. Figure 4 also reports the results of tests for lagged effects of drought on residential water demand using both the AOC and "drought months" approach to characterizing drought conditions. We estimate a small negative effect of drought two years prior on demand in the current year, which is weakly significant in some of the specifications in Figure 4, and a positive and significant effect of drought four years prior in all four panels. In none of the four panels of Figure 4 does drought in prior years appear to have a systematic, negative effect on current water demand that would be consistent with the "drought shadow" hypothesis.[14]

Our final set of models test for lagged effects of drought on price elasticity, with results reported in Figure 5. Similar to Figure 4, in Figure 5 we graph coefficient estimates from four different models – those using two different drought variables (AOC and drought months) and two different water price variables (marginal and average water fees) – testing for effects of drought up to four years prior to the current year on the price elasticity of water demand in the current year. In this set of models, drought in all four prior years reduces price elasticity, and these effects are larger than those of drought in the current year. The results reported in Figure 5 are consistent with the "demand hardening" hypothesis. Households may make some capital investments (for example, switching to water-efficient appliances or landscaping) or behavioral changes that persist after a drought and reduce their sensitivity to price increases going forward.

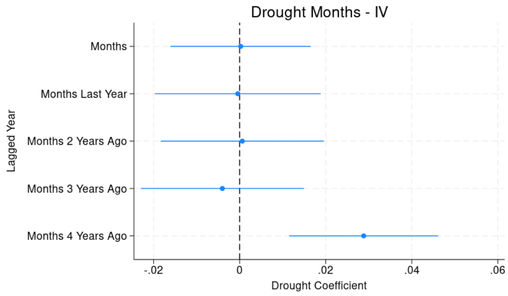
5 Conclusion

This paper explores the impact of exposure to drought on water demand and the price elasticity of water demand in the United States, with a focus on the West. We compile a novel, aggregate dataset to support this effort: a utility-year panel tracking average per capita monthly residential water consumption and water fees in the states of Arizona, California, Texas, and Washington. We add drought indicators to the dataset and econometrically estimate water demand functions, using instrumental variables to deal with endogenous

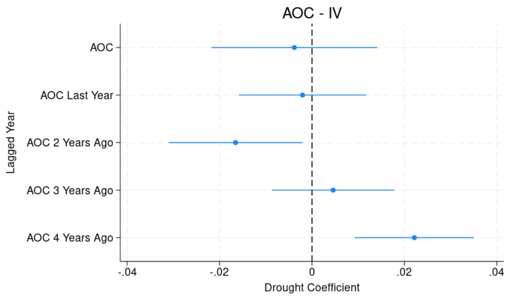
[14] Appendix Table A7 reports the coefficient estimates and standard errors used to create Figures 4 and 5. As in the prior tables, we report the results of Conditional Likelihood Ratio and Anderson-Rubin tests for robustness to weak instruments at the bottom, though the associated confidence intervals are reported separately in Table A8. Both tests reject the null hypothesis that the coefficient estimates on the endogenous regressors (prices and price-drought interactions) are equal to zero for all four models.



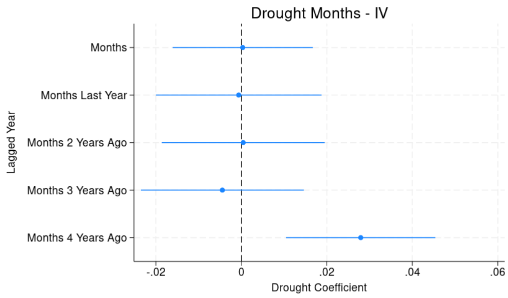
(a) AOC - Average Fees



(b) Drought Months - Average Fees



(c) AOC - Marginal Fees



(d) Drought Months - Marginal Fees

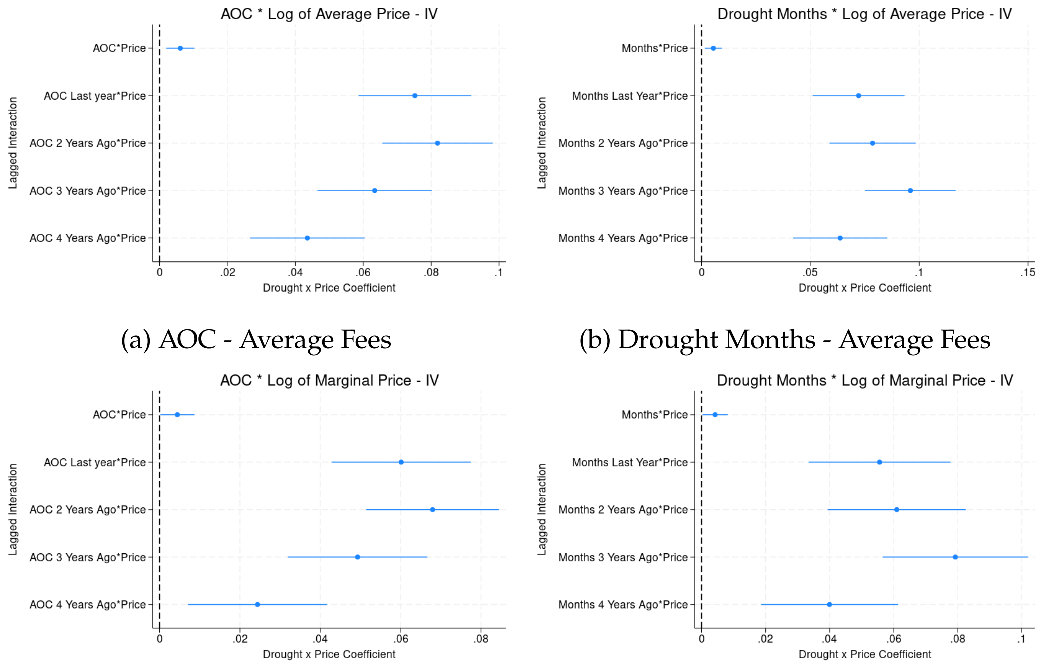
Figure 4: Lagged effect of drought on water consumption

Notes: The figure plots coefficient estimates and 95% confidence intervals from IV models of contemporaneous and lagged effects of drought (1-4 years) on water consumption. Panels (a) and (b) use average water fees in the demand equations, and panels (c) and (d) use marginal fees. Drought is represented by the AOC measure in panels (a) and (c), and by the count of months with scPDSI≤ -3 in panels (b) and (d). Coefficient estimates are reported in Appendix Table A7.

prices, including both marginal and average water fees to accommodate the possibility that households respond to either of these under tiered water prices, and controlling comprehensively and flexibly for potential confounders.

Our results using data collected from the western United States suggest a likely causal relationship between drought and the price elasticity of water demand; households exposed to drought are less price-responsive in future years. This effect is commonly referred to as "demand hardening" and is well-described theoretically (Howe and Goemans, 2007), but it has been infrequently tested in the empirical literature (Brent, 2016).

In contrast, we do not find consistent empirical support for the hypothesis that exposure to drought has a direct effect on water consumption in subsequent years, a phenomenon known as the "drought shadow." Empirical evidence of a drought shadow in the prior literature, resulting either from exposure to drought, itself, or response to regulations and behavioral nudges implemented to reduce demand during a drought, is mixed. While hysteresis of conservation has been documented for electricity use in Brazil (Costa and Gerard, 2021), as well as in some cases for water use in the United States (Bolorinos et al., 2022), other prior work finds that water usage appears to return quickly to prior levels after a drought (Soliman, 2022; Ferraro and Price, 2013; Jessoe et al., 2021). Our results are consistent with this latter group of papers; at our broader regional scale and using econometric approaches designed to obtain plausibly causal estimates, we find no lasting



(a) AOC - Average Fees

(b) Drought Months - Average Fees

(c) AOC - Marginal Fees

(d) Drought Months - Marginal Fees

Figure 5: Lagged effect of drought on price elasticity

Notes: The figure plots coefficient estimates and 95% confidence intervals from IV models of contemporaneous and lagged effects of drought (1-4 years) on price elasticity. Panels (a) and (b) use average water fees in the demand equations, and panels (c) and (d) use marginal fees. Drought is represented by the AOC measure in panels (a) and (c), and by the count of months with scPDSI≤ -3 in panels (b) and (d). Coefficient estimates are reported in Appendix Table A7.

effects of drought on residential water consumption.

Our work is limited by the challenge of water demand data collection (prices and quantities) at broad geographic scale in the United States. Future work on demand hardening, the drought shadow, and other behavioral responses to this important hydrologic extreme in countries where water prices and consumption data are collected systematically across jurisdictions could provide richer insights.

In the face of increasing challenges for urban water demand management (Obringer et al., 2024), information about the likely response of water demand to drought at broad regional scale is a critical input to planning. This work contributes to a small but growing literature on this issue, focusing on the western United States, where drought may be increasing in frequency, intensity and duration. Because water pricing and demand management are typically local and state matters, while infrastructure investments occur at the state and even federal level, additional work on the likely response of water demand behavior to extreme conditions provides important input to policymaking at many different levels.

Appendix A: Tables and Figures

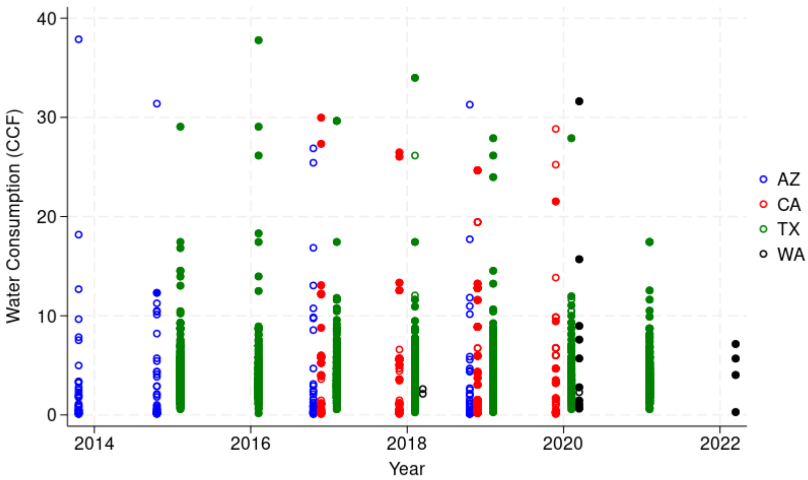


Figure A1: Magnitude of water consumption (CCF) over time and by state

Notes: The filled markers represent utility-years in which our AOC drought measure is equal to zero (there were no months in severe-or-worse drought), and open markers indicate utility-years in which the AOC is positive.

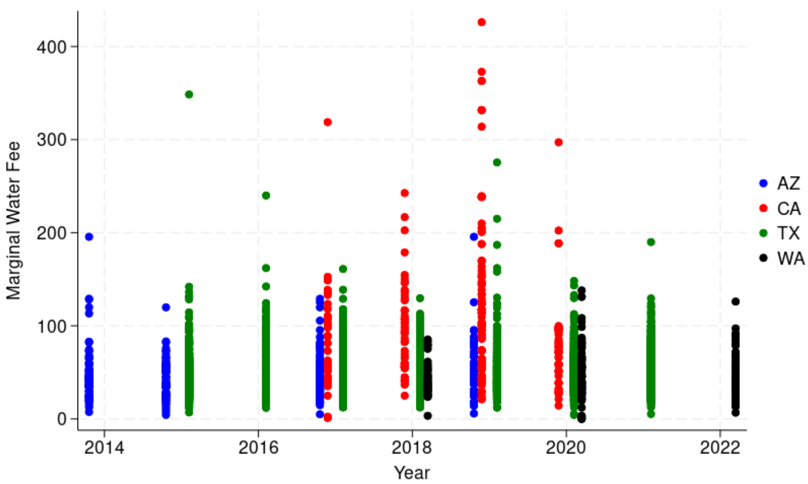


Figure A2: Magnitude of marginal water fees (dollars per CCF) over time and by state

Table A1: Water demand models using drought months with average water fees

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV	(6) IV
Drought Months	0.00	0.00	0.00	0.00	−0.50	−0.49
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)
Drought Months × lnP					0.12	0.13
					(0.01)	(0.04)
lnP	0.55	0.57	−0.11	−0.10	−0.34	−0.35
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)
Utility FE	X	X	X	X	X	X
Year FE	X		X		X	
State x year FE		X		X		X
U (utilities)	1730	1730	1730	1730	1730	1730
T (years)	8	8	8	8	8	8
N (observations)	4872	4872	4872	4872	4872	4872
R^2(overall)	0.03	0.01	0.01	0.11	0.01	0.01
First Stage F Statistics			8.54	8.34	8.48	8.17
Conditional LR Test Stat.			5.52	4.47	102.52	94.90
...p-value			(0.01)	(0.03)	(0.00)	(0.00)
Anderson-Rubin Test Stat.			78.88	87.97	538.19	546.02
...p-value			(0.00)	(0.00)	(0.00)	(0.00)

Note: Table reports coefficient estimates and standard errors (in parentheses) from regressing the log of average monthly per capita water consumption on the annual number of severe or worse drought months (scPDSI≤ -3), the log average water fee, and a (drought months × average fee) interaction. Observations are utility-years. The weak-instrument-robust 95% confidence intervals using the CLR test for lnP are [-0.23, -0.02], [-0.21, -0.01], [-0.43, -0.22], and [-0.45, -0.23] for columns 3, 4, 5, and 6, and for Drought Months × lnP they are [0.02, 0.23] and [0.03, 0.22] for columns 5 and 6.

Table A2: Water demand models using AOC drought measure with average water fees

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV	(6) IV
AOC	0.01	0.00	0.00	0.00	−0.41	−0.37
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)
AOC × lnP					0.10	0.10
					(0.01)	(0.01)
lnP	0.55	0.57	−0.12	−0.10	−0.23	−0.21
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)
Utility FE	X	X	X	X	X	X
Year FE	X		X		X	
State x year FE		X		X		X
U (utilities)	1730	1730	1730	1730	1730	1730
T (years)	8	8	8	8	8	8
N (observations)	4872	4872	4872	4872	4872	4872
R^2(overall)	0.03	0.01	0.01	0.11	0.01	0.01
First Stage F Statistics			8.55	8.36	8.92	8.62
Conditional LR Test Stat.			5.52	4.47	18.83	18.48
...p-value			(0.01)	(0.03)	(0.00)	(0.00)
Anderson-Rubin Test Stat.			78.96	88.02	214.66	229.81
...p-value			(0.00)	(0.00)	(0.00)	(0.00)

Notes: Table reports coefficient estimates and standard errors (in parentheses) from regressing the log of average monthly per capita water consumption on the AOC drought measure, the log average water fee, and a (AOC × average fee) interaction. Observations are utility-years. The weak-instrument-robust 95% confidence intervals using the CLR test for lnP are [-0.23, -0.02], [-0.21, -0.01], [-0.33, -0.12], and [-0.33, -0.12] for columns 3, 4, 5, and 6, and for Drought Months × lnP they are [0.03, 0.20] and [0.02, 0.20] for columns 5 and 6.

Table A3: Water demand models using AOC results with marginal water fees, dropping AZ

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV	(6) IV
AOC	0.00	0.00	0.00	0.00	−0.13	−0.14
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)
AOC × lnP					0.03	0.03
					(0.01)	(0.01)
lnP	0.39	0.40	−0.07	−0.06	−0.09	−0.08
	(0.00)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)
Utility FE	X	X	X	X	X	X
Year FE	X		X		X	
State x year FE		X		X		X
U (utilities)	1605	1605	1605	1605	1605	1605
T (years)	8	8	8	8	8	8
N (observations)	4571	4571	4571	4571	4571	4571
R^2(overall)	0.03	0.03	0.01	0.11	0.01	0.01
First Stage F Statistics			4.03	3.98	3.96	3.91
Conditional LR Test Stat.			3.29	2.24	6.22	5.86
...p-value			(0.06)	(0.13)	(0.04)	(0.05)
Anderson-Rubin Test Stat.			6.29	5.18	13.68	12.56
...p-value			(0.09)	(0.15)	(0.03)	(0.05)

Notes: Table reports coefficient estimates and standard errors (in parentheses) from regressing the log of average monthly per capita water consumption on the AOC drought measure, the log marginal water fee, and a (AOC × marginal fee) interaction. Arizona is dropped from the sample. Observations are utility-years. The weak-instrument-robust 95% confidence intervals using the CLR test for lnP are [-0.12, -0.00], [-0.11, -0.01], [-0.14, -0.01], and [-0.13, -0.00] for columns 3, 4, 5, and 6, and for Drought Months × lnP they are [0.00, 0.10] and [0.00, 0.11] for columns 5 and 6.

Table A4: Water demand models using AOC with marginal water fees, dropping CA

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV	(6) IV
AOC	0.01	−0.01	0.00	−0.02	−0.40	−0.40
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
AOC × lnP					0.11	0.11
					(0.01)	(0.01)
lnP	0.62	0.62	−0.14	−0.13	−0.22	−0.22
	(0.01)	(0.01)	(0.06)	(0.06)	(0.06)	(0.06)
Utility FE	X	X	X	X	X	X
Year FE	X		X		X	
State x year FE		X		X		X
U (utilities)	1584	1584	1584	1584	1584	1584
T (years)	9	9	9	9	9	9
N (observations)	4551	4551	4551	4551	4551	4551
R^2(overall)	0.02	0.01	0.01	0.26	0.01	0.01
First Stage F Statistics			3.39	3.40	3.41	3.41
Conditional LR Test Stat.			8.59	8.85	38.67	46.93
...p-value			(0.00)	(0.00)	(0.00)	(0.00)
Anderson-Rubin Test Stat.			74.30	83.73	217.18	232.27
...p-value			(0.00)	(0.00)	(0.00)	(0.00)

Notes: Table reports coefficient estimates and standard errors (in parentheses) from regressing the log of average monthly per capita water consumption on the AOC drought measure, the log marginal water fee, and a (AOC × marginal fee) interaction. California is dropped from the sample. Observations are utility-years. The weak-instrument-robust 95% confidence intervals using the CLR test for lnP are [-0.30, -0.05], [-0.30, -0.06], [-0.40, -0.15], and [-0.40, -0.15] for columns 3, 4, 5, and 6, and for Drought Months × lnP they are [0.00, 0.22] and [0.00, 0.22] for columns 5 and 6.

Table A5: Water demand models using AOC with marginal water fees, dropping TX

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV	(6) IV
AOC	0.01	0.00	0.00	0.00	−0.32	−0.32
	(0.02)	(0.02)	(0.02)	(0.02)	(0.07)	(0.07)
AOC × lnP					0.08	0.08
					(0.02)	(0.02)
lnP	0.40	0.44	−0.19	−0.15	−0.32	−0.29
	(0.02)	(0.03)	(0.18)	(0.18)	(0.18)	(0.17)
Utility FE	X	X	X	X	X	X
Year FE	X		X		X	
State x year FE		X		X		X
U (utilities)	390	390	390	390	390	390
T (years)	7	7	7	7	7	7
N (observations)	812	812	812	812	812	812
R^2(overall)	0.02	0.01	0.01	0.01	0.01	0.01
First Stage F Statistics			3.92	3.88	3.90	3.86
Conditional LR Test Stat.			1.47	1.84	6.02	5.87
...p-value			(0.22)	(0.30)	(0.04)	(0.05)
Anderson-Rubin Test Stat.			16.97	17.76	44.42	46.81
...p-value			(0.00)	(0.00)	(0.00)	(0.00)

Notes: Table reports coefficient estimates and standard errors (in parentheses) from regressing the log of average monthly per capita water consumption on the AOC drought measure, the log marginal water fee, and a (AOC × marginal fee) interaction. Texas is dropped from the sample. Observations are utility-years. The weak-instrument-robust 95% confidence intervals using the CLR test for lnP are [-0.51, 0.11], [-0.48, 0.14], [-0.64, 0.00], and [-0.61, 0.03] for columns 3, 4, 5, and 6, and for Drought Months × lnP they are [0.00, 0.19] and [0.00, 0.18] for columns 5 and 6.

Table A6: Water demand models using AOC with marginal water fees, dropping WA

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV	(6) IV
AOC	0.01	0.00	0.00	0.00	−0.31	−0.32
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)
AOC × lnP					0.07	0.08
					(0.01)	(0.01)
lnP	0.49	0.50	−0.14	−0.11	−0.21	−0.20
	(0.04)	(0.04)	(0.15)	(0.46)	(0.04)	(0.06)
Utility FE	X	X	X	X	X	X
Year FE	X		X		X	
State x year FE		X		X		X
U (utilities)	1611	1611	1611	1611	1611	1611
T (years)	8	8	8	8	8	8
N (observations)	4682	4682	4682	4682	4682	4682
R^2(overall)	0.02	0.01	0.01	0.13	0.01	0.06
First Stage F Statistics			3.94	3.93	3.92	3.89
Conditional LR Test Stat.			8.06	6.97	27.43	27.07
...p-value			(0.00)	(0.00)	(0.00)	(0.00)
Anderson-Rubin Test Stat.			83.93	93.56	226.87	242.34
...p-value			(0.00)	(0.00)	(0.00)	(0.00)

Notes: Table reports coefficient estimates and standard errors (in parentheses) from regressing the log of average monthly per capita water consumption on the AOC drought measure, the log marginal water fee, and a (AOC × marginal fee) interaction. Washington is dropped from the sample. Observations are utility-years. The weak-instrument-robust 95% confidence intervals using the CLR test for lnP are [-0.23, -0.04], [-0.22, -0.03], [-0.31, -0.11], and [-0.31, -0.11] for columns 3, 4, 5, and 6, and for Drought Months × lnP they are [0.00, 0.15] and [0.00, 0.15] for columns 5 and 6.

Table A7: Coefficient estimates graphed in Figures 4 & 5 using marginal water fees

	(1) AOC	(2) Drought Months	(3) AOC	(4) Drought Months
Price	−0.13	−0.13	−0.31	−0.44
	(0.06)	(0.06)	(0.06)	(0.07)
Drought	0.00	0.00	−0.14	−0.24
	(0.01)	(0.00)	(0.03)	(0.04)
Drought last year	0.00	0.00	−0.22	−0.18
	(0.00)	(0.00)	(0.03)	(0.04)
Drought 2 years ago	−0.01	0.00	−0.25	−0.23
	(0.00)	(0.00)	(0.03)	(0.04)
Drought 3 years ago	0.00	0.00	−0.13	−0.23
	(0.00)	(0.00)	(0.03)	(0.05)
Drought 4 years ago	0.02	0.03	−0.03	−0.09
	(0.00)	(0.00)	(0.03)	(0.04)
Drought × Price			0.03	0.06
			(0.00)	(0.01)
Drought last year × Price			0.06	0.04
			(0.00)	(0.01)
Drought 2 years ago × Price			0.06	0.06
			(0.00)	(0.01)
Drought 3 years ago × Price			0.03	0.05
			(0.00)	(0.01)
Drought 4 years ago × Price			0.01	0.03
			(0.00)	(0.01)
Utility FE	X	X	X	X
Year FE	X	X	X	X
U (utilities)	1656	1656	1656	1656
T (years)	6	6	6	6
N (observations)	4272	4272	4272	4272
R^2(overall)	0.01	0.01	0.01	0.01
First Stage F Statistics	3.65	3.82	3.73	3.80
Conditional LR Test Stat.	8.24	9.40	35.97	56.73
...p-value	(0.00)	(0.00)	(0.00)	(0.00)
Anderson-Rubin Test Stat.	77.57	79.63	111.40	142.86
...p-value	(0.00)	(0.00)	(0.00)	(0.00)

Notes: Table reports coefficient estimates and standard errors (in parentheses) for the marginal water fee results graphed in panels c and d of Figure 4 (columns 1-2 above) and Figure 5 (columns 3-4 above) in the paper. Observations are utility-years.

Table A8: Weak-instrument-robust 95% confidence intervals using Conditional LR test for coefficient estimates graphed in Figures 4 and 5

	(1) AOC	(2) Drought Months	(3) AOC	(4) Drought Months
Price	[-0.23, -0.04]	[-0.23, -0.03]	[-0.39, -0.19]	[-0.61, -0.34]
Drought × Price			[0.00, 0.07]	[0.00, 0.12]
Drought last year × Price			[0.00, 0.13]	[0.00, 0.09]
Drought 2 years ago × Price			[0.00, 0.12]	[0.00, 0.12]
Drought 3 years ago × Price			[0.00, 0.06]	[0.00, 0.11]
Drought 4 years ago × Price			[0.00, 0.03]	[0.00, 0.06]
Utility FE	X	X	X	X
Year FE	X	X	X	X

Notes: Table reports weak-instrument-robust 95% confidence intervals (using the Conditional Likelihood Ratio test) for the coefficient estimates graphed in panels c and d of Figure 4 (columns 1-2 above) and Figure 5 (columns 3-4 above) in the paper.

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